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Université Clermont-Auvergne
École doctorale des Sciences de la vie, Santé, Agronomie & Environnement



THÈSE

Pour l'obtention du grade de
DOCTEUR D'UNIVERSITÉ

Spécialité : Gestion de l'environnement

Présenté par Donald A. LUNA

**Évaluation de la réponse des prairies à la sécheresse grâce à des séries
chronologiques d'images satellites**

Assessing grassland response to drought using satellite image time series

Soutenue le 20 juin 2023, devant le jury composé de :

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Sommaire Exécutif

La sécheresse est un phénomène naturel associé à des pénuries extrêmes de précipitations entraînant des déficits hydriques. La diminution de la quantité d'eau présente dans le sol a un impact sur l'approvisionnement en eau des plantes. Elle a des conséquences diverses et complexes sur les écosystèmes et menace la qualité et la durabilité de leurs services écosystémiques. Les sécheresses ont des conséquences graves pour les agroécosystèmes, y compris les prairies gérées. En effet, le déficit en eau met en péril la capacité des agroécosystèmes et des prairies gérées à assurer la sécurité alimentaire (Jiang and Wang, 2022 ; O'Mara, 2012 ; Soussana et al., 2013). Les prairies sont des écosystèmes dominés par les graminées, avec une couverture limitée d'arbustes et de plantes pérennes ligneuses dépassant 5 mètres de hauteur (Suttie et al., 2005). Elles fournissent des services écosystémiques, tels que la production de lait et de viande pour nourrir les animaux (Jiang and Wang, 2022 ; O'Mara, 2012) et le piégeage du carbone (Bai et Cotrufo, 2022 ; Bardgett et al., 2021 ; Jones and Donnelly, 2004), qui contribuent à l'atténuation du changement climatique et à l'habitat de la biodiversité pour la faune et la flore (Binder et al., 2018; van Oijen et al., 2018). Une meilleure compréhension des facteurs qui influencent la sensibilité, la résistance et la résilience à la sécheresse des prairies gérées permettra d'orienter les mesures d'atténuation.

De nombreuses études ont mené des expériences de sécheresse en conditions plus ou moins contrôlées, i.e. en pots, en mésocosmes ou sur le terrain afin de mieux comprendre les processus associés aux réponses des prairies à la sécheresse (Ogbaga et al., 2020). Par exemple, les organes des tissus végétaux et les plantes présentent un stress lié au déficit hydrique sous la forme de changements anormaux dans leurs propriétés physiologiques (Volaire, 2018). Les impacts négatifs sont visibles dans le développement des feuilles et des racines (Volaire, 2018). Les plantes présentent une diminution des activités photosynthétiques et révèlent des taux de sénescence plus rapides. Les changements dans les processus physiologiques dus à la sécheresse varient en fonction des capacités et des stratégies de croissance des plantes (Volaire et al., 2009). L'importance des propriétés du sol a été mise en évidence sur différentes espèces de graminées et dans différents milieux pédologiques (Buttler et al., 2019). Les interactions entre les populations végétales mettent en évidence l'influence des diversités taxonomiques et fonctionnelles (Schnabel et al., 2021) et de la composition des communautés végétales (Fry et al., 2021) sur la réponse à la sécheresse. Les pratiques de gestion influencent également la réponse des prairies à la sécheresse. Par exemple, il a été constaté que la fertilisation azotée atténue l'impact de la sécheresse dans une expérience en mésocosme avec des sols riches en argile à Münster, en Allemagne (Klaus et al., 2020). Cependant, la fertilisation azotée a des effets néfastes sur les communautés de prairies si elle est excessive en période de sécheresse (Klaus et al., 2020). Zwicke et al. (2013), dans une expérience menée avec des espèces typiques des prairies tempérées françaises de moyenne montagne, ont montré que des coupes fréquentes peuvent renforcer l'impact négatif de la sécheresse, mais Deléglise et al. (2015) ont constaté que le pâturage augmente davantage l'impact de la sécheresse que la fauche dans les prairies montagneuses de Suisse. Malgré les contributions significatives de ces études sur les effets de la sécheresse sur les prairies, les approches expérimentales en conditions contrôlées et sur le terrain sont encore limitées dans leur couverture spatiale et temporelle. De plus, comme elles sont assez déconnectées des conditions réelles, en raison de certaines limitations de leurs configurations, il a été démontré que les expériences sous-estiment l'impact de la sécheresse sur les prairies (Kröel-Dulay et al. 2022). D'autres approches sont donc nécessaires pour mieux évaluer les réactions de la végétation aux déficits hydriques.

Le développement de produits et de techniques de télédétection (RS) ouvre des voies prometteuses pour la recherche sur les écosystèmes. Les informations sur la réflectance recueillies par les capteurs optiques des satellites permettent d'estimer les propriétés de la végétation sur la base de la théorie du transfert radiatif (Drusch and Crewell, 2006 ; Turner et al., 2003). Les surfaces terrestres, telles que la

végétation, absorbent ou réfléchissent une certaine quantité d'énergie électromagnétique provenant du soleil ou de sources artificielles. Les capteurs embarqués à bord des satellites détectent différents niveaux d'énergie réfléchi en fonction de l'état de la végétation. Une feuille saine absorbe le rouge et le bleu et réfléchit le vert et le proche infrarouge, tandis qu'une feuille stressée absorbe davantage le proche infrarouge et réfléchit le rouge et le bleu. De même, une feuille très humide absorbe davantage dans l'infrarouge court, entre 1 500 et 2 300 nanomètres (nm), et réfléchit le signal lorsque la feuille devient sèche (Summy et al., 2003).

En complément des expériences traditionnelles de déficit hydrique et des observations sur le terrain, cette thèse de doctorat visait principalement à tirer parti du potentiel des séries temporelles d'images satellite pour améliorer les connaissances sur la réponse des prairies gérées à la sécheresse dans des conditions réelles. Elle a d'abord passé en revue les approches méthodologiques actuelles pour l'évaluation de la réponse des prairies à la sécheresse à l'aide de la RS et a analysé les intrants, les applications, les avantages et les inconvénients de chaque approche (chapitre 1). Il a ensuite été évalué la variabilité et les facteurs de la sensibilité des prairies à la sécheresse à l'échelle régionale (Massif central) à l'aide d'une approche d'inférence statistique (chapitre 2). Elle a déterminé l'influence du pédoclimat, des pratiques de gestion, de la diversité de la végétation et des structures des communautés sur la sensibilité des prairies à travers cinq échelles de temps d'intégration de la sécheresse. Enfin, cette thèse a analysé les différences de résistance et de résilience des prairies à la sécheresse en cas de fauche ou de pâturage à l'aide d'un modèle basé sur les processus qui assimile les données de réflectance satellitaire (chapitre 3).

L'examen de l'état de l'art des études sur la réaction des prairies à l'évaluation de la sécheresse à l'aide de la télédétection (chapitre 1) a débuté par une recherche d'articles dans le Web of Science le 31 janvier 2022. Les mots-clés utilisés ont permis de trouver 304 articles, puis un processus de sélection a mis en évidence l'utilisation de la télédétection pour quantifier les propriétés des prairies et identifier ou évaluer les épisodes de sécheresse. Après le processus de sélection, la collection d'articles a été réduite à 64 articles.

L'évaluation des impacts de la sécheresse sur les prairies, basée sur les RS, a révélé l'existence de cinq approches méthodologiques. Avec des complexités et des apports croissants, ces approches ont été classées comme suit : seuil de l'indice de végétation (VI), comparaison des années, analyse des séries temporelles, inférences statistiques et modélisation mécaniste. L'approche de loin la plus courante est l'inférence statistique, qui consiste à déduire l'impact de la sécheresse à partir de la relation statistique entre la réflectance de la végétation obtenue par les satellites et les indices météorologiques de sécheresse en utilisant des ensembles de séries temporelles météorologiques à long terme.

Les résultats de cette analyse bibliographique ont révélé l'utilisation générique du terme "réponse" dans les études d'évaluation, la distribution mondiale inégale des études de RS évaluant la réponse des prairies à la sécheresse et les différences de réponse des prairies par rapport à d'autres écosystèmes et entre les différents types de prairies. La réponse est un terme qui peut faire référence à la résistance, à la résilience ou à la récupération. Seuls certains contextes dans les discussions de l'article examiné ont permis de déterminer l'utilisation spécifique du terme "réponse". En conséquence, cette thèse a suivi les définitions proposées et l'utilisation des concepts de stabilité et de résilience par Van Meerbeek et al. (2021). Les défis identifiés dans la revue se sont concentrés sur le décalage entre les échelles spatiales et temporelles de la réflectance de la végétation et les indicateurs ou indices de sécheresse ; la gamme temporelle limitée ; et les impacts mixtes de la sécheresse et d'autres impacts de perturbation. Les possibilités présentées ont mis en évidence la nécessité de comparer les études entre les types de prairies et les régions biogéographiques, d'utiliser des produits et des techniques de RS nouveaux et existants, et d'évaluer la réponse en fonction d'autres propriétés des prairies. En fin de compte, l'utilisation d'une terminologie commune pour la "réponse" et la normalisation plus poussée des paramètres d'évaluation permettront d'améliorer les comparaisons mondiales des réponses des prairies.

En conclusion, l'examen de l'état des connaissances a révélé les approches méthodologiques existantes pour l'évaluation de la réponse des prairies à la sécheresse à l'aide de la télédétection et a mis en évidence des biais et des lacunes dans la distribution mondiale des études. Elle a appelé à l'identification de l'utilisation spécifique de la "réponse" afin de normaliser et de comparer les études d'évaluation. Enfin, le chapitre 1 a présenté les possibilités offertes par les données et les techniques de télédétection en constante évolution.

Le chapitre 2 a deux objectifs principaux, à savoir quantifier la sensibilité des prairies gérées à la sécheresse à cinq échelles de temps d'intégration de la sécheresse, et évaluer l'influence du pédoclimat, des pratiques de gestion agricole et de la diversité de la végétation sur cette sensibilité.

De nombreuses études basées sur la télédétection et portant sur la sensibilité de la végétation à la sécheresse ont révélé l'importance de la capacité de rétention d'eau du sol (Ji et Peters, 2003), de la topographie (Cartwright, 2020), de la gestion agricole (Burrell et al., 2020) et de la diversité de la végétation (De Keersmaecker et al., 2015). Toutefois, l'influence relative des différents facteurs moteurs (c'est-à-dire la diversité pédoclimatique, la gestion et la végétation) n'a pas encore été évaluée simultanément.

Le chapitre 2 a une couverture à l'échelle régionale et nécessite des informations sur les conditions hétérogènes des prairies. Les données de terrain sur la caractérisation des parcelles de prairies proviennent de trois projets menés dans la région du Massif central entre 2008 et 2019 (Galliot et al., 2020). La gravité de la sécheresse a été évaluée à l'aide d'un indice standardisé modifié de précipitations et d'évapotranspiration (SPEI). Ensuite, les anomalies des indices de végétation (VI), dérivées d'images Landsat multitemporelles, ont été soumises au même processus d'extraction et de normalisation que l'indice SPEI modifié. Les images Landsat ont été sélectionnées en raison de leur longue couverture temporelle.

Dans cette étude, nous avons d'abord évalué les sensibilités de toutes les parcelles de prairies à l'aide d'une approche d'inférence statistique. Les sensibilités des prairies ont été basées sur la relation linéaire entre les anomalies normalisées de la VI et l'indice SPEI. Environ 24 VI ont été testés dans la dérivation de la sensibilité à la sécheresse. Ensuite, nous avons utilisé une procédure de sélection de modèles pour déterminer les facteurs les plus significatifs de la sensibilité des prairies à la sécheresse à partir de trois catégories de facteurs pédoclimatiques, de gestion et de diversité de la végétation. Une répartition de la variance des facteurs les plus significatifs, à partir du modèle final, a permis de rendre compte de l'influence globale de chaque facteur sur la sensibilité des prairies à la sécheresse.

Les résultats du premier objectif ont révélé un coefficient de variation moyen de 27 % pour les cinq échelles temporelles. Ensuite, la VI a été la source la plus importante de variation des sensibilités estimées par rapport à l'échelle de calcul de la sécheresse et à la variabilité géographique.

Les sensibilités dérivées de l'indice de différence normalisé de l'eau (NDWI) et de l'indice global d'humidité de la végétation (GVMI) ont présenté les pentes les plus élevées et la meilleure adéquation entre les anomalies VI normalisées et l'indice SPEI modifié. Cependant, malgré la forte réactivité des anomalies de ces deux indices basés sur l'humidité avec l'indice SPEI modifié, leurs valeurs R² maximales n'ont pas dépassé 0,35.

Conformément aux attentes, les facteurs pédoclimatiques, comme la capacité de rétention d'eau du sol, ont été les principaux facteurs d'atténuation de la sensibilité à la sécheresse. Toutefois, ce qui est nouveau, c'est que ces facteurs n'exercent une grande influence que sur des périodes courtes, inférieures ou égales à 30 jours. Ensuite, les facteurs de gestion ont été significatifs sur toutes les échelles de temps. L'influence la plus forte a été observée à partir de la date de la première utilisation de la prairie par le pâturage, une utilisation tardive augmentant la sensibilité à la sécheresse. Enfin, les facteurs liés à la diversité de la végétation et à la structure des communautés ont atténué l'impact de la sécheresse à long terme, mais les effets étaient faibles à modérés. Les résultats de la répartition de la

variance suggèrent des effets en cascade complexes entre les pratiques de gestion et la diversité de la végétation et la structure des communautés, qui doivent encore être étudiés.

En conclusion, le chapitre 2 a révélé la grande variabilité de la sensibilité des prairies à la sécheresse dans la région du Massif central grâce à la télédétection. Il a souligné l'importance de l'échelle de temps d'intégration de la sécheresse lors de l'évaluation de l'influence des facteurs déterminants de la sensibilité à la sécheresse. Outre les effets en cascade, le chapitre 2 a également soulevé des questions essentielles sur l'importance de la date de première utilisation de la prairie par le pâturage, peu étudiée à toutes les échelles temporelles, et de la moyenne pondérée par la communauté de la masse des graines à des échelles temporelles courtes.

Certaines limites de l'évaluation régionale étaient liées à la relation bruitée entre les anomalies VI normalisées et l'indice SPEI modifié, et à l'incapacité de l'approche d'inférence statistique à distinguer les composantes de résistance et de résilience de la réponse ou de la sensibilité des prairies à la sécheresse.

Le chapitre 3 de cette thèse a fourni une évaluation plus complète des réponses des prairies. Il visait à comparer la résistance et la résilience à la sécheresse des parcelles de prairies fauchées et pâturées. Pour ce faire, cette étude d'évaluation locale a créé et utilisé un modèle simple et parcimonieux de la dynamique de l'indice de surface foliaire verte (LAI). Ce modèle simple est basé sur trois composantes : la croissance de la végétation, la sénescence et l'impact du prélèvement de l'herbe par la gestion agricole. Les paramètres du modèle reflètent l'augmentation maximale quotidienne de l'indice foliaire (g_{max}), l'eau maximale disponible pour les plantes (w_{max}), le taux de sénescence (s_{max}) et le pic de floraison. Un modèle à une couche, basé sur les précipitations et l'évapotranspiration, a été considéré pour la disponibilité de l'eau. Les entrées du modèle ont été limitées à trois facteurs climatiques et deux facteurs de gestion. La gestion a été incorporée dans le modèle sur la base des résultats du chapitre 2.

Le chapitre 3 a été réalisé à l'échelle d'une exploitation ou l'échelle locale et nécessitait des facteurs environnementaux homogènes. Les données détaillées sur la gestion des prairies utilisées pour cette étude proviennent du projet Systèmes d'élevage ALLaitants herbagers : Adapter le type génétique et MIXer les espèces pour renforcer leur durabilité (SALAMIX), qui s'est déroulé de 2015 à 2020 (Prache et al., sous presse). Le SPEI modifié a été utilisé pour évaluer et identifier les événements de sécheresse à partir d'une station météorologique de terrain sur le site. Leurs sévérités respectives (sans unité) ont été basées sur l'aire sous la courbe à partir du seuil de sécheresse. Le modèle PROSAIL et la méthode d'inversion par table de recherche, ainsi que les données Sentinel 2, ont été utilisés pour estimer la dynamique observée de l'indice LAI.

Les valeurs LAI dérivées du satellite ont été assimilées dans le modèle simple pendant la phase d'étalonnage. Deux approches de calibration des paramètres ont également été testées pour le modèle. La première était l'approche d'étalonnage des paramètres fixes, qui utilisait une valeur pour les quatre paramètres pendant toute la période de simulation (2016 à 2020). La seconde est l'approche de calibration des paramètres variables dans le temps, qui tente de reproduire les changements possibles de la capacité de croissance (g_{max}) qui peuvent être dus à des changements dans la composition de la végétation et/ou dans le stockage des ressources.

Une procédure de validation interne et externe du modèle a permis de déterminer le meilleur modèle sur la base des deux approches d'étalonnage. A partir de là, nous avons simulé avec le meilleur modèle le LAI de prairies gérées dans deux conditions, à savoir : les conditions ambiantes (avec la présence de sécheresse), et les conditions sans stress hydrique. Les deux simulations ont permis de déterminer le rapport logarithmique de réponse à la sécheresse. L'étude a estimé la résistance et la résilience des prairies gérées selon la formule de Van Meerbeek et al. (2021).

L'approche d'étalonnage de g_{max} variable dans le temps a donné de meilleurs résultats que l'étalonnage de paramètres fixes dans la validation interne du modèle. Cependant, aucune distinction

claire n'a été trouvée dans la validation externe du modèle. En conséquence, les conditions de stress hydrique ambiant et sans stress hydrique ont été simulées à l'aide du modèle d'étalonnage g_{max} variable dans le temps.

La relation négative entre la résistance des prairies gérées et la gravité de la sécheresse était celle attendue. Cependant, la présence d'un seuil de sécheresse qui a entraîné une relation négative non linéaire est une nouveauté. Le seuil de gravité de la sécheresse de 80 peut correspondre soit à des sécheresses d'une durée supérieure à 40 jours avec une valeur SPEI modifiée constante de -2,0 (extrêmement sec), soit à des sécheresses d'une durée de 80 jours avec une valeur SPEI constante de -1,0 (modérément sec). La résistance des prairies fauchées et des prairies pâturées n'était pas significativement différente. En ce qui concerne la résilience et la sévérité de la sécheresse, une diminution de la résilience a été observée après le seuil de 80 jours de sécheresse. Ici et en accord avec les expériences de terrain de Deléglise et al. (2015) et de Bütof et al. (2012), le pâturage était légèrement plus résilient que la fauche.

En conclusion, de bons ajustements ont été obtenus avec le modèle parcimonieux basé sur les processus du LAI vert assimilé avec Sentinel 2 dans le cadre de la validation interne du modèle. Le modèle a démontré la valeur de l'approche d'étalonnage des paramètres variables dans le temps, qui nécessite des modèles plus complexes. Cependant, l'absence de différence significative entre le pâturage et la fauche était inattendue.

Enfin, le chapitre 3 doit être considéré comme des résultats préliminaires en raison du nombre limité d'enclos de prairies (6 sur 33) considérés dans l'analyse. Une autre limite a été l'hypothèse forte selon laquelle les pratiques de gestion sont restées inchangées pour les conditions de stress hydrique ambiant et sans stress hydrique. Dans ces dernières, la production élevée de biomasse, due à l'absence de sécheresse, devrait encourager une utilisation plus fréquente de l'herbe.

En résumé, cette thèse de doctorat a réalisé des études évaluant la réponse des prairies à la sécheresse à l'aide de la télédétection, ce qui a mis en évidence les approches méthodologiques existantes, les lacunes et les opportunités. Elle a mené deux études complémentaires sur la réponse des prairies à la sécheresse, à savoir : les évaluations à l'échelle régionale et locale en utilisant des modèles linéaires et un modèle simple basé sur le processus assimilé avec les données Sentinel 2, respectivement. Le chapitre 2 ou l'évaluation régionale a révélé l'importance des échelles temporelles de la sécheresse dans l'évaluation de la sensibilité des prairies à la sécheresse. Il a mis en évidence l'influence significative des pratiques de gestion à toutes les échelles temporelles et a appelé à une étude plus approfondie sur les facteurs de gestion et de diversité de la végétation. Le chapitre 3, ou l'évaluation à l'échelle locale à l'aide d'un modèle simple basé sur des processus et assimilé à des données satellitaires, s'appuie sur les résultats et les limites de l'évaluation régionale. Le chapitre 3 a abordé la relation bruitée en utilisant le rapport de réponse logarithmique à la sécheresse sur la base de trajectoires simulées avec le modèle. La réponse logarithmique a permis de déterminer les composantes de résistance et de résilience de la réponse des prairies à la sécheresse selon la formule de Van Meerbeek et al. (2021). Les résultats préliminaires du chapitre 3 mettent en évidence la bonne adéquation des modèles parcimonieux basés sur les processus. Il reste nécessaire d'inclure des dynamiques écologiques plus réalistes dans le modèle. Aucune différence significative n'a été trouvée dans la résistance et la résilience des prairies fauchées et pâturées. Cependant, les prairies pâturées ont révélé une résilience à la sécheresse légèrement supérieure à celle des prairies fauchées, ce qui est cohérent avec les expériences menées sur le terrain.

Dans l'ensemble, le modèle linéaire du chapitre 2 et le modèle basé sur les processus du chapitre 3 peuvent être interchangeables si l'on dispose respectivement de données sur les caractéristiques des prairies et les informations détaillées de gestions agricoles. La prise en compte d'autres facteurs plus liés à la réponse à la sécheresse, tels que la longueur des racines, la surface spécifique des racines et d'autres caractéristiques des plantes, pourrait améliorer les évaluations. Le chapitre 2 peut également prendre

en compte les conditions microclimatiques générées par la couverture végétale environnante. Le chapitre 3 peut envisager deux directions de développement en incorporant des processus écophysologiques plus détaillés ou en reflétant l'influence de la dynamique des communautés végétales sur la productivité et la réaction à la sécheresse des prairies gérées.

Executive Summary

Drought is a natural phenomenon associated with extreme precipitation shortages leading to water deficits. The decrease in the amount of water is exhibited in the soil and impacts the water supply for plants. It causes various and complex consequences on ecosystems and threatens the quality and sustainability of their ecosystem services. Droughts have serious implications for agroecosystems, including managed grasslands. Indeed, the deficit in available water for agroecosystems and managed grasslands endangers their ability to address food security (Jiang and Wang, 2022; O'Mara, 2012; Soussana et al., 2013). Grasslands are graminoid-dominated ecosystems with limited shrubs and woody perennial covers exceeding 5 meters in height (Suttie et al., 2005). They provide ecosystem services, such as the production of milk and meat as feed to animals (Jiang and Wang, 2022; O'Mara, 2012), and carbon sequestration (Bai and Cotrufo, 2022; Bardgett et al., 2021; Jones and Donnelly, 2004) supporting the mitigation of Climate Change and biodiversity habitat for fauna and flora (Binder et al., 2018; van Oijen et al., 2018). A better understanding of factors that influence the sensitivity, resistance, and resilience to drought of managed grasslands will help guide mitigation measures.

Many studies have conducted controlled pot, mesocosm, or field drought experiments to better understand the processes associated with grassland responses to drought (Ogbaga et al., 2020). For example, plant tissue organs and individual plants exhibit water deficit stress as anomaly changes in their physiological properties (Volaire, 2018). The negative impacts are visible in the development of leaves and roots (Volaire, 2018). Plants exhibit a decrease in photosynthetic activities and reveal faster plant senescence rates. Changes in the physiological processes due to drought vary based on plant capabilities and growth strategies (Volaire et al., 2009). The importance of soil properties is highlighted with the comparison of the growth of prominent grass species in different soil mediums (Buttler et al., 2019). The interactions among plant populations demonstrate the influence of taxonomic and functional diversities (Schnabel et al., 2021) and vegetation community composition (Fry et al., 2021) on the response to drought. Management practices also influence the response of grasslands to drought. For example, it has been found that Nitrogen fertilization mitigates drought impact in a mesocosm experiment with clay-rich soils in Münster, Germany (Klaus et al., 2020). However, Nitrogen fertilization causes detrimental effects on grassland communities if done excessively during drought (Klaus et al., 2020). Zwicke et al. (2013) in an experiment conducted with species typical of French temperate grasslands showed that frequent cuts may enhance drought impact, but Deléglise et al. (2015) found that grazing increases drought impact more than mowing in the mountainous grasslands of Switzerland. Despite the significant contributions of these grassland-drought studies, controlled and field water deficit experimental approaches are restricted still in their spatial and temporal coverages. Moreover, as they are disconnected from real-life conditions, due to some limitations of their setups, it has been shown that experiments underestimate the impact of drought on grasslands (Kröel-Dulay et al. 2022). Thus, additional approaches are needed to provide a better assessment of vegetation responses to water deficits.

The development of remote sensing (RS) products and techniques opens promising avenues for ecosystem research. The reflectance information collected by optical satellite sensors allows the estimation of vegetation properties based on the radiative transfer theory (Drusch and Crewell, 2006; Turner et al., 2003). Surfaces on the Earth, such as vegetation, either absorb or reflect a certain amount of electromagnetic energy from the sun or artificial sources. Sensors, onboard the satellites, detect different levels of reflected energy depending on the vegetation condition. A healthy leaf absorbs red and blue, and reflects green and near-infrared reflectance, while a stressed leaf absorbs more near-infrared and reflects the visible red and blue. Similarly, high leaf moisture absorbs more shortwave-infrared reflectance, between 1,500 and 2,300 nanometers (nm), and reflects the signal as the leaf turns dry (Summy et al., 2003).

Complementary to traditional water deficit experiments and field observations, this Ph.D. thesis primarily aimed to take advantage of the potential of satellite image time series for improving knowledge on the response of managed grasslands to drought in real-life conditions. It first reviewed the current methodological approaches for the assessment of grassland response to drought using RS and analyzed the inputs, applications, advantages, and disadvantages of each approach (Chapter 1). Then it assessed the variability and drivers of grassland sensitivity to drought at a regional scale (the Massif central region) using a statistical inference approach (Chapter 2). It determined the influence of pedoclimate, management practices, and vegetation diversity and community structures on grassland sensitivity across five drought integration timescales. Finally, this thesis analyzed differences in grassland resistance and resilience to drought under mowing or grazing using a process-based model that assimilates satellite reflectance data (Chapter 3).

The state-of-the-art review of studies on grassland response to drought assessment using remote sensing (Chapter 1) was initiated with an article search in the Web of Science on 31 January 2022. The implemented keywords resulted in 304 articles, then a screening process highlighted the use of RS in quantifying grassland properties and identifying or assessing drought events. After the screening process, the article collection was reduced to 64 preliminary articles.

The RS-based assessment of drought impacts on grasslands revealed the existence of five methodological approaches. With increasing complexities and inputs, these approaches were classified as vegetation index (VI) threshold, year comparison, time series analysis, statistical inferences, and mechanistic modelling. By far, the most common approach is statistical inference, which consists of inferring the impact of drought from the statistical relationship between vegetation satellite reflectance and meteorological drought indices using long-term time series datasets.

The findings of this bibliographic analysis revealed the generic use of “response” in the assessment studies; the uneven global distribution of RS studies assessing grassland response to drought; and the differences in responses of grasslands compared to other ecosystems and among different grassland types. Response is a term that can refer to either resistance, resilience, or recovery. Only certain contexts in the discussions of the reviewed article allowed the determination of the specific use of “response”. Accordingly, this thesis followed the proposed definitions and use of stability and resilience concepts by Van Meerbeek et al. (2021). The identified challenges in the review focused on the mismatch between the spatial and temporal scales of the vegetation reflectance and drought indicators or indices; the limited temporal range; and the mixed impacts of drought and other disturbance impacts. The presented opportunities highlighted the need for study comparisons among grassland types and biogeographic regions; the utilization of new and existing RS products and techniques; and the assessment of response based on other grassland properties. Ultimately, the use of common terminology for “response” and the further standardization of assessment parameters will lead to better global comparisons of grassland responses.

In conclusion, the state-of-the-art review revealed the existing methodological approaches for the assessment of grassland response to drought using remote sensing and found biases and gaps in the global distribution of studies. It called for the identification of the specific use of “response” to standardize and compare assessment studies. Finally, Chapter 1 presented opportunities from the continuously developing RS data and techniques.

Chapter 2 has two main objectives, namely, to quantify the sensitivity of managed grassland to drought at five drought integration timescales, and to assess the influence of the pedoclimate, agricultural management practices, and vegetation diversity on said sensitivity.

Multiple remote sensing-based studies on vegetation sensitivity to drought revealed the importance of soil water holding capacity (Ji and Peters, 2003), topography (Cartwright, 2020), agricultural management (Burrell et al., 2020), and vegetation diversity (De Keersmaecker et al., 2015). However,

the relative influence of different driving factors (i.e., pedoclimatic, management, and vegetation diversity) has yet to be assessed at the same time.

Chapter 2 has regional coverage and requires information on heterogeneous grassland conditions. The input field data on grassland parcel characterizations were from three conducted programs and projects in the Massif central region from 2008 to 2019 (Galliot et al., 2020). Drought severity was assessed using a modified Standardized Precipitation and Evapotranspiration Index (SPEI). Then the anomalies of vegetation indices (VI), derived from multi-temporal Landsat images, underwent the same extraction and standardization process of the modified SPEI. Landsat images were selected because of their long temporal coverage.

In this study, we first assessed the sensitivities of all grassland plots using a statistical inference approach. Grassland sensitivities were based on the linear relationship of standardized VI anomalies and drought severity index. About 24 VI were tested in the derivation of sensitivity to drought. Then, we used a model selection procedure to determine the most significant drivers of grassland sensitivity to drought from three categories of pedoclimate, management, and vegetation diversity factors. A variance partitioning of the significant driving factors, from the final model, accounted for the overall influence of each category on grassland sensitivity to drought.

The results of the first objective revealed a 27% mean coefficient of variation across the five timescales. Then VI was the most important source of variation of the estimated sensitivities compared to drought timescale of computation, and geographic variability.

The Normalized Difference Water Index (NDWI) and the Global Vegetation Moisture Index (GVMI) derived sensitivities exhibited the highest slopes and goodness-of-fit between the standardized VI anomalies and modified SPEI. However, despite the high responsiveness of the anomalies of these two moisture-based indices with the modified SPEI, their maximum R² values did not exceed 0.35.

Within expectation, pedoclimatic factors, like the soil water holding capacity, were key mitigating drivers of sensitivity to drought. However, something new is its high influence only in short timescales equal to and less than 30 days. Then, management factors were significant across all timescales. The highest influence was from the date of first use, where late use increased drought sensitivity. Finally, vegetation diversity and community structure factors mitigated drought impact at long timescales, but the effects were weak to moderate. The findings of the variance partitioning suggest complex cascading effects between management practices and vegetation diversity and community structure that still need to be addressed.

In conclusion, Chapter 2 revealed the high variability of grassland sensitivity to drought in the Massif central region using remote sensing. It underscored the importance of drought integration timescale when assessing the influence of driving factors of sensitivity to drought. Apart from the cascading effects, Chapter 2 also raised key questions on the importance of the understudied date of first use across all timescales and the community weighted mean of seed mass at short timescales.

Some limitations of the regional assessment were related to the noisy relationship between the standardized VI anomalies and modified SPEI, and the inability of the statistical inference approach to distinguish the resistance and resilience components of the grassland response or sensitivity to drought.

Chapter 3 of this thesis provided a more comprehensive assessment of grassland responses. It aimed to compare the resistance and resilience to drought of mowed and grazed grassland paddocks. To do so, this local assessment study created and used a simple and parsimonious process-based model of the dynamics of the green leaf area index (LAI). The simple process-based model is based on three components including vegetation growth, senescence, and impact of herbage uptake. The model parameters reflected the daily maximum increase in LAI (gmax), maximum available water for plants (wmax), rate of senescence (smax), and the peak of flowering. A one-layer bucket model, based on

precipitation and evapotranspiration, was considered for the water availability. Model inputs were limited to three climatic and two management factors. Management was incorporated into the model based on the results of Chapter 2.

Chapter 3 was conducted on a farm or local scale and required homogeneous environmental factors. The detailed grassland management data for this study was from the Systèmes d'élevage ALlaitants herbagers : Adapter le type génétique et MIXer les espèces pour renforcer leur durabilité (SALAMIX) project, which was conducted from 2015 to 2020 (Prache et al., in press). The modified SPEI was used to assess and identify drought events based on a field meteorological station on the site. Their respective drought severities (unitless) were based on the area under the curve from the drought threshold. The PROSAIL model and look-up table inversion method, together with Sentinel 2 data, were used to estimate the observed dynamics of LAI.

The satellite-derived LAI values were assimilated in the simple model during the calibration phase. Two parameter calibration approaches were also tested for the model. First was the fixed parameter calibration approach, which used one value for all four parameters during the entire period of simulation (2016 to 2020). The second was the time-varying parameter calibration approach, which attempts to replicate the possible changes in growth capacity (g_{max}) that may be due to changes in vegetation composition and/or resource storage.

An internal and external model validation procedure determined the better model based on the two calibration approaches. From here, we simulated with the better model the LAI of managed grasslands under two conditions, namely: the ambient (with the presence of drought), and the without water stress conditions. The two simulations allowed the determination of the logarithmic drought response ratio. The study estimated the resistance and resilience of managed grasslands according to the formula in Van Meerbeek et al. (2021).

The time-varying g_{max} calibration approach performed better than the fixed parameter calibration in the internal model validation. However, no clear distinction was found in the external model validation. Accordingly, the ambient and without water stress conditions were simulated using the time-varying g_{max} calibration model.

The negative relationship between the resistance of the managed grasslands and drought severity was within expectation. However, something new was the presence of a drought threshold that resulted in a non-linear negative relationship. The drought severity threshold of 80 can either be droughts with durations longer than 40 days with a constant modified SPEI value of -2.0 (extremely dry) or durations of 80 days with a constant -1.0 SPEI value (moderately dry). Then, the resistance between mowed and grazed grasslands was not significantly different. While for resilience and drought severity, a decrease in resilience was observed after the 80 drought threshold. Here and consistent with the field experiments in Deléglise et al. (2015) and in Bütof et al. (2012), grazing was slightly more resilient than mowing.

In conclusion, good fits were obtained with the parsimonious process-based model of green LAI assimilated with Sentinel 2 under the internal model validation. The model demonstrated the value of the time-varying parameter calibration approach, which calls for more complex models. However, the lack of a significant difference between grazing and mowing was unexpected.

Finally, Chapter 3 should be considered as preliminary results due to the limited number of grassland paddocks (6 of 33) in the analysis. Another limitation was the strong assumption that management practices remained unchanged for both the ambient and without water stress conditions. During the latter, the high production of biomass, due to the absence of drought, is expected to encourage more frequent herbage use.

In summary, this Ph.D. thesis conducted a review of studies assessing grassland response to drought using remote sensing, which highlighted existing methodological approaches, gaps, and opportunities.

It conducted two complementary studies on grassland response to drought, namely: the regional and local scale assessments using linear models and a simple process-based model assimilated with Sentinel 2 data, respectively. Chapter 2 or the regional assessment revealed the importance of drought timescales in grassland sensitivity to drought assessment. It highlighted the significant influence of management practices across all the timescales and called for further investigation into the partition of explained variance shared by management and vegetation diversity drivers. Chapter 3, or the local scale assessment using a simple process-based model assimilated with satellite data was built on the results and limitations of the regional assessment. Chapter 3 addressed the noisy relationship using the logarithmic response ratio to drought based on simulated trajectories with the model. The log response ratio allowed the determination of the resistance and resilience components of the grassland response to drought according to the formula by Van Meerbeek et al. (2021). Chapter 3 preliminary results highlight the good fit of parsimonious process-based models. There remains the need to include more realistic ecological dynamics in the model. No significant differences were found in the resistance and resilience of mowed and grazed grasslands. However, grazed grasslands revealed slightly higher resilience to drought than mowed ones which is consistent with field-conducted experiments.

Overall, the linear model of Chapter 2 and the process-based model of Chapter 3 can be interchanged if data on grassland characteristics and detailed management records, respectively, are available. Consideration of other drivers more related to the response to drought, such as root length, specific root area, and other plant traits, may improve the assessments. Chapter 2 may also account for microclimate conditions generated by surrounding vegetation cover. Chapter 3 may consider two directions for development by incorporating either more detailed eco-physiological processes or reflecting the influence of vegetation community dynamics on the productivity and response to drought of managed grasslands.

For the love of science...

Résumé

Les sécheresses deviennent plus fréquentes et intenses avec le changement climatique, ce qui menace la durabilité des services écosystémiques fournis par de nombreux agroécosystèmes, y compris les prairies gérées, dans de nombreuses régions du monde. L'anticipation et l'atténuation des effets de la sécheresse ont motivé les recherches scientifiques en agronomie, écophysiologie et écologie. Pour mieux comprendre les processus associés à la réponse des prairies aux sécheresses, de nombreuses études ont mené des expérimentations en pot, en mésocosme ou sur le terrain. Malgré leur rôle primordial dans l'élaboration de nos connaissances actuelles, ces approches font face à des limitations cruciales comme leur étendue spatio-temporelle restreinte et leur disjonction des conditions réelles. Le développement de produits et de techniques de télédétection ouvre des pistes prometteuses pour le suivi des écosystèmes terrestres et leur réponse aux diverses sources de perturbations. En complément des expérimentations plus classiques sur la sécheresse et des observations sur le terrain, cette thèse a pour objectif de tirer parti des données de télédétection satellitaires à long terme pour évaluer la variabilité et les déterminants de la réponse des prairies à la sécheresse dans les systèmes agricoles du Massif central. Pour ce faire, cette thèse examine d'abord les approches méthodologiques actuelles pour l'évaluation de la réponse des prairies à la sécheresse par télédétection. Elle révisé ensuite à déterminer la variabilité et les facteurs de sensibilité des prairies à la sécheresse à l'échelle régionale. Enfin, elle approfondit l'analyse de ces réponses en s'affranchissant de facteurs confondants, grâce à l'assimilation de données de télédétection à un modèle simple de croissance des prairies permanentes gérées.

La revue bibliographique des analyses par télédétection des effets de la sécheresse sur les prairies a révélé l'existence de cinq approches méthodologiques alternatives. De loin, l'approche méthodologique la plus courante appelée ici « inférence statistique » consiste à inférer l'impact de la sécheresse à partir de la relation statistique entre la réflectance de la végétation et les indices météorologiques de sécheresse à l'aide de données chronologiques à long terme. Cette analyse bibliographique a également montré que la plupart des recherches ont été menées dans les Grandes Plaines (Amérique du Nord) et le Plateau mongol (Asie centrale) laissant de nombreux vides biogéographiques, en particulier dans les régions tempérées de l'Europe occidentale.

La deuxième partie de cette thèse souligne la forte variabilité de la réponse des prairies gérées tempérées dans une région montagneuse hétérogène (le Massif central en France). Plus important encore, cette variabilité pourrait s'expliquer par un ensemble de facteurs pédoclimatiques, la diversité végétale et les pratiques de gestion. Conformément à l'attendu, certains facteurs pédologiques et topographiques, comme la capacité de rétention en eau du sol, ont été identifiés comme des facteurs d'atténuation clés des effets de la sécheresse. En outre, nos résultats ont montré une sensibilité plus faible des prairies préférentiellement fauchées plutôt que pâturées et avec une utilisation précoce. Pour les sécheresses longues et peu fréquentes, la diversité végétale a eu d'importants effets atténuants, mais nos conclusions suggèrent des effets en cascade complexes entre les pratiques de gestion et la structure des communautés végétales qui doivent encore être examinés.

Enfin, la dernière partie de cette thèse a fourni une évaluation plus complète des réponses des prairies à la sécheresse en décomposant ses composantes de résistance et de résilience et en isolant l'impact de la sécheresse des influences confondantes des événements de gestion (coupe ou rotations de pâturage) et la phénologie de la végétation. Pour ce faire, l'information sur la réflectance du satellite Sentinel 2 a été assimilée dans la phase de calibrage d'un modèle simple basé sur un processus simulant la dynamique de l'indice de surface foliaire vert. Avec des pratiques de gestion détaillées et des données météorologiques comme variables d'entrée, les simulations des pâturages et des prairies fauchées dans des conditions normales et avec un approvisionnement en eau illimité ont permis d'extraire les composantes de résistance et de résilience de la réponse des prairies à des événements de

sécheresse de gravité variable entre 2016 et 2020. Les pâturages et les prairies fauchées ne présentaient pas de différences significatives en termes de résistance à la sécheresse. Cependant, les pâturages ont montré une résilience légèrement supérieure à celle des prairies fauchées.

En conclusion, cette thèse appuie l'avantage des séries chronologiques d'images satellites pour évaluer la réponse des prairies aménagées à la sécheresse comme approche complémentaire aux expérimentations en conditions contrôlées et aux observations sur le terrain. Les résultats ont confirmé une plus grande sensibilité à la sécheresse des pâturages que des prairies fauchées et le rôle atténuant de la diversité végétale dans des conditions réelles en utilisant l'approche de l'inférence statistique. Cependant, la grande variabilité de la sensibilité des prairies à la sécheresse dans l'espace et dans le temps suggère des interactions complexes entre les facteurs déterminants et la nécessité de séparer les effets de la sécheresse des autres sources de perturbation des signaux de télédétection. L'assimilation des données de télédétection à un simple modèle de prairies offre une nouvelle perspective à cet égard. En priorité, les développements de futurs modèles devraient se concentrer sur l'intégration du rôle de la diversité végétale et de sa dynamique dans la modulation des impacts de la sécheresse sur les stades de végétation.

Mots-clés : résilience, télédétection, SPEI, modèle mécaniste, échelles de temps, sécheresse météorologique

Abstract

Drought events are becoming more frequent and severe with climate change, threatening the sustainability of ecosystem services provided by many agroecosystems, including managed grasslands in many regions of the world. The anticipation and mitigation of drought impacts have motivated scientific researches in agronomy, ecophysiology, and ecology. To better understand the processes associated with grassland responses to drought, many studies have conducted controlled pot, mesocosm, or field experiments. Despite their crucial role in building our current knowledge, these approaches face critical limitations such as their restricted spatio-temporal coverage and their disconnection from real-life conditions. The development of remote sensing (RS) products and techniques opens promising avenues for monitoring terrestrial ecosystems and their response to various sources of disturbances. As a complement to more traditional drought experiments and field observations, this Ph.D. thesis aimed at taking advantage of long-term satellite RS data, together with climate and field data, to assess the variability and drivers of grassland response to drought in agricultural systems in the Massif central. To do so, this thesis first reviewed the current methodological approaches for the assessment of grassland response to drought using RS. It addresses the central objective of determining the variability and drivers of grassland sensitivity to drought at the regional scale. Finally, it sought to comprehensively analyze the impact of drought, amidst the confounding factors, by assimilation of RS data with a simple model of grassland growth.

The review of RS-based analyses of drought impacts on grasslands revealed the existence of five alternative methodological approaches. By far, the most common one called here as the “statistical inference” approach consists of inferring the impact of drought from the statistical relationship between vegetation reflectance and meteorological drought indices using long time series datasets. This bibliographic analysis also showed that most of the researches were conducted in the Great Plains (North America) and Mongolian Plateau (Central Asia) leaving many biogeographic gaps, particularly in the temperate regions of Western Europe.

The second part of this thesis emphasized the strong variability of the response of temperate managed grasslands across a heterogeneous mountainous region (the Massif central, France). Most importantly, such variability could be explained by a set of pedoclimatic factors, vegetation diversity, and management practices. As expected, some soil and topographic factors, like the soil water holding capacity, were identified as key mitigating factors of drought impacts. In addition, our results showed lower sensitivity of grasslands predominantly mown rather than grazed and with early herbage uptake. For long and infrequent drought events, vegetation diversity had significant mitigating effects, but our findings suggest complex cascading effects between management practices and plant community structure that still need to be addressed.

Finally, the last part of this thesis provided a more comprehensive assessment of grassland responses to drought by decomposing its resistance and resilience components and by isolating the impact of drought from the confounding influences of management events (cutting or grazing rotations) and vegetation phenology. To do so, Sentinel 2 satellite reflectance information was assimilated in the calibration phase of a simple process-based model simulating the dynamics of the green Leaf Area Index. With detailed management practices and meteorological data as input variables, the simulations of pastures and meadows under normal conditions and unlimited water supply allowed the extraction of the resistance and resilience components of grassland response to drought events of varying severity between 2016 and 2020. Pastures and meadows were insignificantly different in terms of resistance to drought. However, pastures showed slightly higher resilience than meadows.

In conclusion, this thesis supports the benefit of satellite image time series for assessing the response of managed grasslands to drought as a complementary approach to controlled experiments and field observations. The results detected higher sensitivity to drought of pastures than meadows and the mitigating role of vegetation diversity in real-life conditions using the statistical inference approach. However, the high variability of grassland sensitivity to drought in space and time suggests complex interactions between the driving factors and the need to separate drought effects from other sources of disturbance in RS signals. The assimilation of RS data with a simple grassland model offers a new perspective in this respect. In priority, future model developments should focus on incorporating the role of vegetation diversity and its dynamics in modulating drought impacts on vegetation states.

Keywords: resilience, remote sensing, SPEI, mechanistic model, time scales, meteorological drought

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List of Abbreviations

AEOLE	<i>Atout Economique pour cOnstruire des systèmes d'ÉLevage</i>
AOP	<i>Appellations d'Origine Protégées</i>
ARVI	Atmospherically Resistant Vegetation Index
ATOUS	<i>Approche Territoriale de l'Autonomie Fourragère et des services</i>
AVHRR	Advanced Very High Resolution Radiometer
BT	Brightness temperature
C: N	Carbon to Nitrogen Ratio
CBN	<i>Conservatoire Botanique National</i>
CHRIS	Compact High-Resolution Imaging Spectrometer
CNES	<i>Centre National d'Etudes Spatiales</i>
CNRM	<i>Centre National de Recherches Météorologiques</i>
CWM	Community Weighted Mean
DALEC	Data Assimilation-Linked ECosystem
DIVGRASS	Plant Functional DIVersity of GRASSlands
DS	Drought severity
DVI	Difference Vegetation Index
EOS	End of season
ESDAC	European Soil Data Centre
ET	Evapotranspiration
EVI	Enhanced Vegetation Index
EVI2	Enhanced Vegetation Index 2
FAO	Food and Agriculture Organization of the United Nations
Fdis	Functional dispersion
GCI	Green Chlorophyll Index
GDD	Growing degree days
GEE	Google Earth Engine
GEMI	Global Environment Monitoring Index
GNDVI	Green Normalized Difference Vegetation Index
GPP	Gross primary productivity
GVMi	Global Vegetation Moisture Index
GWP	Global Water Partnership
HysIS	Hyperspectral Imaging Satellite
INRAE	<i>Institut national de recherche pour l'agriculture, l'alimentation et l'environnement</i>
IPCC	Intergovernmental Panel on Climate Change
IPVI	Infrared Percentage Vegetation Index
IWUE	Instantaneous water use efficiency
K ₂ O	Potassium oxide
LAI	Leaf area index
LaSRC	Land Surface Reflectance Code
LEWT	Leaf equivalent water thickness
LINGRA	Light INTerception and UtIlisation simulator (LINTUL)-GRASS
LOS	Length of season
LRR	Log response ratio
LSWI	Land Surface Water Index
LUE	Light-use efficiency
LUT	Look-Up Table

MAE	Mean absolute error
MAJA	MACCS – ATCOR Joint Algorithm
MaxAE	Maximum absolute error
MetOp	Meteorological Operational Satellite Program
MgO	Magnesium oxide
MODIS	Moderate Resolution Imaging Spectroradiometer
MRE	Mean relative error
MSI	MultiSpectral Instrument
mSPEI	Modified SPEI
MSR	Modified Simple Ratio
MTVI2	Modified Triangular Vegetation Index 2
MVC	Maximum-value composite
NDSVI	Normalized Difference Senescence Vegetation Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NetCF	Network Common Data Form
NIR	Near Infrared
NLI	Non-Linear Index
NMDI	Normalized Multi-band Drought Index
NOAA	National Oceanic and Atmospheric Administration
NPP	Net primary production
NRI	Nitrogen Reflectance Index
ORCHIDEE-GM	Organizing Carbon and Hydrology in Dynamic Ecosystems – Grassland Management
OSAVI	Optimized Soil-Adjusted Vegetation Index
P ₂ O ₅	Phosphorus pentoxide
PaSiM	Pasture simulation model
PDSI	Palmer’s Drought Severity Index
PET	Potential Evapotranspiration
RMSE	Root mean square error
RRMSE	Relative root mean square error
RS	Remote sensing
RTM	Radiative transfer model
SAFRAN	<i>Système d’Analyse Fournissant des Renseignements Adaptés à la Nivologie</i>
SAFY	Simple Algorithm for Yield Estimate
SAIL	Scattering by Arbitrary Inclined Leaves
SALAMIX	<i>Systèmes d’élevage ALLaitants herbagers: Adapter le type génétique et MIXer les espèces pour renforcer leur durabilité</i>
SAR	Synthetic aperture radar
SAU	<i>Surface Agricole Utile</i>
SAVI	Soil-Adjusted Vegetation Index
SCOPE	Soil-Canopy Observation of Photosynthesis and Energy fluxes
SIF	Solar-induced fluorescence
SIPI	Structure Insensitive Pigment Index
SITS	Satellite image time series
SLA	Specific Leaf Area
SLA	Specific leaf area
SLAVI	Specific Leaf Area Vegetation Index
SOC	Soil Organic Carbon
SOM	Soil Organic Matter

SON	Soil Organic Nitrogen
SOS	Start of season
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SPOT	<i>Satellite pour l'Observation de la Terre</i>
SRVI	Simple Ratio Vegetation Index
STH	<i>Surface Toujours en Herbe</i>
STICS	<i>Simulateur multIdisciplinaire pour les Cultures Standard</i>
SWHC	Soil Water Holding Capacity
SWIR	Shortwave Infrared
TCI	Temperature Condition Index
TIROS	Television Infrared Observation Satellite
TVI	Transformational Vegetation Index
TWI	Terrain Wetness Index
UREP	<i>Unité Mixte de Recherche sur l'Ecosystème Prairial</i>
VARI	Visible Atmospherically Resistant Index
VCI	Vegetation Condition Index
VegDRI	Vegetation Drought Response Index
VEN _μ S	Vegetation and Environment New micro (μ) Satellite
VH	Vertical - Horizontal
VHI	Vegetation Health Index
VI	Vegetation Index
VISTOCK	Virtual Fencing for precision management of beef cattle farms
VNIR	Visible and near-infrared
WMO	World Meteorological Organization

GENERAL INTRODUCTION

GENERAL INTRODUCTION

A. Under the context of climate change and drought

The Intergovernmental Panel on Climate Change (IPCC) revealed that human-induced climate change started as early as the 1980s (Hansen et al., 2006; Houghton et al., 1990). Climate change is a statistically significant shift in the mean and variability of climatic properties caused by natural unpredictability and the influence of anthropogenic activities (Pielke, 2004).

The degradation of ecosystems and the decline of biodiversity due to the increasing temperature and occurrence of extreme climatic events are among the impacts of climate change (Clarke et al., 2022; Hansen et al., 2012; IPCC, 2022). For example, climate change has caused shifts in the distribution of plant species to higher elevation gradients due to changes in environmental properties (Davis and Shaw, 2001; Van der Putten, 2012). Climate change impairs the realization of ecosystem processes like carbon, water and nutrient cycles, water use, and community dynamics (Grimm et al., 2013; Yvon-Durocher et al., 2010), which is hampered also by biodiversity decline (Beier et al., 2012; Loreau et al., 2001; Tilman et al., 2014).

One critical aspect of climate change is the increase in frequency, intensity, and duration of droughts (Leng et al., 2015; Mukherjee et al., 2018; Sperry and Love, 2015). Drought events occur with a drastic reduction of precipitation and higher air temperature and solar radiation that leads to faster evapotranspiration rates that result in deficits in the climatic water balance (Dai, 2011). Drought threatens system productivity and longevity due to water stress impacts on plants and ecosystems (Porporato et al., 2001). The altered water supply to rain-fed agroecosystems, due to variabilities in precipitation and temperature, threatens food security (Bandara and Cai, 2014; Muluneh, 2021).

1. Managed grasslands

Grasslands are graminoid-dominated ecosystems with limited cover of tall shrubs and woody perennials that exceed 5 meters in height (Suttie et al., 2005; Xu and Guo, 2015). They cover about 20 to 40% of the Earth's terrestrial surface (Bardgett et al., 2021; Dixon et al., 2014) and are distributed in various topographic and climatic regions of the world (Dixon et al., 2014; Godde et al., 2020; Xu and Guo, 2015). Grassland distribution depends on local climate, soil, water, topography, and disturbance regimes that prevent the course of the ecological succession from pioneer stages dominated by herbs and grasses to mature stages dominated by trees (Petermann and Buzhdygan, 2021). Alpine and tundra grasslands are maintained by cold seasons that naturally hinder the development of woody ecosystems. Tropical regions have wet and dry seasons that promote vegetation growth, thus requiring

fire or other forms of disturbance to maintain grassland cover (Dixon et al., 2014; Strömberg and Staver, 2022). Flooded plains impede the recruitment of trees by preventing seed germination with water inundation. Aside from these natural determinants of distribution, anthropogenic activities play an extensive role in the maintenance of grasslands, through grazing of livestock and agriculture practices. The need to address the food security demands of the human population influences the greater use of pastures and meadows for milk and meat production.

The grassland classifications change between regions of the world (Bai and Cotrufo, 2022; Pellaton et al., 2022). Concerning agricultural management, graminoid-dominated ecosystems are classified as natural, semi-natural, and improved grasslands (Bengtsson et al., 2019; Chang et al., 2021). Improved grasslands resemble agricultural lands due to intensive management practices (plowing and sowing) for high production yield (Pilgrim et al., 2010). On the other side, natural grasslands are free from anthropogenic management pressures (Parr et al., 2014). In between these two extreme types, semi-natural or managed grasslands are characterized by either sown mixtures or spontaneous vegetation dynamics, influenced by agricultural practices of herbage usage by grazing or mowing and nutrient fertilization. The grazing and mowing activities in managed grasslands may promote higher biodiversity depending on their intensity (Pulungan et al., 2019) and prevent the growth of unwanted invasive plant species (Kun et al., 2021).

Managed grasslands provide key ecosystem services that benefit both humans and the environment. The most obvious is the provisioning service, which allows billions of employment opportunities related to meat and milk production (Jiang and Wang, 2022; O'Mara, 2012; Soussana et al., 2013). Regarding, regulating services, grasslands sequester and store about 34% of terrestrial carbon, where about 90% is below ground (Bai and Cotrufo, 2022; Bardgett et al., 2021; Jones and Donnelly, 2004). Managed grasslands contribute also to the cultural landscape and recreational activities despite their main use for production (Dengler et al., 2014; Pellaton et al., 2022). Part of these services is supported by high biodiversity hosted by grasslands (Binder et al., 2018; van Oijen et al., 2018), which can reach, for example, a maximum of 89 plant species per m² (Wilson et al., 2012).

Compared to other ecosystems and within agroecosystems, grasslands are negatively impacted by drought (Deng et al., 2021; Ji and Peters, 2003; Teuling et al., 2010; Tollerud et al., 2018). The aboveground and belowground grassland biomass can decrease by at least 25% due to drought and heat stress during the summer season (De Boeck et al., 2008; Gao et al., 2019). Drought impacts lead to the reduced coverage, quantity, and quality of grasslands and their ecosystem services, which eventually leads to scarcity of herbage for livestock, lesser milk and meat production, and a decline in economic benefits. The estimated economic losses from the grassland yield start at about a 28% reduction in profits based on 5-year drought field experiments (Finger et al., 2013). Grasslands turn

from carbon sinks to sources beyond the ecosystem respiration threshold of $0.171 \mu\text{mol m}^{-2} \text{s}^{-1}$ of carbon due to drought based on a net ecosystem productivity regression model of grasslands in Inner Mongolia, China (Zhang et al., 2020).

Managed grasslands are widely distributed all over the world and contribute to the conservation of biodiversity and numerous provisioning, supporting, regulating, and cultural services. Grasslands are threatened by the increased severity and frequency of drought events that negatively impact their biodiversity and ecosystem services (Thornton et al., 2009; Zhang et al., 2021). Better knowledge of how these agroecosystems respond to droughts is necessary to predict and mitigate the drought impacts under different environmental contexts (Mejía and Wetzel, 2023).

2. Drought assessment

Drought is a natural hazard generally associated with extreme precipitation and water shortages (Mishra and Singh, 2010). It has various and complex consequences on ecosystems and human societies (Mishra and Singh, 2010; Slette et al., 2019). Drought covers a variety of definitions (Palmer, 1965; Slette et al., 2019) that can be classified according to the level of integration of water deficit consequences (Figure 1). The first level, defined as the climatological or meteorological drought, refers to the deficit in the climatic water balance, i.e., the difference between precipitation and potential evapotranspiration (Zargar et al., 2011). Then, agricultural drought refers to the consequences of meteorological droughts on soil water availability for plants (Cao et al., 2022; Zargar et al., 2011). Depending on the actual evapotranspiration (i.e., plant-specific water consumption) and the water holding capacity of the soil, a given deficit of the climatic water balance result in soil moisture stress that negatively affects the individual plant. Afterward, the hydrological drought refers to the deficiency of water to the surfaces or sub-surfaces of streams, lakes, other bodies of water, and wetlands. (Zargar et al., 2011). The sources of water recharge in hydro systems are mainly from precipitation, soil infiltration, and surface run-offs, which are thus affected by meteorological and agricultural droughts. Lastly, socioeconomic drought refers to the unavailability of water supply for basic societal water demand, such as for hydroelectric power generation and human use and consumption (Zargar et al., 2011).

Drought can be classified as a pulse type of disturbance (Hoover and Rogers, 2016). It is a stress that results to pulse type of response of ecosystem variable state. A general interest of this Ph.D. thesis is to understand the response of grassland vegetation to drought. Accordingly, drought impact was characterized, in the following chapters, as the deficit of the climatic water balance or as a meteorological drought. Then the vegetation response to drought was characterized as the negative change of variable states (i.e., standing biomass, growth, vegetation moisture content) or detectable

signs of plant water stress exhibited under agricultural drought events. The decreased soil water content in single plants due to agricultural drought leads to reduced photosynthesis causing declined leaf growth and lamina turgescence, eventually leading to lamina mortality (Volaire et al., 2009). The impacts on a single plant are then visible in ecosystems as fluctuations in the gross primary production, microbial activity, and soil respiration (Burri et al., 2018; Lei et al., 2020).

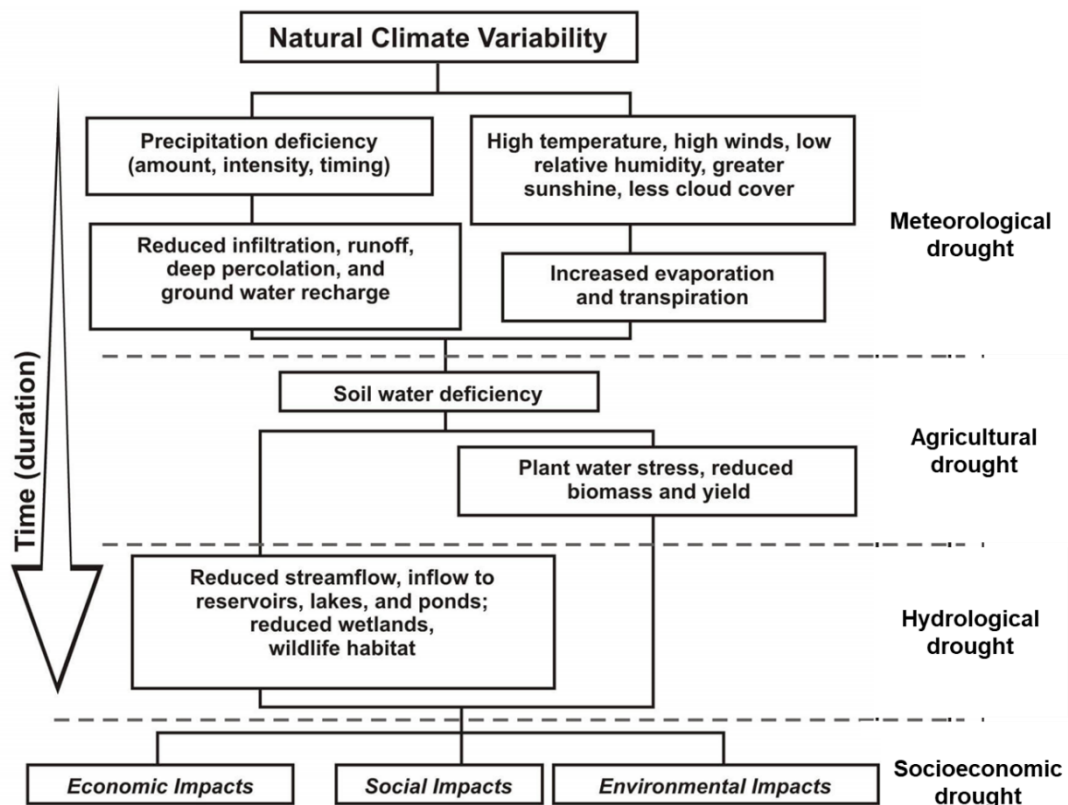


Figure 1. Chronological relationship of the four main types of drought and their respective indicators. The image was modified from the National Drought Mitigation Center (NDMC; <https://drought.unl.edu>)

Meteorological droughts occur more frequently and induce other types of droughts (Hao and Singh, 2015; Rahmat et al., 2015; Zargar et al., 2011). The World Meteorological Organization (WMO) and Global Water Partnership (GWP; 2016) have summarized and assessed the use of various drought indices and indicators for drought identification and quantification. The largest number of drought indices refer specifically to the meteorological drought (WMO and GWP, 2016). Such indices are based on the precipitations or the climatic water balance. The climatic water balance is computed as the difference between precipitation (P) and the potential evapotranspiration (PET) variables over a given period (Allen et al., 1998; Yang et al., 2021). Depending on the method used, PET can account

for the influence of additional climatic variables such as temperature, solar radiation, and wind velocity (Allen et al., 1998; Yang et al., 2021). The Thornthwaite (1948), Hargreaves (1975), and Penman-Monteith (Monteith, 1965) methods are the three commonly used formulas to generate PET (Allen et al., 1998; Yang et al., 2021). The Thornthwaite (1948) equation is based on the air temperature and duration of sunlight. While the Hargreaves (1975) method requires the minimum and maximum air temperature and extra-terrestrial radiation. Lastly, the Penman-Monteith method, which is recommended by the Food and Agriculture Organization of the United Nations (FAO; Allen et al., 1998), requires data on air temperature, wind speed, solar radiation, and air vapor pressure. When certain input data are unavailable, the Thornthwaite and Hargreaves methods are used as alternatives.

Among the existing meteorological drought indices (Kchouk et al., 2021; Yihdego et al., 2019; Zargar et al., 2011), authors have widely used the Standardized Precipitation Index (SPI; McKee et al., 1993), and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) (Wei et al., 2021). The SPI and SPEI are based on the normalized time series anomalies of precipitation; and climatic water balance, respectively (Chamorro et al., 2020; Stagge et al., 2015). When PET is available, SPEI should be preferred as it performs better than SPI (Hayes et al., 2012; Ojha et al., 2021).

Both the SPI and SPEI allow the integration of the respective climatic variables into monthly timescales usually from 1 month to 2 years (Salehnia et al., 2017). The integration timescales reflect the frequency and duration of drought. For example, 3 months or less integration has been used to assess short-term but frequent droughts, and greater than 4 for long-term but rare droughts (Faye, 2022; Yihdego et al., 2019).

The time series of drought indices such as SPI and SPEI enable the identification and characterization (Figure 2) of drought events (Pei et al., 2020). The main drought characteristics are their intensity, duration, and severity (McKee et al., 1993; Mishra, et al., 2007; Ojha et al., 2021). The drought duration is the length of time (e.g., days) of drought events. It begins when the drought index value goes below a given threshold and ends when the index is above the threshold (Dracup et al., 1980; Mishra, et al., 2007). Then the drought intensity is the mean value of the drought index below the threshold. It is quantified by dividing drought severity index and duration (Dracup et al., 1980; Lee et al., 2017; Mishra, et al., 2007). The drought severity is the total area below the drought threshold within the drought duration (Lee et al., 2017; Mishra, et al., 2007). The assessments of these drought characteristics allow quantitative comparisons between different drought events.

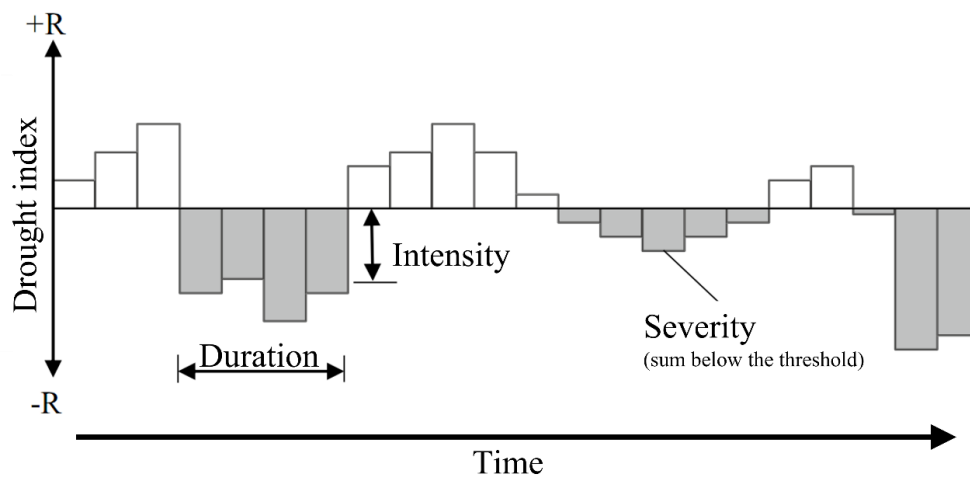


Figure 2. Illustration of the drought characteristics of duration, intensity, and severity (Mishra et al., 2007; the image was modified from Leng et al., 2020).

3. Grassland responses

Ecological resistance and resilience are two prominent components of ecosystem responses to disturbances, including drought. In the early 1970s, resistance was a synonymous term to ecological resilience (Gunderson, 2000; Holling, 1973, 1996), while resilience was synonymous with engineering resilience and stability (Gunderson, 2000; Holling, 1973, 1996). According to these definitions, high ecosystem resistance is the ability of a system to remain slightly changed or unchanged during a disturbance. Resilience and recovery refer to a positive trajectory of the system toward the previous state after disturbances. In some studies, both resistance and resilience are considered ecosystem responses to disturbance, which to a certain extent, also reflect ecosystem stability (Hossain and Li, 2021). In most cases, the concepts of stability and resilience exhibit blurred distinctions in ecological studies. Some authors have attempted to clarify these concepts with the assessment of stability definitions (Grimm and Wissel, 1997; Pimm, 1984), measured metrics (Kéfi, et al., 2019; Pimm et al., 2019), and consistency of their use (Donohue et al., 2016). Among the most recent attempt, Van Meerbeek et al. (2021) considered stability as the main ecological concept and categorized resistance, resilience, recovery, latitude, and tolerance as properties of ecological stability (Figure 3). In this Ph.D. thesis, I adopted these definitions of resistance and resilience for the assessment of the grassland response to a particular disturbance, which is the meteorological drought.

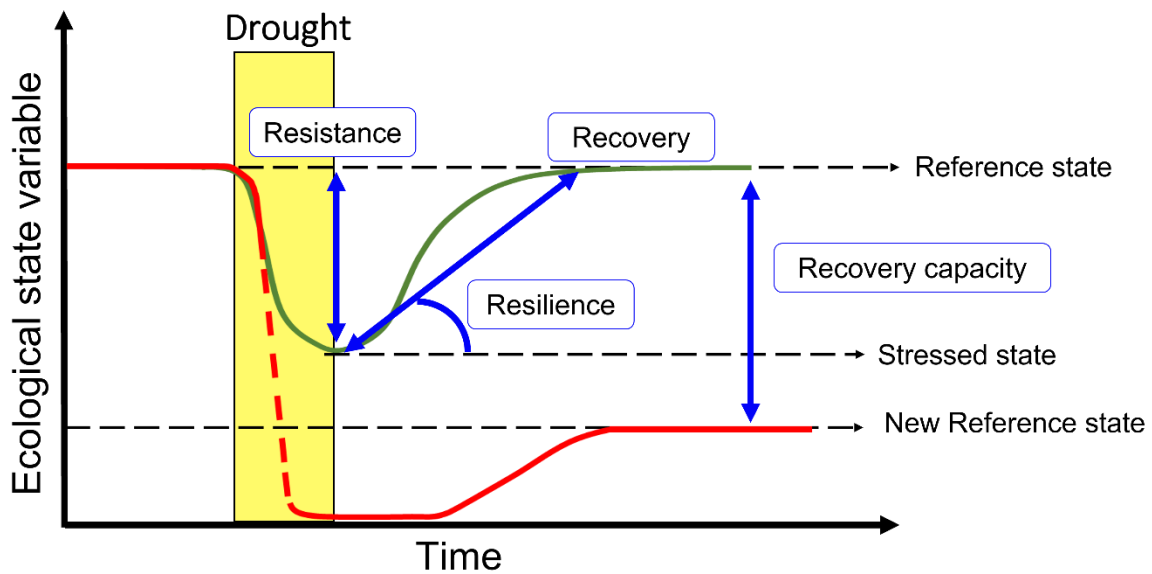


Figure 3. Illustration of the stability properties as response to drought. The tolerance was excluded in the plot due to need for quantified drought severity. The image was adapted from Van Meerbeek et al., 2021.

Two ecosystem states are presented in Figure 3, namely: the alternative stable or stressed state (bold green line), where the ecosystem has a larger tolerance to disturbances, such as drought, and the new reference state or changed state (bold red line), where drought impact is larger than the ecosystem tolerance. The changes in ecosystem states are based on the basin of attraction region of the resilience concept (Holling, 1996; Walker et al., 2004). This Ph.D. thesis focused on the alternative stable state (green line), where grasslands retained their identity as grassland ecosystems.

In the stability framework, resistance is the ability of the ecosystem state to withstand disturbance (Van Meerbeek et al., 2021). While both resilience and recovery are associated with the positive trajectories from the stressed state toward the pre-drought reference state. Resilience specifically refers to the rate of return to the reference state, while recovery is achieved when a 100% return to the reference state is attained (Van Meerbeek et al., 2021). The latitude is estimated as the difference between the reference state condition and the identified threshold before major changes in the system are observed. Tolerance, on the other hand, refers to the maximum disturbance endured by the system without change in the reference state.

The quantifications of stability properties are based on changes in the ecosystem state. The reference state, before a disturbance, serves as a baseline for the resistance and resilience quantifications. Resistance is the distance between the reference state and the disturbed state due to a disturbance. Ecosystems are characterized by low resistance when the gap between reference and disturbed states is considerably large. The resilience of the ecosystem starts with the positive trajectory from the

disturbed state or when the disturbance, such as drought, has ended. A high resilience is depicted by a steep slope towards the reference or new reference state of the system.

Beyond the correct assessment of vegetation response to drought, and with a considerably sound decomposition of its components (resilience, resistance, and recovery), one important issue of this thesis is to assess the variability of grassland response to drought and identify the drivers of said variability.

B. The potential of remote sensing for studying drought impacts on grasslands.

Grassland response to drought is an important topic in ecology, ecophysiology, and agronomy that has encouraged multiple studies. A large body of the corresponding literature reports on pot or field experiments where water inputs can be easily controlled and mixed with other treatments aiming at revealing drivers of vegetation response to drought from the molecular scale to paddock management regimes. More recently, and due to rapid technological developments, remote sensing has been used for assessing the response of a variety of ecosystems to a variety of disturbances. I here aim to show the potential of remote sensing as a complementary approach to controlled experiments and field observations for assessing grassland response to drought and its drivers.

1. Drought experiments of different scales

Drought-related experiments in laboratories, growth chambers, greenhouses, and research fields provide key knowledge on the response of plants to drought (Ogbaga et al., 2020). The scale of drought experiments, such as pot, mesocosm, and field, partly dictates the monitored plant characteristics or processes (Volaire, 2018). For example, plant tissue organs and individuals exhibit the response to water deficit stress as anomaly changes in the physiological properties (Volaire, 2018). Then the shift of organization level to population, and vegetation communities allows the detection of response to drought from ecological properties (Volaire, 2018).

a. Pot experiments

Pot experiments involve the growing of plants in small volumes of soil in small containers under different levels of stress (Hohmann et al., 2016). Such an experiment replicates drought impact by imposing water deficits on the pot set-ups (Turner, 2019). Due to the restrictions from pot containers, the investigated plant responses to water deficit are related to physiological changes in individual plants (Hohmann et al., 2016). The monitored parameters are usually related to processes involved in the development of leaves and roots (Volaire, 2008). The results of conducted pot experiments were able to reveal the dynamics of plant senescence (Volaire et al., 2009) and decrease in photosynthetic processes (Fariaszewska et al., 2017; Staniak et al., 2020) during induced water stress. They further revealed the crucial role of carbohydrates stored by plants during mild environmental conditions for their recovery after drought (Karsten and MacAdam, 2001). The use of nutrients and ecophysiological changes in plants are related to inherent plant growth strategies (Balachowski and Volaire, 2017). To exhibit tolerance to water stress, specific plants demonstrate conservative growth strategies by decreasing productivity through smaller specific leaf areas and specific root lengths (Balachowski and Volaire, 2017). Pot experiments have demonstrated the important role of soil properties in grassland response to drought (Buttler et al., 2019). For example, using ryegrass (*Lolium preenne*, L.), Buttler et al. (2019) determined that the soils with high soil organic matter (SOM) were more resistant to drought than soils with low SOM. These results were explained based on the available soil microbes, which influence nutrient availability, in the high SOM soils. Then also with ryegrass and soils from forest and grassland, Zhao et al. (2008) found higher sensitivity of ryegrass to water deficit when grown on grassland soil than forest soil. This was exhibited by a greater reduction of the leaf relative water and chlorophyll contents. Pot experiments are not usually designed to assess the impact of droughts on the response of higher levels of organization than the plant individual or population, Barkaoui and Volaire (2023) found that heterospecific plant-plant interactions positively modify their tolerance to drought and their recovery.

However, one main concern with pot experiments is the implementation of water stress on the plant, which is related to the soil medium (lack of porosity), and pot size and shape (water retention and root growth)(Turner, 2019). Usually, pot experiments have faster drying than in real-life soil conditions (Earl, 2003; Ogbaga et al., 2020; Turner, 2019).

b. Mesocosm experiments

Mesocosm experiments, similar to microcosms, are bordered, partially enclosed, or large container outdoor experiments (Crossland and La Point, 1992; Odum, 1984). It aims to replicate to some extent natural environmental conditions and ecological effects (Crossland and La Point, 1992; Ledger et al.,

2013). Accordingly, the simulation of drought-induced impacts involves the use of rainfall manipulation shelters (Karlowsky et al., 2018). Mesocosm experiments shift towards the population and community organizational levels. They address the role of different facets of the plant community structure in their response to drought and sought to test theoretical predictions related to the role of diversity (De Boeck et al., 2018; Loreau, 2010) on grassland stability against drought.

Among the different facets of the plant community structure (Keddy, 2007), drought experiments focus on species composition, species diversity, functional identity, and functional diversity. The first two facets rely on the collection of the co-occurring species in the grassland of interest in terms of what they are, how many, and in which proportion. Functional identity and diversity rely on the pattern of trait values exhibited by the species. A trait is defined as a measure of plant morphology, physiology, or phenology that impacts the performance of plant individuals in terms of survival, vegetation biomass, vegetation reproductive outputs, and ultimately their fitness (Violle, 2007). Trait values of different species can then be integrated at the community level. The first community metric is the mean trait value weighted by the species abundance (Diaz et al 1998, Garnier 2004). Because of the weighting term, it reflects the functional identity of the dominant species. The diversity of trait values within a community can be appreciated with numerous metrics, sometimes redundant or complementary (Mouchet et al., 2010). They usually represent one or mix several of the following aspects: richness (i.e., the total volume of the trait space occupied by the species), divergence (i.e., the variance in the distribution of species abundances in this volume), or evenness (i.e., the regularity of the distribution of species abundances in the same volume) (Villéger 2008).

Drought experiments have largely focused on the role of species richness. Indeed, theoretical developments on the role of the diversity-stability relationship are largely grounded on the number of co-occurring species (Loreau, 2010; McCann, 2000). It is also easier to manipulate than taxonomic and functional metrics based on species abundance. The positive effect of species richness on stability predicted by theoretical developments is not always supported by drought mesocosm experiments. Some authors have found the diversity buffering effect during induced drought events (Hernandez and Picon-Cochard, 2014; Niboyet et al., 2017; Padilla et al., 2019), but not during post-drought recovery (Hernandez and Picon-Cochard, 2014; Kreyling et al., 2017; Padilla et al., 2019). In a review, De Boeck et al. (2018) also concluded that the response of above-ground biomass to drought is not significantly influenced by species richness.

Beyond the influence of the number of species, the positive effect of diversity on community stability, related to the insurance hypothesis, may theoretically be associated with different responses of species to environmental changes (Loreau et al., 2021; Yachi and Loreau, 1999) suggesting a link between the diversity of plant functional attributes and stability. Yet, there are still few experimental

tests of the role of functional diversity on vegetation response to drought, sometimes supporting (Schnabel et al., 2021) or refuting its positive role (Miller et al., 2019).

The composition of communities is also well recognized to influence the grassland response to drought. Fry et al. (2021) tested two plant community compositions to determine their effect on the resilience of root functional traits to drought. The plant community that resembles intensive management demonstrated higher drought resilience than the diverse plant community of extensive management (Fry et al., 2021). The authors further showed that this effect was related to differences in root traits between the two types of communities, more exploitative root traits for the plant community composition that resembled intensively managed grasslands.

Beyond playing a role in the stability of broad vegetation properties like biomass, plant community composition may also change due to droughts. It has been found that drought-induced reduction in the biomass of native species may enhance the growth of invasive species (Manea et al., 2016).

Mesocosms experiments have also been used to assess the effect of some management practices but are usually restricted to fertilization and/or artificial cuts. A mesocosm experiment on the influence of Nitrogen fertilization during drought has recommended the avoidance of excessive N fertilization to dry soils to prevent the risk of nitrate leaching (Klaus et al., 2020). Cuttings were implemented to maintain the conditions within mesocosm set-ups and extract biomass at the before, during, and after stages of induced drought (Hernandez and Picon-Cochard, 2014).

The weaknesses of mesocosm experiments are related to the logistical restrictions necessary for experimental set-ups (Ledger et al., 2013; Lütke Schwienhorst et al., 2022). Then despite the outdoor experimental set-ups, which allow natural light, air temperature, and humidity, the presence of experiment enclosures still limits the replication of real-life conditions (Stewart et al., 2013).

Finally, in some instances, pot and mesocosm experiments show blurred distinctions due to many possible ways to conduct experimental manipulations. In a microcosm experiment using pots, Xu et al. (2022) showed the possible interaction between species richness and functional dispersion (Fdis). But Fdis only mediated the impact of species richness on ecosystem functioning, while species richness demonstrated the insurance effect against drought impact (Xu et al., 2022). Then the principal components of the community-weighted means of leaf carbon content and plant height traits contributed to the facilitation of conservative growth strategies of *Caragana microphylla* Lam. (Xu et al., 2022). Pot experiments may be conducted indoors, inside greenhouses, or under outdoor conditions. While mesocosms can also be conducted in similar locations depending on the questions being investigated. In terms of scale, mesocosms may involve the use of containers, which share similar techniques with pot experiments. Nevertheless, we highlight the knowledge of how each method/approach/design focuses on specific levels of organization.

c. Field experiments

Field experiments generally involve the control of the amount of rainfall with shelters placed over established grasslands. Compared to pot and mesocosm experiments, field experiments allow the investigation of the influence of herbage use treatments (Deléglise et al., 2015; Munjonji et al., 2020; Volaire, 1994; Zwicke et al., 2013) on grassland response to drought. It has been shown that grazed grasslands were more negatively responsive to drought than mowed grasslands in mountain areas of Switzerland (Deléglise et al., 2015). Regarding fertilization effects, results from different studies were mixed. Consistent with mesocosm experiments, some studies support the negative influence of excessive nutrient addition on the grassland response to drought (Bharath et al., 2020; Rose et al., 2012), while other studies did not find any significant effect of fertilization (Vogel et al., 2012; Weisser et al., 2017).

The influence of community structure has also been largely investigated in field drought experiments, usually reporting that grassland diversity can buffer drought impacts on grasslands (Griffin-Nolan et al., 2019; Isbell et al., 2015). Barkaoui et al. (2016) found that by manipulating the composition of Mediterranean perennial herbaceous species that the functional identity, related to the root morphology, had more influence on the community response to drought than their functional diversity.

Under water-limited conditions, plant growth promotes changes in plant traits as a response to stressed conditions (Berdugo et al., 2022). The functional diversity of grasslands, measured as functional dispersion, showed lower sensitivity to water-limited climate variabilities in ultramafic rocks and soils (Harrison et al., 2020). The interannual precipitation variability also increases the functional diversity of the grasslands (Gherardi and Sala, 2015; Harrison et al., 2020). At the same time, high functional diversity mitigates the alternating wet and dry (or drought) interannual precipitation variability on grassland primary production over a six-year experiment (Gherardi and Sala, 2015). The presence of three plant functional types was unable to exhibit the species richness buffering effect (Zwicke et al., 2013) found in mesocosm experiments (Hernandez and Picon-Cochard, 2014; Niboyet et al., 2017; Padilla et al., 2019). Zwicke et al. (2013) highlighted that the role of stability drivers, such as nitrogen, requires longer experiment durations (> 3 years) to detect the influence on grassland resilience. Similar to mesocosm experiments, the role of functional diversity on grassland response to drought requires additional examinations compared to measures of species richness and diversity, which have been a long-running part of ecosystem stability studies (de Bello et al., 2021).

Drought field experiments share restricted spatial coverage and limited replication of real-life conditions. It has also been argued that these studies should be correctly termed as water deficit experiments, instead of drought experiments (Ogbaga et al., 2020). Because these experiments are unable to replicate the increased temperature and evapotranspiration rate. Grassland drought experiments (in pots, mesocosms, or fields) have provided significant knowledge on the effect of drought at different organizational levels, namely the plant individual, and the mixtures of interacting plants of conspecifics (population) or heterospecific (communities) composition. From the results from multiple experiments, we can presume that the response of grassland to drought depends on three main types of factors including the (i) soil properties, like the water holding capacity, the (ii) plant community structure (composition and diversity of species and functional traits), and (iii) management practices related to fertilization and regimes of herbage use (by mowing or grazing).

2. Shortfalls of grassland-drought experiments and field observations

Observation and controlled or semi-controlled experiments are of utmost value for analyzing drought impacts on grasslands and understanding the mechanisms underlying their resistance and resilience. Whether they were set up in pots, in mesocosms, or the field, experiments provide significant knowledge on grassland responses to drought at the local scale. However, they face several shortfalls. Some of the experiment shortfalls can be considered similar to the shortfalls of biodiversity knowledge (Cardoso et al., 2011; Hortal et al., 2015; Ribeiro et al. 2016).

First and related to the Prestonian shortfall of biodiversity knowledge, drought experiments, and field observations have restricted knowledge of the spatial and/or temporal coverages (Leuzinger et al., 2015). Beyond the obvious spatial restriction of experiments and observatories, drought experiments, especially pots, and mesocosms, are usually performed under short durations (Beier et al., 2012; Hoover et al., 2018). Thus, short-term experiments have limited capacity to consider the consequences of long-term or repeated drought events (Beier et al., 2012; Leuzinger et al., 2011). On the other hand, observational studies may be conducted for longer duration, but with low record frequency which may lead to poorly evaluated vegetation responses. The second shortfall is the Hutchinsonian shortfall of biodiversity knowledge, which pertains to the poor assessment of the global variability of ecosystem responses to changes in abiotic conditions. Despite coordinated experiments and large-scale observations (i.e., Drought-Net / Smith et al., 2015), grassland responses to drought have been studied in a limited number of combinations of pedoclimatic contexts, management regimes, and levels of biodiversity (Leuzinger et al., 2011; Vicca et al., 2012). Lastly, drought experiments reduce real-life complexity by essence. Although such reduction is necessary for establishing cause-

and-effect relationships, drought experiments lead to an underestimation of grassland biomass compared to observation drought studies (Kröel-Dulay et al., 2022).

Anticipating and/or mitigating the impact of droughts on managed grasslands require complementary approaches to assess the variability of vegetation responses in real-life conditions and multiple contexts. The foundation of this thesis lies in the potential of remote sensing to move beyond the limits of drought experiments and ground observations identified above.

3. Satellite remote sensing data and techniques

a. A brief introduction to remote sensing data

Among the existing technologies, remote sensing has the potential to determine the response of ecosystems to disturbances on large spatial extents for the past few decades (Li et al., 2014; Soubry et al., 2021; Xu and Guo, 2015). Remote sensing is the science of acquiring information about an object or area of interest without physical contact with the said object or area. In this thesis, I focused on the use of satellite-based remote sensing due to its wider and more consistent spatio-temporal coverage compared to cameras and sensors attached to unmanned aerial vehicles (Alvarez-Vanhard et al., 2021) or mounted to ground monitoring set-ups.

In 1960, the Television Infrared Observation Satellite (TIROS)-1 was launched into space as the very first observational satellite to monitor the Earth's meteorological condition (Tatem et al., 2008). Then in 1972, the Landsat 1 satellite was launched to monitor forest and agriculture resources (Tatem et al., 2008). Since then, the development of new sensors and the launch of new satellites have continuously progressed, increasing exponentially the quality and quantity of images of the Earth's surface.

There are two main types of satellite images depending on the sensor being used (Ali et al., 2016; Turner et al., 2003; Weiss et al., 2020). The optical remote sensing images are collected using passive sensors that receive the reflected natural radiation that bounces from the Earth's surface from the sun (Turner et al., 2003). Meanwhile, microwave remote sensing images are collected using active sensors that receive reflected artificial energy that is emitted from the sensor towards the Earth's surface and back. The received intensities of energy signals are recorded in channels or bands at distinct ranges of the electromagnetic spectrum and are interpreted using the radiative transfer principle (Drusch and Crewell, 2006; Turner et al., 2003).

Optical satellite images record object reflectance in the visible and infrared reflectance bands between 0.4 and 14 micrometres (μm) spectral wavelengths (Figure 4). These reflectance values are related to the biophysical and biochemical vegetation properties that can be used to assess the presence

of multiple vegetation stresses (Campbell et al., 2007; Carter, 1993; Ramoelo et al., 2015). On the other hand, microwave or radar images provide information for longer wavelengths at 0.75 to 30 centimetres (cm). The radar bands are linked mainly to the vegetation's physical and moisture properties (Figure 4) (Hill et al., 2005).

Optical images are more commonly used than microwave images, even though the presence of clouds hinders the clear view of features on the Earth (Ali et al., 2016; Hill et al., 2005). One reason for favoring optical images rather than microwave images is that microwave images require challenging and multiple pre-processing (Hill et al., 2005; Schumann, 2020). In addition, reliable images are hardly obtained in highly mountainous areas (Vreugdenhil et al., 2022).

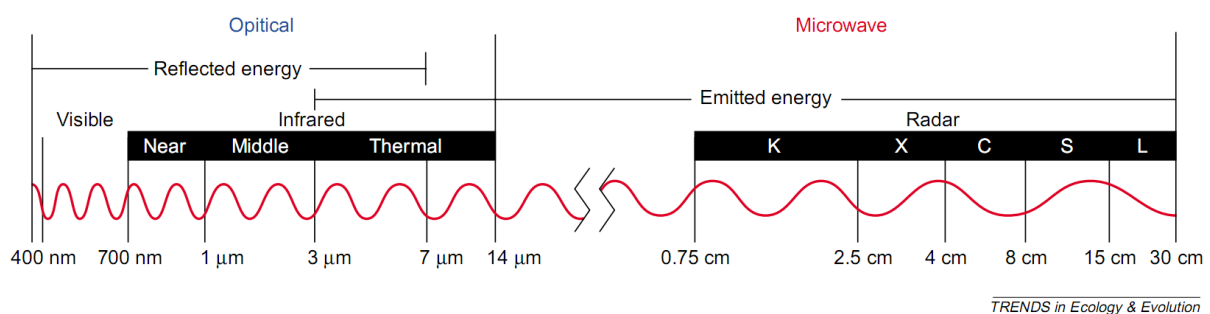


Figure 4. Differences of reflectance band wavelengths between optical images and microwave images. Image was adapted from Turner et al., 2003.

Remote sensing data have varying characteristics that determine their use. Focusing on optical images, the main characteristics are spatial, temporal, spectral, and radiometric resolutions. The spatial resolution relates to the ground area covered by each pixel of the images. Belward and Skøien (2015) proposed five classes of spatial resolutions, namely (i) the low spatial resolution at 250.0 m and above, (ii) moderate resolution at 40.0 to 249.9 m, (iii) medium resolution at 10.0 to 39.9 m, (iv) the high resolution at 5.0 to 9.9 m; and lastly, (v) the very high spatial resolution for images at 0.5 to 4.9 m. The high and very high spatial resolutions allow for more detailed measurements of grassland features and have been used to assess the species richness and composition of grasslands (Fauvel et al., 2020; Hall et al., 2010; Lu and He, 2014). Then, the low spatial resolutions are commonly preferred for large or even global-scale grassland monitoring or mapping (Gong et al., 2013; Klein Goldewijk et al., 2007). The temporal resolution, on the other hand, is the number of days before the satellite revisits the same location on the Earth's surface. A satellite 1-day revisit is a high temporal resolution and allows the capture of the daily changes in vegetation conditions. The spectral resolution is the number and width of the reflectance bands (Govender et al., 2007). The higher number and finer width of bands

allow better identification of objects on the Earth's surface (Govender et al., 2007). Optical satellite images commonly usually encompass visible and near infrared wavelengths. Then the width of each band influences the accuracy of estimated vegetation properties. The radiometric resolution is the fourth but seldom presented characteristic. It is the distinction of grey-scale values, or bit size, for a satellite image reflectance band. The radiometric resolution determines thus the amount of information within each band.

The last decades have experienced the launch of multiple satellite missions orbiting the planet (Kramer and Cracknell, 2008). There are varying resolutions for each of the satellite sensors depending on the satellite mission (Ustin and Gamon, 2010) (Appendix A). Optical satellite sensors have varying spatial, temporal, and spectral resolutions (Figure 5). The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, Landsat missions, and Sentinel 2 satellite are among the top five satellite sensors for grassland monitoring (Reinermann et al., 2020). These satellite images provide global spatial coverage and are easy to use and provide derived products that are made directly available like atmospherically corrected images, gross primary productivity, land cover, and global water reservoir, which are all freely accessible. The continuous missions, operation, distribution, and no-charge access to remote sensing products are due to government funding of respective countries (Zhu et al., 2019) or organizations. New satellite sensors like the Vegetation and Environment monitoring on a New MicroSatellite (VENuS) have limited mission coverage (Upreti et al., 2020), but improved characteristics like high spatial and temporal resolutions of 5m and 2 days (Baba et al., 2020). Meanwhile, the very high spatial and temporal resolution satellite sensors are generally managed by private companies and entail additional cost to acquire (i.e., Quickbird and WorldView by Digital Globe; IKONOS and GeoEye by Space Imaging) (Bayik et al., 2016).

Among the existing remote sensing data, this Ph.D. thesis used satellite-based remote sensing to assess the response of grasslands to drought across multiple years. Doing so, it took advantage of the freely accessible optical images, which encourages duplicability of the thesis without additional cost. The best spatial and temporal satellite image resolutions that support the thesis objectives (see Section C) were considered. It was with close consideration of the inherent limitations and trade-offs of satellite image resolutions and operational mission continuity. The high daily revisit of MODIS is at the expense of low spatial resolution. The medium spatial resolution of Landsat is paired with 16 days of revisit time. Then the high spatial and temporal resolutions of Sentinel 2 are constrained by the short temporal operation for image acquisition.

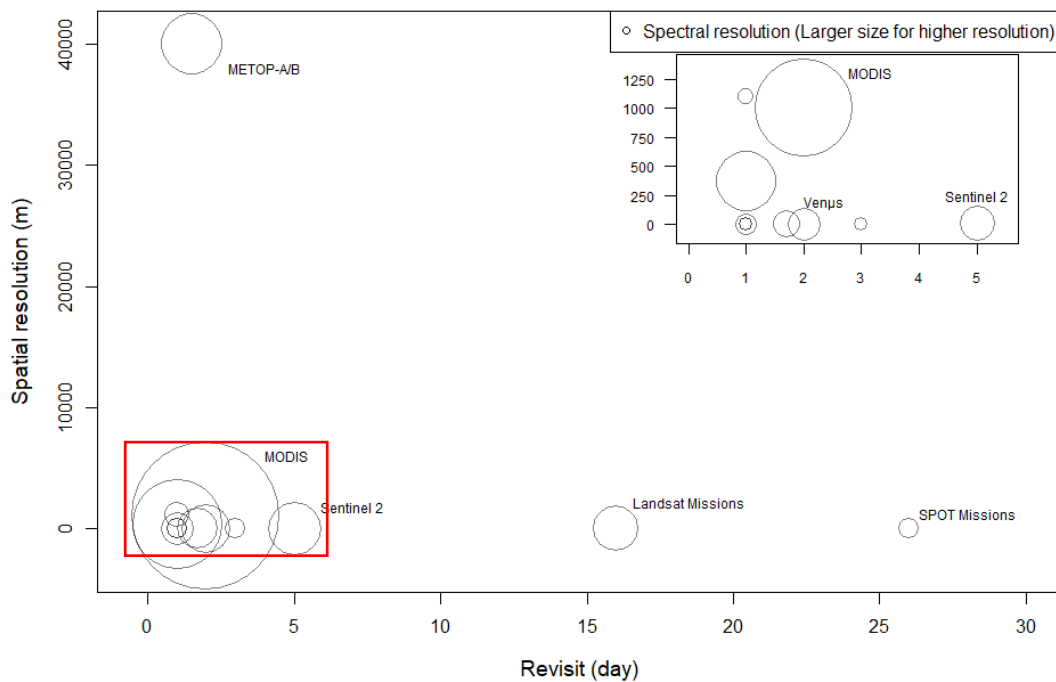


Figure 5. Spatial, temporal, and spectral resolutions of selected optical satellite-sensors used for ecological and environmental studies. The resolution values were collected from the descriptions of each satellite-sensors or missions. A summary is presented in Appendix A.

b. The link between vegetation properties and satellite reflectance

The electromagnetic radiations received by the sensors are key to determining vegetation properties (Campbell et al., 2007; Carter, 1993; Ramoelo et al., 2015). Electromagnetic radiation is first emitted by the sun. Upon contact with the vegetation surface, the different wavelengths of electromagnetic radiation are either reflected, absorbed, or transmitted (Figure 6; Summy et al., 2003). Depending on the leaf chlorophyll content, the radiations in the green and near infrared regions of the electromagnetic spectrum are mostly reflected while in the red and blue they are absorbed by the pigments and converted into chemical energy (i.e., the photosynthesis) Gitelson et al., 2002). The reflected GREEN band explains the visible green color of the leaves. However, if the leaves are under stress, such as drought, the activity of the chlorophyll layers either stops or declines. This causes a change in the leaves from green to yellow or brown. As a consequence, the decrease in leaf conditions can be detected by remote sensing due to the lower absorption of RED and BLUE reflectance and the drop in reflected GREEN and NIR (Gitelson et al., 2002).

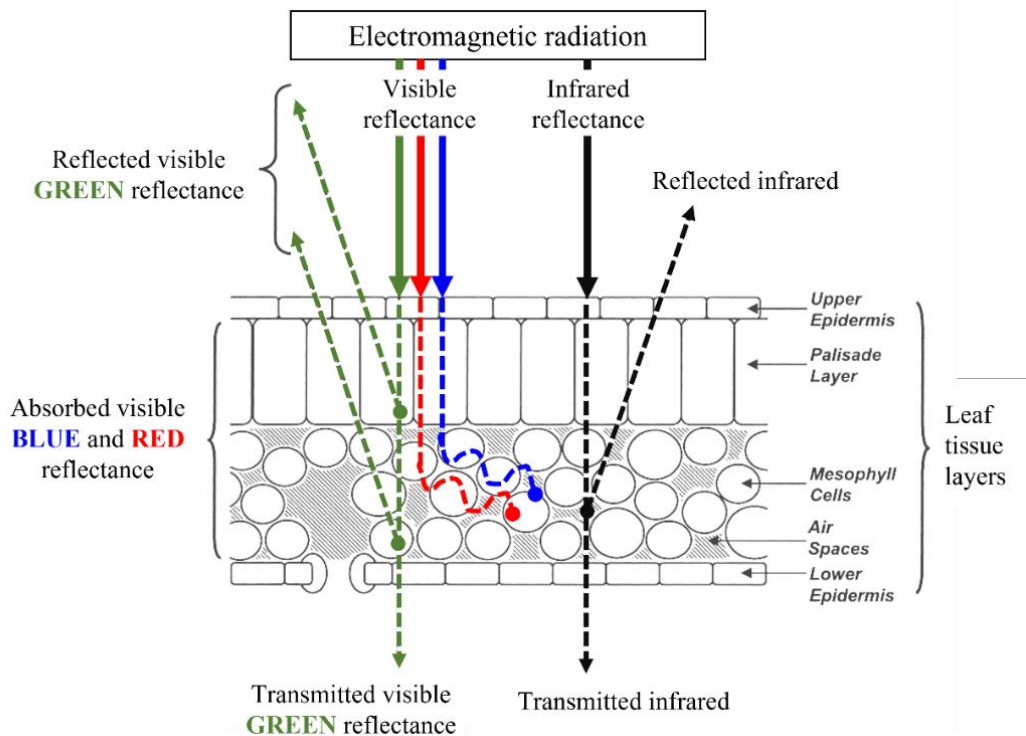


Figure 6. Radiative transfer principle of the visible and infrared reflectance bands on a leaf surface. Depending on the characteristics of the object's surface, the amount of absorbed, reflected, and transmitted energy will change. A healthy leaf will absorb more RED and reflect more NIR reflectance. Image was adapted from Summy et al., 2003.

The radiative transfer theory establishes the link between the plant chlorophyll content and satellite reflectance bands. This theory mathematically accounts for energy conservation with matter (Knyazikhin et al., 2005). Accordingly, there are radiative transfer models (RTM) that use the reflected solar radiation from matter to generate their reflectance signature (Figure 7). Concerning plants, RTMs have been developed at the leaf level and canopy level (Mohammed et al., 2019). Apart from the chlorophyll contents, the leaf reflectance signature depends on brown pigments, dry matter, carotenoid contents, and leaf equivalent water thickness (LEWT) (Jacquemoud, 1993; Jacquemoud and Baret, 1990). The canopy reflectance further depends on soil wetness information, leaf area index (LAI), and leaf angle distribution parameters. Finally, the reflectance signatures are affected by external parameters namely the satellite and solar angles (Jacquemoud, 1993; Verhoef, 1984).

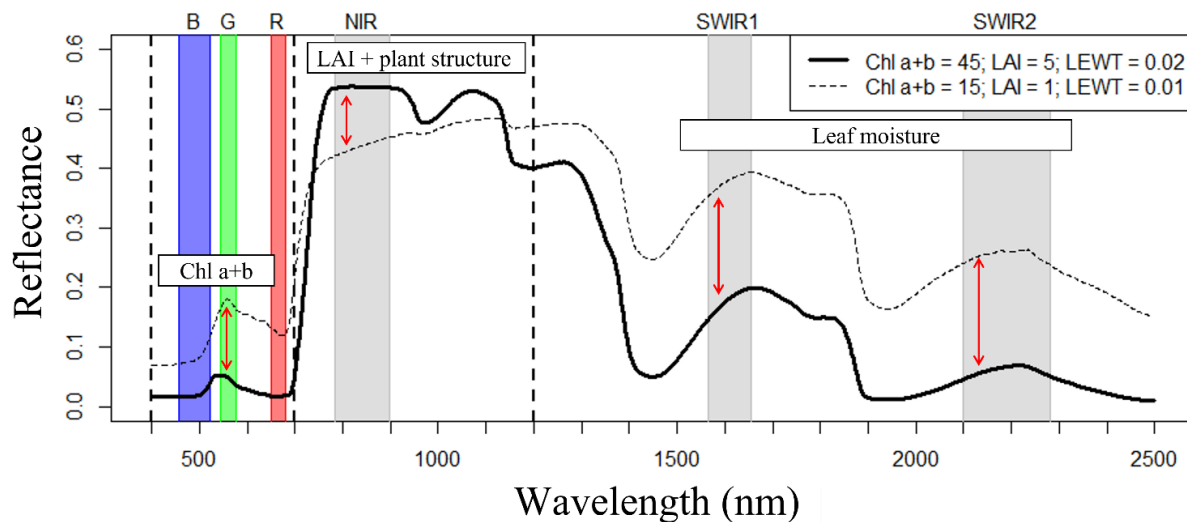


Figure 7. Spectral signature of two different grassland health conditions. The spectral signatures were generated using the PROSAIL radiative transfer model, where only the chlorophyll contents (Chl a+b), leaf area index (LAI), and leaf equivalent water thickness (LEWT) were contrastingly tuned. The shaded wavelength ranges represent the Sentinel 2 reflectance bands as an example. Along the electromagnetic spectrum, the visible bands (Red, Green, and Blue) are associated with the Chl a+b (Jacquemoud et al., 2000). While the NIR and SWIR bands are sensitive to LAI and LEWT, respectively.

The relationship between the spectral signatures and the vegetation properties at the leaf and canopy levels was the basis for the development of spectral or vegetation indices. The vegetation indices are transformations, using mathematical equations of selected reflectance bands to acquire proximal information on the properties of ground vegetation. For instance, the so-called Normalize Difference Vegetation Index (NDVI; Rouse et al., 1974) is used as a standardized estimate of vegetation productivity and greenness. It is derived using the RED and NIR reflectance bands, which are sensitive to the leaf chlorophyll pigments and LAI. The vegetation moisture content, on the other hand, can be estimated using the Land Surface Water Index (LSWI; Xiao et al., 2004). The LSWI also uses the NIR, which responds to the structural properties of the vegetation, and the SWIR1, which responds to the leaf water status. A large number of vegetation indices have been developed for estimating vegetation greenness, productivity, cover, senescence, chlorophyll content, moisture content, and plant nitrogen content (Bajgain et al., 2015; Davidson et al., 2006; Wu, 2014).

The potential of satellite remote sensing in quantifying and monitoring grassland properties has been largely demonstrated (Ali et al., 2016; Reinermann et al., 2020; Wang et al., 2022). The relationship between vegetation reflectance has been assessed for several grassland properties including productivity, moisture content, and stress conditions (Andreatta et al., 2022a; Bajgain et al., 2015). For example, Zha et al. (2003) used Landsat-derived NDVI to map the percent grass cover of semi-natural grasslands in western China. Using a classification confusion matrix, they obtained an

overall accuracy of 89%. With the use of radiative transfer model inversions and Landsat data, Yin et al. (2016) obtained an R^2 of 0.85, with a root-mean-square error (RMSE) of 0.43 between the estimated and field-measured canopy chlorophyll content of arid grasslands. Using Sentinel 2 for the model inversion, Schwieder et al. (2020) showed an R^2 of 0.90, with a normalized RMSE of 0.47 between the estimated and measured biomass of a temperate managed grassland. Then with Sentinel 2 time series observations, Kolečka et al. (2018) mapped and detected mowing events in the grasslands of Switzerland with a classification overall accuracy of 77% (metric from Congalton, 1991).

The reflectance signals of satellite optical images provide significant estimates of biophysical and biochemical vegetation properties that are susceptible to being impacted by droughts. Grassland properties can be retrieved from vegetation reflectance with vegetation indices and the inversion of radiative transfer models of the leaf and canopy among other methods. Several authors have demonstrated the successful application of remote sensing to assess drought impacts. However, apart from the various review on the use of remote sensing for grassland monitoring, there is a lack of a focused review on the assessment methods for grassland response to drought. This review gap limits the comparison between assessment studies and prevents the selection of appropriate methods in answering key grassland responses to drought questions.

C. Thesis objectives and plan

Drought events are expected to be more frequent and intense due to climate change. At the same time, this increases the threat of drought to the sustainability of natural ecosystems and agroecosystems. Among the affected agroecosystems, managed grasslands cover about one-third of the global terrestrial areas and are distributed in almost all biogeographic regions of the world. Since they provide key ecosystems services and host a wide range of biodiversity, the threats of drought on managed grasslands motivates numerous research in various scientific fields (agronomy, ecology, ecophysiology, environmental management, and related fields) with the ultimate goal to provide warning for imminent drought impacts and promote measures for grassland resistance and recovery from drought.

A large body of research analyzed the impacts of drought on grasslands by setting controlled experiments in pots, mesocosms, or grassland fields. They provided a better understanding of the sequence of eco-physiological processes occurring during droughts and recovery. They further acknowledge the influence of multiple factors modulating the resistance and resilience capacity of grasslands which can be categorized into pedoclimatic factors, vegetation diversity, and management practices. However, the controlled and constrained set-ups of experiments have led to shortfalls, especially in their low spatio-temporal coverage of grassland responses and the application of artificial

conditions, which limit the generalization of their results to real-life conditions. Satellite remote sensing can fill these shortfalls as they cover large spatio-temporal extents and represent vegetation properties sensitive to drought impacts. Together with time series of drought severities derived from basic meteorological records (precipitation, temperature, radiations, and/or potential evapotranspiration), satellite image time series can assess the dynamics of several vegetation properties in response to drought.

The primary motivation of this thesis was to take advantage of the potential of satellite image time series for improving knowledge on the response of managed grasslands to drought in real-life conditions. To do so, this thesis pursues three main objectives.

- a. The recent developments of remote sensing based environmental monitoring goes with various and scattered scientific developments. There is thus a need to first review the current approaches developed for assessing drought impacts on grasslands to select the best analytical designs specific to the two following objectives.
- b. The central objective is to quantify the variability of grassland sensitivity to drought at a regional scale and identify the drivers of such variability using satellite image time series of 30 years. The Massif central in France is used as a case study where managed grasslands cover a large geographic area, which is among the highest in Western Europe.
- c. Since long-term optical image time series are usually of low frequency, due to cloud cover and low revisits, they can hardly be used to decompose the response of grasslands to drought into its resistance and resilience components. The last objective aims to develop a more comprehensive assessment of grassland response to drought by the assimilation of satellite data with a simple model of grassland growth. This requires detailed knowledge of grassland management events. In this regard, a farm experiment conducted between 2016 and 2020 was used as a case study.

The design of this Ph.D. thesis (Figure 8) is centralized on the dynamics of grassland vegetation properties in response to drought. The framework identifies the influence of environmental, biological, climatic, and anthropogenic factors on vegetation dynamics. It highlights how different sources of data, namely: satellite images, field measurements, and meteorological data can be combined to better understand vegetation dynamics during and after droughts.

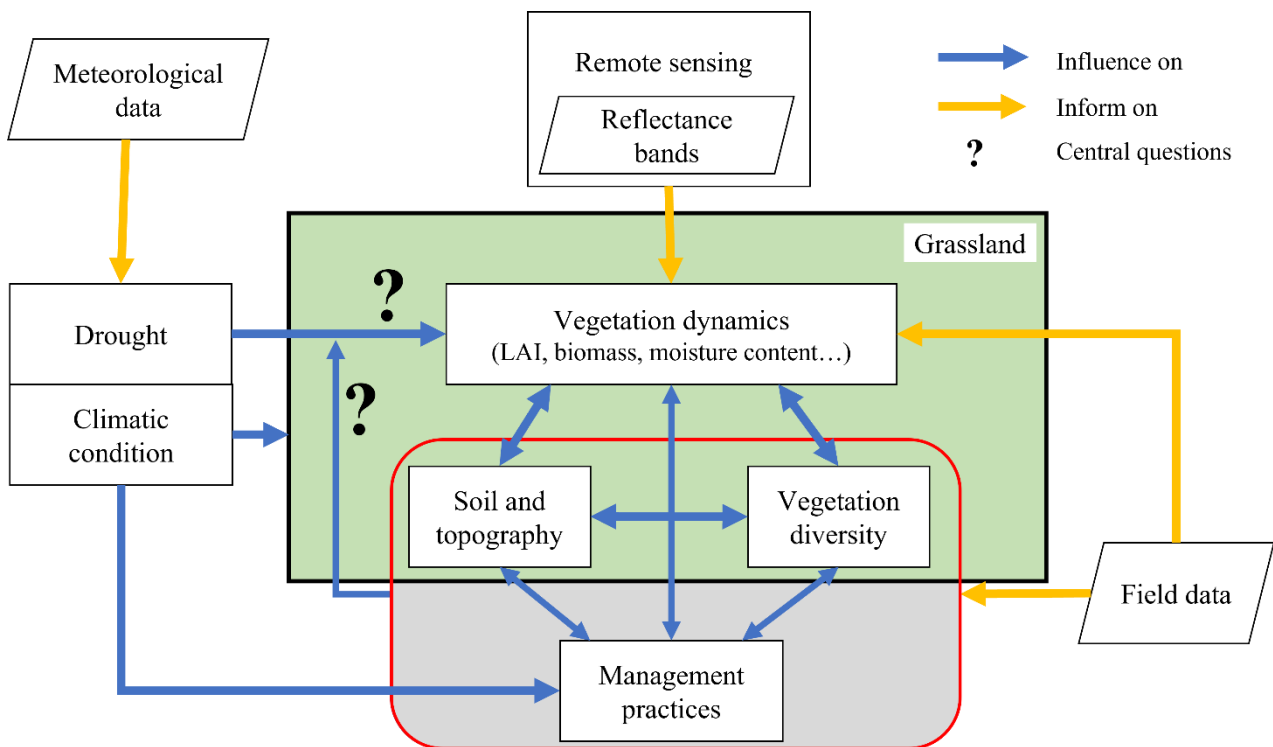


Figure 8. Conceptual diagram relating the drought impacts, their drivers, and ways to assess it with remote sensing data of the Ph.D. thesis.

This Ph.D. thesis has six main components. This General introduction is followed by the General data and methods, which describe the data used, their sources, and some analyses conducted to justify their selection for the respective research objectives. The three chapters of this thesis correspond to the specific objectives. Chapter 1 is the review classification and analysis of the existing remote sensing approaches to assess grassland response to drought. Chapter 2 is a regional-scale assessment of grassland sensitivity to drought. It presents the variability of grassland sensitivities within the Massif central regions and the relative importance of the pedoclimate, vegetation diversity, and management practices in modulating these sensitivities. Then, Chapter 3 aims at providing a more comprehensive assessment of drought impacts on vegetation dynamics within the influence of grassland management and plant phenology. It starts with the presentation of a parsimonious process-based model of grassland growth assimilated with Sentinel 2 data. As a result of a simulation protocol, results on the resistance and resilience capacity of mown and grazed grasslands are presented. The final component of this thesis is General synthesis.

As a logical flow (Figure 9), Chapter 1 (the review of grassland response to drought assessment using remote sensing) supports the selection of analytical methods for Chapters 2 (regional scale assessment of grassland sensitivity to drought) and 3 (local scale grassland response to isolated drought

impact). Chapter 3 further attempts to move beyond the limitations of Chapter 2 inherent to the use of long satellite times series over regional scales.

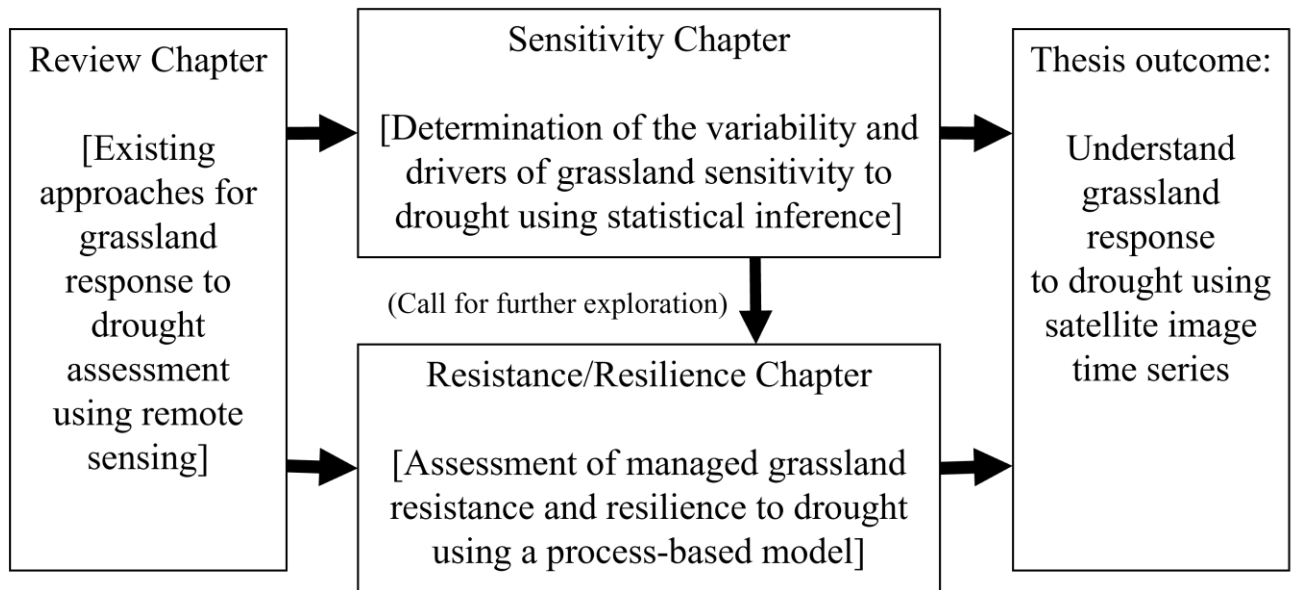


Figure 9. Connectivity of the three research chapters toward the main objective of this Ph.D. thesis.

GENERAL DATA AND METHODS

GENERAL DATA AND METHODS

This component presents additional details on preliminary analyses conducted for the selection of the best input data (especially satellite products) and methods. Specifically, I focus here on the second and third objectives of the Ph.D. thesis (i.e., data analysis at the Massif central area and data from local experiments at the Herbipôle experimental site). The second objective, or Chapter 2, aimed to assess the variability and drivers of grassland sensitivity to drought from pedoclimatic, vegetation diversity, and management practices at the regional scale. Then the third objective, or Chapter 3, aimed to evaluate the responses of managed grasslands to isolated drought impact at the local scale. The first research objective, or Chapter 1, was a literature review of the assessment approaches of grassland response to drought using remote sensing. The initial step for Chapter 1 involved the examination of published journal articles from the Web of Science. Additional details are provided in Chapter 1.

D. Study areas

Overall, the research activities of this Ph.D. thesis were conducted within the Massif central region (45°18'48.10"N, 2°54'30.43"E; Figure 10) of France at two spatial scales. The first study, dedicated to objective 2 (Chapter 2), is at the regional scale and it aimed to capture the “real-life” conditions of managed grasslands. Located at the central portion of the Massif central, the wide area coverage supports the availability of heterogeneous environmental, climatic, and soil properties needed for the second objective. The other study, dedicated to objective 3 (Chapter 3), is at the local scale, as it requires detailed and accurate grassland monitoring data. Contrary to the regional study, the closely managed grassland parcels provide homogenous but still realistic field conditions, which are necessary to address the third objective.

1. The Massif central region

The Massif central region is administratively composed of the Auvergne-Rhône-Alpes, Bourgogne-Franche-Comté, Nouvelle-Aquitaine, and Occitanie regions. It is a mountainous area with 85,000 km² of coverage that features highly heterogeneous topographic, geologic, pedologic, climatic, and vegetation characteristics (Galliot et al., 2020; Hulin et al., 2019a). The region has 41,000 km² of agricultural land areas (*Surface Agricole Utile*, SAU). Where about 60% of the SAU is always covered by perennial grasslands (*Surface Toujours en Herbe*, STH; Agreste, 2017). These grasslands host relatively high biodiversity that supports the quality and quantity of agricultural products from the region (Galliot et al., 2020; Hulin et al., 2019b).

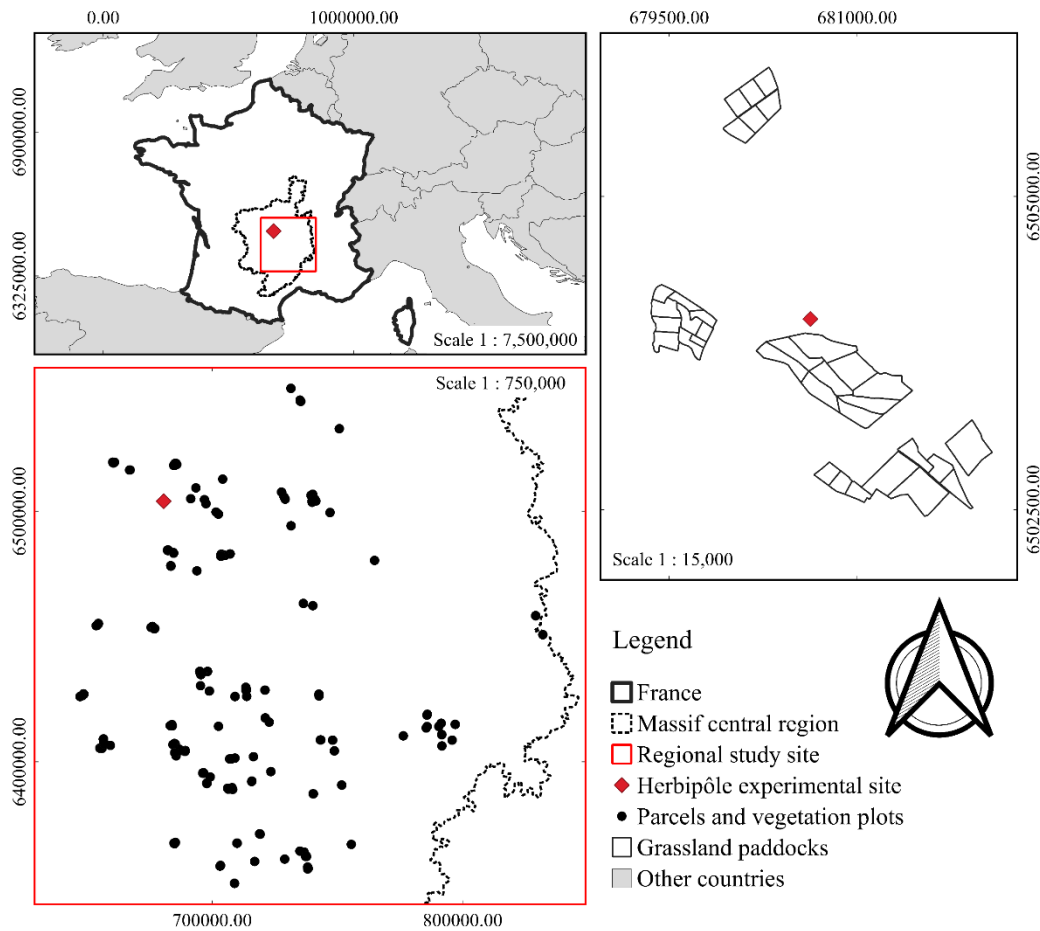


Figure 10. Location map of the two study sites for Chapters 2 (regional spatial scale) and 3 (local spatial scale) objectives of this thesis. Data sources: Massif central boundary: <https://www.prefectures-regions.gouv.fr/auvergne-rhone-alpes>; and country boundaries: <https://datacatalog.worldbank.org/>.

The Massif central has an average elevation of 700 meters above sea level (a.s.l.) with the lowest and highest elevations at 300 and 1,885 m a.s.l., respectively. The region is comprised of about 11 soil units (Appendix B). The cambisols, which represent 62% of the region [European Soil Data Centre (ESDAC); Panagos et al., 2022], are widely distributed within the region. The central and eastern portions of the region are of volcanic origin and date to the early 65 million years (Gorshkov and Gaudemer, 2019; Soubrand-Colin et al., 2007; Quantin, 2004). Located in the central and eastern portions are andosols and podzols, which were each 6% of the whole Massif central (ESDAC; Panagos et al., 2022; Quantin, 2004). To the northern part of the region are albeluvisols (6%), phaeozems (<1%), and vertisols (< 1%); then to the west and south are luvisols (6%). Present also in the southern part are regosols (1%). The leptosols (6%) are situated in the central and southern portions of the region (ESDAC; Panagos et al., 2022). The histosols (< 1%) were scattered sparsely across the Massif central,

and the fluvisols (2%) were found along the river channels of the region (ESDAC; Panagos et al., 2022). The formation and distribution of these soil units are attributed partly to the varying effects of long-term climatic conditions on the pyroclastic materials of the region (Quantin, 2004; Soubrand-Colin et al., 2007). Then the climatic zones across the Massif central varies from oceanic in the northern and western areas, mountainous and semi-continental for the central areas, and Mediterranean near the southeastern areas (Joly et al., 2010).

The parcel data of 143 temperate managed grasslands, with 396 corresponding vegetation plots, were available for the Massif central region. The grassland parcels are composed of 95% permanent grasslands and 5% temporary grasslands. These are topographically distributed between 272 to 1,442 m a.s.l. with an average elevation of 890 m a.s.l. The parcels have surface areas that range from 0.06 to 36.61 hectares (ha) with an average area of 4.12 ha. The implemented herbage uses among the parcels were grazing (52%) and mowing (48%). Being located in the central part of the Massif central region, the dominant soil types of the grassland parcels are andosols (45%), followed by cambisols (30%) and podzols (14%). The remaining 11% were combinations of leptosols, luvisols, fluvisols, and albeluvisols. The vegetation plots were irregularly distributed among the grassland parcels based on the parcel surface area. The sizes of the vegetation plots range from 2 to 100 square meters (m²) with an average of 25 m². In each plot, phytosociological surveys were conducted together with the characterization of the plot elevation, slope, and aspect.

2. The Herbipôle experimental site

The Herbipôle is an experimental Unit of the French National Research Institute for Agriculture, Food, and Environment (INRAE). It implements farm-scale experiments for research projects. The Herbipôle experimental site (45°38'7.64"N, 2°45'4.77"E; Figure 10), in Laqueuille, Puy-de-Dôme, France, is one of the three sites managed by the Herbipôle Unit. This site is composed of permanent grasslands, distributed between 1,000 and 1,450 m a.s.l., and covers a total area of 560 ha with homogenous basaltic andosols (Prache, 2017; Sepchat et al., 2020; Vazeille et al., 2018). The climate is characterized by an annual precipitation of 1,100 mm and an annual mean temperature of 8.0°C. Despite, the homogenous environmental and climatic conditions of the site, some parcels are bordered by trees, shrubs, and rock surfaces.

The data used for the purpose of this Ph.D. thesis were part of the *Systèmes d'élevage Allaitants herbagers: Adapter le type génétique et MIXer les espèces pour renforcer leur durabilité* (SALAMIX) project implemented on the Herbipôle site in Laqueuille. Conducted between May 2015 and November 2020, the SALAMIX project has access to 118 ha of permanent grassland managed under an organic farming system (Prache et al., in press; Vazeille et al., 2018; Veysset et al., 2016). There are 33

paddocks in all, and the area of each paddock ranged from 1.52 to 8.55 ha with an average of 3.56 ha. About 18 paddocks were solely used for grazing, while 15 paddocks were dominantly used for mowing followed by grazing depending on the remaining grassland biomass.

E. Field measurements of managed grasslands

To address the second and third objectives of this thesis, various field measurements were necessary with varying types of information and level of detail. The assessment of variability and drivers of grassland sensitivity to drought using remote sensing (Chapter 2) required several farm observations with heterogeneous grassland parcel characteristics related to pedoclimate, vegetation diversity, and management practices. However, the high number of observations, such as for management, was at the expense of detailed and continuous field monitoring, and data collection. Meanwhile, the evaluation of managed grassland resistance and resilience to drought impact using a process-based model (Chapter 3) required more detailed parcel data. For example, the type of herbage use, and the specific dates and duration of use were essential in creating the dynamic model of vegetation growth. To summarize, the field data used in this thesis were based on four completed research projects implemented within the Massif central region. All the projects monitored temperate managed grasslands at varying scales, details, and durations.

1. Data for regional assessment of drought sensitivity drivers

A large set of data was collected during the course of three projects implemented at regional scale in the Massif central from 2008 to 2019. Specifically, these were the (i) Prairies Appellations d'Origine Protégées (Prairies AOP; 2008 – 2012), (ii) Vers une approche Territoriale de l'Autonomie Fourragère et des services rendus par les systèmes fourragers à dominante herbagère en production fromagère AOP de Montagne (ATOUS; 2014 – 2017), and (iii) Les prairies du Massif central, un Atout Economique pour cOnstruire des systèmes d'éLEvage performants (AEOLE; 2016 – 2019). Implemented at different durations, the AEOLE project consolidated the parcel data from the Prairies AOP and ATOUS projects. The AEOLE then continued to characterize the managed grassland and focused on demonstrating the importance of grassland diversity for improving the quality and production of the main agricultural products of the region, which are milk and cheese (Carrère et al., 2012; Hulin et al., 2019a). The three projects monitored a total of 143 parcels from 70 grassland farms, using the same standardized protocols (Galliot et al., 2020). Each parcel was initially selected to represent the heterogeneity of vegetation, soil, climate, and farming system in the region. While phytosociological surveys were conducted in 396 vegetation plots. Other criteria for the farm selection

were the willingness of the farmers to participate in the projects and the lack of change in their respective management practices for several years (Galliot et al., 2020).

For each of the 143 parcels, there were four conducted surveys depicting (i) farm livestock and management practices; (ii) soil physical and chemical properties; (iii) vegetation composition and phytosociology; and (iv) biomass yield and forage quality (Galliot et al., 2020). For this thesis, the focus was on management practices, soil characterization, and vegetation composition.

The management practices were monitored from 2008 to 2009 for herbage use and nitrogen fertilization. Then from 2016 to 2017, additional Nitrogen (N) fertilization practices were recorded. The Prairies AOP project first gathered from the farms the amount of N fertilization inputs (i.e., organic and inorganic), common management practices (i.e., grazing or mowing), and the dates of management implementation from the first to the third use, if possible (Galliot et al., 2020). The parcels received an average total (organic and inorganic) N of 80.18 kg ha⁻¹ per year and were used at least once per year either by mowing or grazing.

The INRAE – UREP protocols were implemented for the soil analysis of 138 parcels. Each parcel was represented by one homogeneous soil sample, which consisted of four samples taken from the topsoil (0 -10 cm) layer during the fall season (Galliot et al., 2020). The soil pH of the parcels ranged from 4.9 to 7.3 with an average of 5.8. Soil pH, percent soil organic carbon and nitrogen, and carbon to nitrogen ratio for all parcels were calculated after measurements by elemental analysis (Carlo-Erba, It). The soil samplings were conducted under two projects and both during the fall seasons in 2009 and 2016 (Galliot et al., 2020). Most of the extracted soil properties, such as soil texture (i.e., percent clay, sand, loam); soil organic matter content; bulk density; potassium, magnesium, and phosphorus contents; rock origin, and rock type, were collected for 74 of the 143 parcels under the Prairies AOP project in 2009 (Galliot et al., 2020).

The *Conservatoire Botanique National du Massif central* (CBN) organized and processed the vegetation surveys from involved botanical conservatories (Le Hénaff, 2021). Specifically, the CBN Massif central surveyed the grasslands within Puy-de-Dôme, Ardèche, Cantal, and Haute-Loire; the CBN Midi Pyrénées surveyed Aveyron; and CBN Méditerranéen surveyed Lozère. About 400 vegetation plots were assessed for phytosociological analysis (Galliot et al., 2020). However, the lack of recorded geographic location resulted in the use of 396 vegetation plots in this thesis. The phytosociological approach implied variations in the size of the vegetation plot being surveyed. In this case, the abundance of plant species was recorded in plots that ranged from 2 to 100 m² with a mean of 25 m² (Galliot et al., 2020), while the number of recorded plant species per plot ranged from 5 to 55 species (Galliot et al., 2020). The AEOLE project determined the species richness and rarity index of each plot. Then for this thesis, the computation of the taxonomic Shannon diversity and Simpson's

diversity indices were based on the phytosociological survey data. While the traits for the plant community weight mean (CWM), and functional dispersion (Fdis) were extracted from existing trait databases of Baseflor (Julve, 1998) and DIVGRASS (Carboni et al., 2016; Violle et al., 2015).

In this thesis, the data from the three consolidated regional projects provided the collection of grassland management practices; soil and topographic conditions; and vegetation taxonomic diversity and species richness of the parcels and plots. These factors were hypothesized to show direct and indirect influences on the response to drought.

2. Data for grassland productivity modelling under drought conditions

The third objective of this Ph.D. thesis, which focuses on the evaluation of the resistance and resilience of managed grasslands to drought, was possible with the data collected from the Herbipôle experimental site in Laqueuille, Puy-de-Dôme, France during the SALAMIX project between 2015 and 2020. SALAMIX evaluated the economic, agricultural, and environmental performance of three farming systems of sheep, cattle, and their combination. The grassland paddocks were dedicated to one of the three tested farming systems for the entire course of the project and with either grazing or mowing treatments. The project was composed of 11 parcels (6 pastures and 5 mowed parcels) per farming system (Vazeille et al., 2018; Veysset et al., 2016) or a total of 33 paddocks with a total paddock area of 117.47 ha.

The SALAMIX project conducted regular monitoring of the grassland paddock productivity and management. The vegetation height was measured from about 80 to 100 equally spaced points per ha along a fixed transect line inside the paddocks. Either a herbometer or a stick was used for the measurements. The herbometer estimates the vegetation height based on the pressed volume of vegetation to estimate biomass combined with density. While for the meter stick, the recorded height is based on the highest part of the vegetation touching the stick and on the identification of touched vegetal organ to evaluate the vegetation structure. The biomass of each paddock was obtained from at least four quadrats with a dimension of 70 cm x 70 cm. The geographic coordinate location of these quadrats allowed the repeated sampling at or near the same point. The field measurements of grassland biomass and height were conducted four to six times annually before the entry of animals or the date of cutting. The detailed paddock management data were based on the diligent recording of the mowing duration and cutting dates.

Together with the SALAMIX data, this thesis used the HerbValo method (Delagarde et al., 2017; 2018) to determine the mowing and grazing impacts. Developed in 2015, HerbValo is a computational method that (i) directly accounts for the removed biomass from cutting events, and (ii) considers the number of grazing days; animal daily grass intake; grazing severity, and supplemental feeding to the

estimate grazing impact (Delagarde et al., 2017; 2018). Equation 1 shows the simple HerbValo formula for one harvest or cycle (Delagarde et al., 2017).

$$I(t) = [\{ (CI/VE) corSEV \} - \sum (QC_i \times TS_i)] \quad \text{Equation 1}$$

Where: the grass intake (I) for a given time is based on the grazing rate [ratio of animal intake capacity (CI) and grass ingestability (VE)] and grazing severity. Then the total amount of supplementary fodder (e.g., dried hays), which is based on the quantity of consumed complementary fodder (QC) and rate of substitution between grass and fodder (TS), is further deducted to get the grass intake (Delagarde et al., 2017).

Chapter 3 took advantage of the rarely available detailed management calendar dates. To evaluate the resistance and resilience of managed grassland to drought, the initial investigation started with six paddocks that equally represented the mowing and grazing treatments. These were used in the creation, calibration, and evaluation of the vegetation growth dynamic model.

F. Climate data and drought severity

Consistent with the use of different field-measured data, Chapters 2 and 3 used climate data with varying spatial coverage and accuracy. Chapter 2 required regional climate data for the assessment of the drought severity of all grassland parcels and vegetation plots, while Chapter 3 benefited from the high accuracy of climatic variable records from a field meteorological station.

1. Climate data records

The first climate data source was the *Système d'Analyse Fournissant des Renseignements Atmosphériques à la Neige* (SAFRAN) data model, which provided hourly to daily gap-free records of climatic variables, as early as 1958. The Météo-France, specifically the *Centre National de Recherches Météorologiques* (CNRM) Unit produced the SAFRAN data, which covers the whole of France. SAFRAN consists of 8 km-sized grids in a Network Common Data Form (NetCF) format and has a Lambert-II coordinate system projection (Durand et al., 1993; Le Moigne, 2002). Accordingly, the SAFRAN data can be converted into other data formats, such as shapefiles or raster, and transformed into table data file format (Le Moigne, 2002). This climate data model originated from climatic variables from ground meteorological stations, which were then interpolated to estimate the climate across mountainous regions covered in snow (Durand et al., 1993). The specific climatic

parameters accessed for Chapter 2 were the Penman-Monteith potential evapotranspiration (in mm); solid and liquid precipitation (in mm); and mean, maximum, and minimum temperatures (in °C).

The second source of climate data was the multiple field meteorological stations distributed across France and managed by Météo-France and their respective partners. The meteorological stations provide hourly to daily climate records of precipitation (in mm); mean, maximum, and minimum temperature (in degree C); calculated solar radiation (in J cm⁻²); and Penman-Monteith potential evapotranspiration (in mm). Overall, the oldest climatic records were from 1981, however, the temporal length and availability of observations vary between stations.

Chapter 2 was supported by the spatial and temporal coverage of the SAFRAN climate data model. Amidst the available meteorological stations within the Massif central, the distribution of the stations was unable to cover all the managed grassland parcels. For instance, the distance between the parcels and meteorological stations often largely exceeded 8 km (Figure 11). The length of climate records per meteorological station varied depending on the date of establishment and operation. With the SAFRAN data model, all parcels have more than 35 years of daily climatic variable records. The World Meteorological Organization (WMO) recommended a 30-year length of climate data to establish the climate normal condition for meteorological studies (Marchi et al., 2020; Rigal et al. 2019).

The SAFRAN data were compared to the field meteorological station measurements to determine its accuracy and to assess its suitability for the regional assessment of drought severity. A total of 91 out of 187 meteorological stations were situated within the Massif central region (Figure 11). Each SAFRAN grid with corresponding meteorological stations was paired and correlated. Multiple meteorological stations within the same SAFRAN grid were averaged before the correlation procedure. The obtained R² for daily precipitation, potential evapotranspiration, and mean temperature were 0.84, 0.88, and 0.96, respectively.

Chapter 3 used the climate records from the Laqueuille field meteorological station (45°38'35.88"N; 2°44'3.73"E), which was within the Herbipôle experimental site. The Laqueuille meteorological station provided site-specific daily climate records as early as July 1995. Despite the 25-year length of climate observations, the field-collected climate data were used to obtain high accuracy in the drought severity assessment. The meteorological station climate data allowed the more realistic simulation of the process-based dynamic model of vegetation growth.

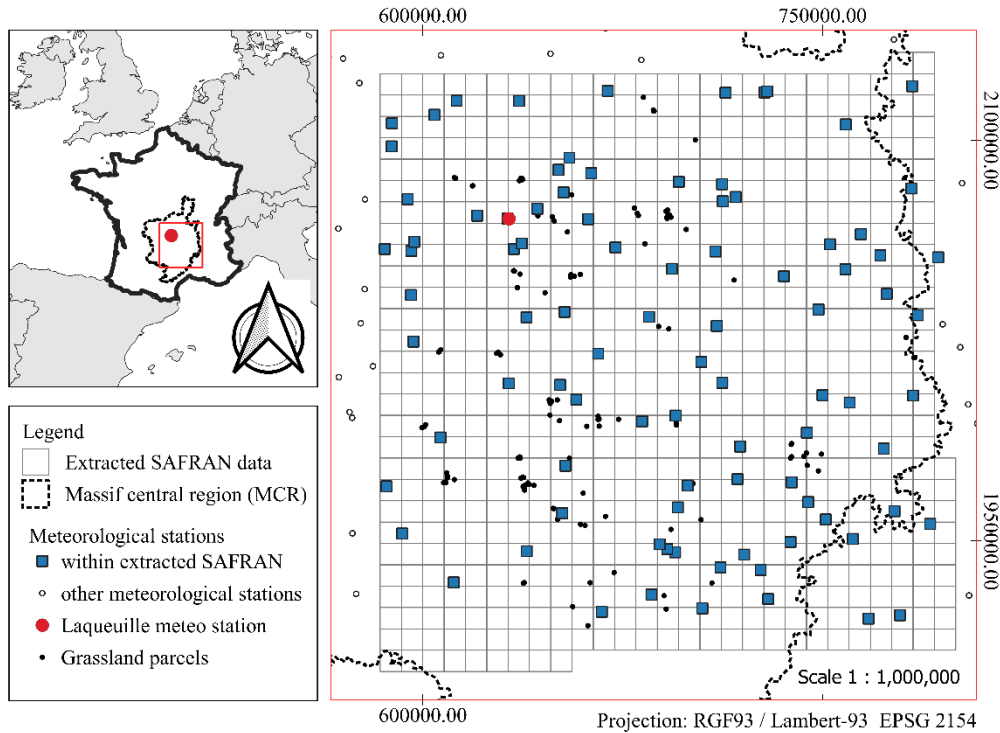


Figure 11. Location of the field meteorological stations within and outside the Massif central region and the grassland 143 parcels in relation to the extracted SAFRAN data for this thesis. The SAFRAN data is consist of 8 km grids.

2. Drought severity assessment

A modified daily version of the Standardized Precipitation and Evapotranspiration Index (SPEI) was used to assess the meteorological drought severities of both Chapters 2 and 3. The classic SPEI is based on the long-term monthly time series of the climatic water balance (D_i), which is the difference between precipitation (P) and potential evapotranspiration (PET). Using the available Penman-Monteith PET , the temperature, humidity, radiation, and wind speed were incorporated in the computation of drought severity. Moreover, SPEI allows the integration of climatic water balance at different timescales from 1, 3, 6, 9, 12 to 24 months (Beguería et al., 2014; Vicente-Serrano et al., 2010). An annual drought timescale corresponds to the integration of the climatic water balance for a given month and the 11 previous months.

$$D_i = P_i - PET_i \quad \text{Equation 2}$$

where $i = \text{month/s}$

The SPEI standardization process involves the fitting of the D time series into a log-logistic distribution using a three-parameter probability distribution function. The probability distribution of

D is then standardized to obtain the SPEI value using the approximation of Abramowitz and Stegun (1965). The statistical distribution seeks to define the normal expectation. Negative SPEI values indicate a deficit from the water balance normal conditions. SPEI values lower than the -1.0 threshold are considered drought months. Accordingly, positive SPEI values indicate a surplus of precipitation.

However, the monthly drought assessment of SPEI presents concerns that are unaligned with Chapters 2 and 3 of this thesis. First, the abrupt change in SPEI values between consecutive months (Figure 12. a) excludes the detection of short-term (< 1 month) grassland response to drought (Salehnia et al., 2018; Wang et al., 2015). Then the monthly inputs result in a lesser number of observations that lead to a weak goodness-of-fit in the probability distribution of climatic water balance during the SPEI standardization step if the time series is too short (Figure 12. b). In this respect, it is recommended by WMO to use at least a 30-year long time series or at best a 50-year long time series.

To address the concerns regarding the abrupt change and the weak goodness-of-fit, I changed the climatic water balance time resolution from monthly to daily and calculated the daily SPEI using a moving window. To do so, I used the method from Russo et al. (2014) where instead of accounting for just the same dates across years (Equation 3), the calculation for a given day includes the same date across the years and days before and after (Equation 4). In the equations, A represents the dataset of climatic water balance ($P - PET$), with d the given day or date of interest; y the year, and i is the considered days around d . I presented in Figure 12 the comparison between the classic and the modified SPEI and the improved probability distribution goodness-of-fit of the climatic water balance.

$$A_d = \bigcup_{y=1996}^{2020} D_{y,d} \quad \text{Equation 3}$$

$$A_i = \bigcup_{y=1996}^{2020} \bigcup_{i=d-15}^{d+15} D_{y,i} \quad \text{Equation 4}$$

Figure 12 shows the improvements between the classic and modified SPEI. The change from monthly to daily time resolution captured the minor drying and wetting events and showed better transitions between months. Then the new set of data increased the number of observations and improved the goodness-of-fit for the log-logistic distribution step in the SPEI standardization procedure.

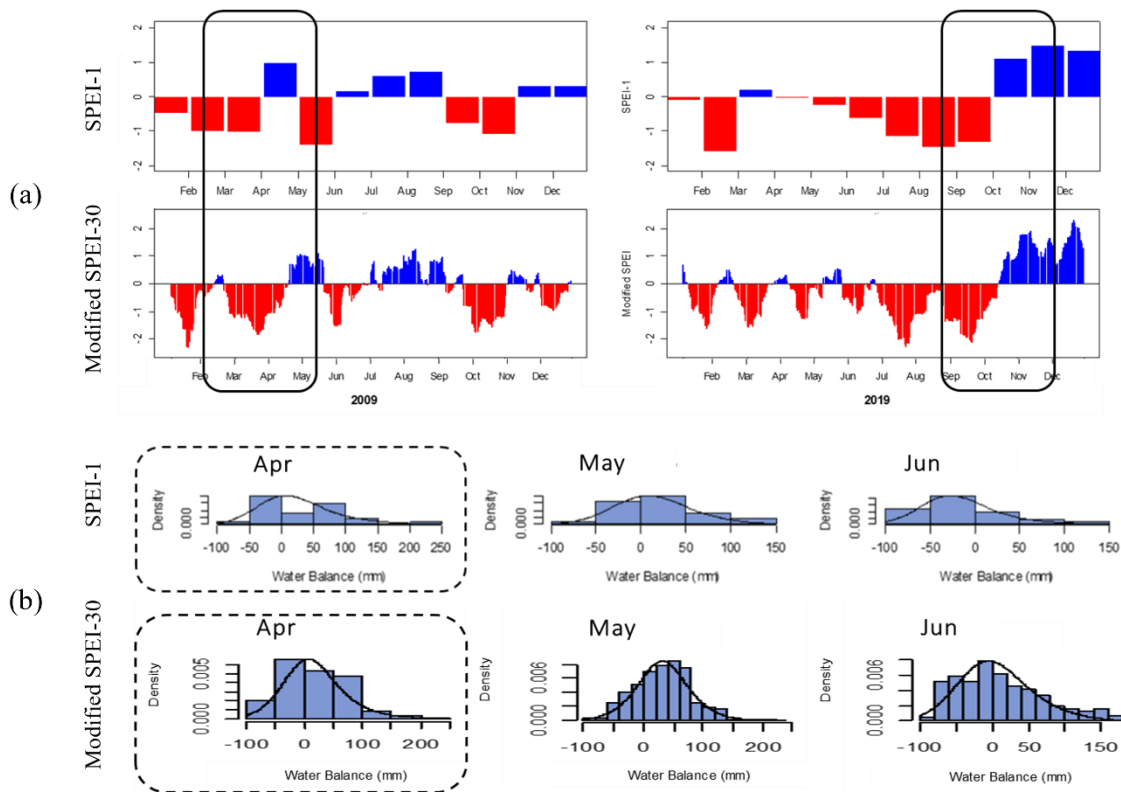


Figure 12. Comparison of (a) the trajectories of the SPEI-1 and modified SPEI-30 at the 1-month equivalent timescales for the sample years of 2009 and 2019, and (b) the probability distributions focusing on April, May, and June. The modified SPEI improved the time resolution, SPEI transition (highlighted with the solid box) and goodness-of-fit of the probability distribution for the month of April (highlighted with the dashed-line box). The climatic data used in the assessment was from the Laqueuille meteorological station record from 1996 to 2020.

In summary, the SAFRAN data allowed the assessment of drought severity of all the grassland parcels and plots distributed across the Massif central region for Chapter 2. While the site-specific meteorological station near the local farm study site provided the much-needed high-accuracy drought severity assessment for Chapter 3. The modified daily SPEI was used to quantify the drought severity for both Chapters.

G. Satellite image time series

This thesis is highly motivated by the potential of satellite remote sensing products and techniques for vegetation monitoring. In this section, I justify the use of optical satellite images, present the selection of satellite data from two main sources, and highlight the reflectance-based remote sensing techniques that were implemented for Chapters 2 and 3 of this thesis.

1. Optical satellite images for the study

The optical satellite images were selected over the microwave images based on the availability of satellite data and the multiple vegetation properties that can be estimated from reflectance bands. Accordingly, the selected images were the satellite sensors of the Landsat missions, Sentinel 2 MSI, and VEN μ S (Vegetation and Environment monitoring on a New MicroSatellite; Hagolle et al., 2010).

The Chapter 2 regional assessment of grassland sensitivity to drought required long-term satellite observations in establishing the baseline reference condition of the grassland parcels in the Massif central. Landsat missions demonstrated comparability in their basic spatial, temporal, and spectral resolutions and improvements in radiometric resolution through the years (Wulder et al., 2022). The 30 m spatial resolution of Landsat depicted vegetation heterogeneities among the parcels, which were more than 30 m apart. Despite the inability of the Landsat 16-day temporal resolution to capture the daily and even weekly changes in grassland conditions, Landsat missions compensated with the long temporal range of 50 years starting from 1972 to 2022. The Landsat spectral resolution allows the computation of vegetation indices with the availability of the visible reflectance bands of RED, GREEN, and BLUE; and the near- and shortwave-infrared bands (NIR and SWIR).

The Chapter 3 local scale evaluation of managed grassland resistance and resilience to drought, on the other hand, requires satellite images with medium to high spatial and temporal resolutions. The high spatial resolution decreases the probability of mixed pixels in representing grasslands on the ground. Mixed pixels refer to the convergence of multiple land cover features in a one-pixel unit (Foschi, 1994). Then to maximize the use of the detailed management records of the SALAMIX project, temporal resolutions higher than a week allowed the finer detection of grassland development.

Sentinel 2 images have medium spatial resolutions of 10, 20, or 60 m depending on the reflectance band. Sentinel 2 is composed of two Earth-orbiting satellites that were launched separately on 23 June 2015 and 7 March 2017. Each satellite has a 10-day revisit, which when combined improves the temporal resolution to 5 days. In terms of spectral resolution, Sentinel 2 has 13 bands, ranging from visible to shortwave infrared. Compared to Landsat images, Sentinel 2 has a red-edge band, which improves the estimation of chlorophyll (Delegido et al., 2011). Thus far, Sentinel 2 is a freely available remote sensing product with overall high spatial, temporal, and spectral resolutions.

Lastly, another satellite mission considered in this thesis was the Vegetation and Environment monitoring on a New MicroSatellite or VEN μ S. This satellite was jointly developed by the French *Centre National d'Etudes Spatiales* (CNES) and the Israeli Space Agency. It collected high spatial resolution (5 m) images with high revisit frequency (2 days) from 2017 to 2020. The VEN μ S spatial coverage is limited to 130 selected experimental sites distributed globally (Baba et al., 2020; Bessin et al., 2022; Upreti et al., 2020). VEN μ S is composed of 12 spectral bands, which uniquely have a digital

elevation model band (Baba et al., 2020; Upreti et al., 2020). The visible, red-edge, and near-infrared bands are also available with VEN μ S similar to Sentinel 2. Unfortunately, the moisture-sensitive shortwave infrared bands are lacking.

Each satellite image satisfies the research requirements of Chapters 2 and 3. Specifically, the long-term temporal range of Landsat missions and the high frequency of revisit of Sentinel 2 and VEN μ S. The comparison of the spatial and temporal resolutions, and temporal range of Landsat, Sentinel 2, and VEN μ S images are summarized in Figure 13. While the spectral resolutions and equivalent reflectance bands of the three satellite images are summarized in Appendix C.

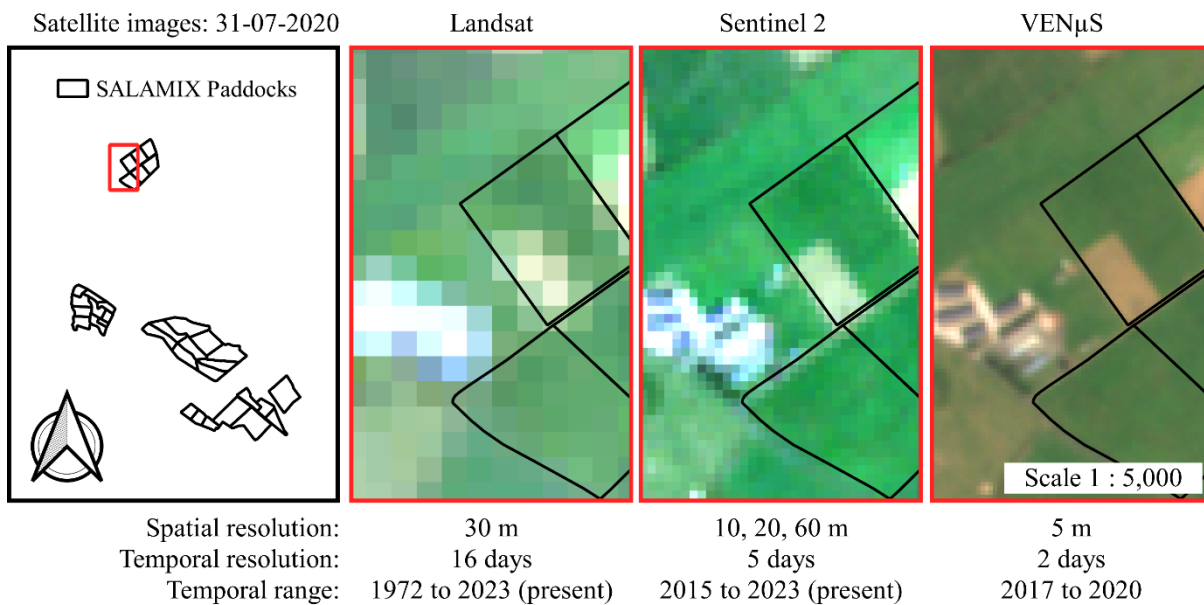


Figure 13. Comparison of the medium to high spatial resolution (from left to right) of Landsat 8, Sentinel 2, and VEN μ S satellite images. The images show paddocks from the SALAMIX project at the Herbipôle experimental site (Laqueuille, Puy-de-Dôme, France).

2. Comparative assessment of satellite data sources

The Landsat and Sentinel 2 images are freely accessible from the official websites of host agencies (e.g., <https://earthexplorer.usgs.gov/> for Landsat and Sentinel 2; and <https://scihub.copernicus.eu/dhus> for Sentinel 2). Similarly, online cloud services, such as the Google Earth Engine (GEE; Amani et al., 2020; Gorelick et al., 2017), Amazon Web Services (AWS; Ferreira et al., 2020; Lee et al., 2010), the Microsoft Planetary Computer, and the Data and Information Access Services (DIAS), store and grant access to the consolidated collections of multiple remote sensing data and products. National research organizations, such as the Theia Data and Service Center (<https://www.theia-land.fr>; referred to in this thesis as Theia) for France, implement improvements and provide similar access to data and products

generally intended for the needs and use of their country. For instance, the VEN μ S (Vegetation and Environment monitoring on a New MicroSatellite) data, which was under the joint Israel and France partnership, are accessible through the Theia website.

This thesis considered two remote sensing product sources, namely the GEE and Theia due to the cloud services and implemented image improvements, respectively. Initially, the goal was to use only one source of remote sensing data. However, the lack of concrete references regarding the advantages and disadvantages of each source prevented the selection of only one data source. Thus, part of this thesis involved the comparative assessment of GEE and Theia.

To do so, the comparative assessment used Landsat images covering the Herbiopôle experimental site in Laqueuille, Puy de Dôme, Massif central, France. The obtained Landsat images were cropped to an extent of 2.7 km x 3.6 km, which covers the SALAMIX parcels (Figure 14). Then the parameters considered in the assessment were (i) the download and storage requirements, (ii) the image availability, (iii) the spatial agreement, (iv) the cloud and shadow masking algorithm, and (v) the reflectance band values.

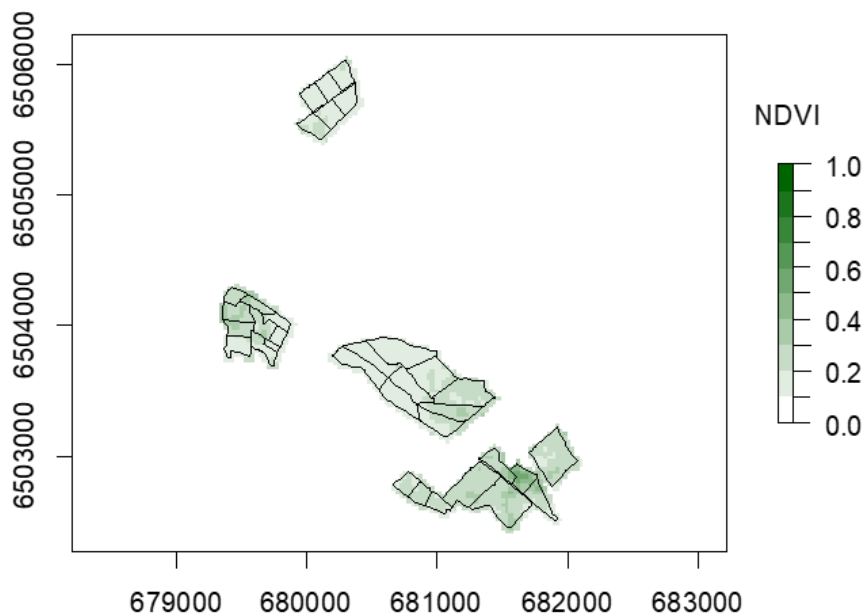


Figure 14. Extent of the SALAMIX paddocks featuring the NDVI values. The NDVI was generated from the 7 January 2015 Landsat 8 image, which was downloaded from Theia Data and Service Center.

For the first criterion of image download and storage requirement, Landsat images from 01 January 2015 to 01 November 2020 were downloaded. Both downloads were performed on a personal computer under the R environment using the `reticulate` and `TheiaR` packages for GEE and Theia,

respectively. The GEE mainly functions under the Python language. The reticulate package (Ushey et al., 2022) allows the use of Python scripts in R. Unfortunately, the rgee package, which is specifically designed for the use of GEE in R (Aybar et al., 2022) was unavailable during the conduct of the comparative assessment. The download of satellite reflectance from GEE was completed in less than 10 minutes. No digital storage of all the Landsat files was necessary with GEE due to the cloud processing service. Instead, the values of the reflectance bands of each Landsat image were summarized in a table data format, which has a file size of at least 0.01 gigabytes. While the extraction from Theia lasted for approximately two weeks due to repeated disconnections from the Theia server. The theiaR package enabled the direct download and management of satellite images from the Theia website (Laviron, 2022). The Landsat files from Theia amounted to 22.4 gigabytes (GB) of digital storage on a personal computer.

The two data sources provided an unequal number of Landsat images (Figure 15) from 2015 to 2020. The GEE provided 106 images, which included Landsat scenes with greater than 90% cloud cover. Meanwhile, Theia provided 66 images, due to the exclusion of Landsat scenes with greater than 90% cloud cover. The oldest available Landsat observations in GEE and Theia were from 1972 and 2009, respectively.

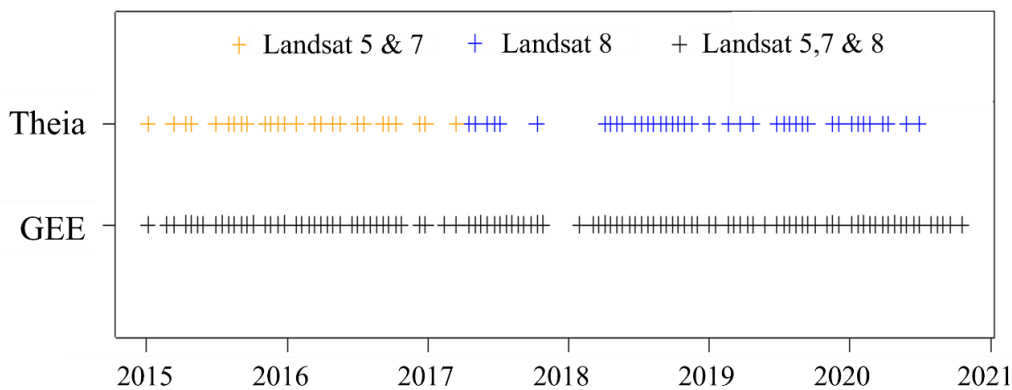


Figure 15. Extracted Theia and GEE Landsat 5, 7, and 8 images from 01 January 2015 to 01 November 2020. The gaps along the observations were due to the percent cloud cover.

The spatial agreements were compared using 30 m grids generated from the pixels of two sets of Landsat images from GEE and Theia (Figure 16). The spatial disagreement was highest at 16.80 m between the GEE and Theia Landsat 5 and 7 and it was 13.23 m for Landsat 8. However, despite the low disagreement between the newer Landsat 8 images, the geometric comparison lacks a true spatial

reference. Possible sources of errors were related to the post-processing and successive projection transformations of the original images.

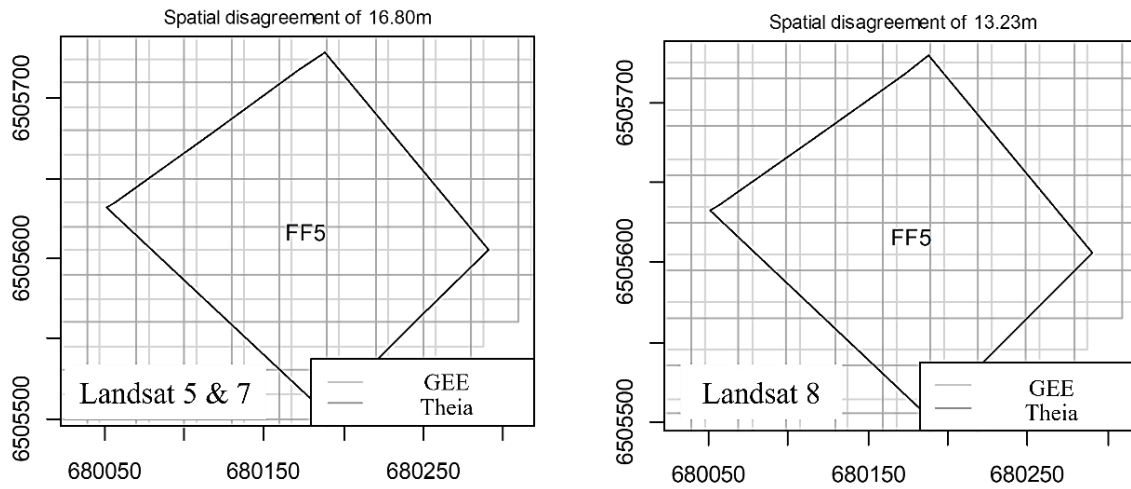


Figure 16. Spatial agreement assessment between GEE and Theia using Landsat 5 & 7 (left) and 8 (right) images. The irregular polygon FF5 is one of the SALAMIX paddocks for mowing.

In terms of the masking algorithms, GEE, specifically, USGS, uses the Land Surface Reflectance Code (LaSRC), while Theia uses the MACCS-ATCOR Joint Algorithm (MAJA; Hagolle et al., 2017). The LaSRC was developed by the University of Maryland together with the National Aeronautics and Space Administration (NASA) of the United States of America, while MAJA was developed by the Centre d’Etudes Spatiales de la Biosphère (CESBIO) joint research Unit of France (Hagolle et al., 2017; Skakun et al., 2022). The comparison was performed with a contingency table of all the cloud and shadow pixels based on the QA_Pixel layer to demonstrate the agreement of masked pixels between the LaSRC and MAJA algorithms (Figure 17).

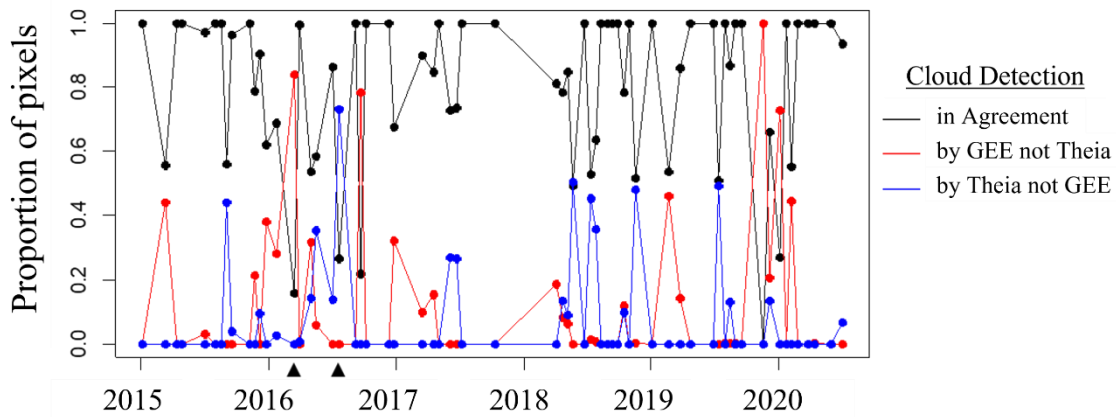


Figure 17. Comparison of cloud mask agreement between GEE and Theia Landsat 8 images. The two triangles at the bottom of the plot highlight dates when cloud detection was erratic.

The mask agreement revealed that cloud detection was variable in time, and it offers a total agreement of 80% based on image observations from 01 January 2015 to 01 November 2020. No clear advantage between the performance of the two algorithms was observed with Landsat in this comparative assessment. Nevertheless, the LaSRC classified 11.2% of pixels as clouds, which were not detected by MAJA. Conversely, the MAJA classified 8.3% of the pixels as clouds, which were not detected by LaSRC.

The authors found that both the LaSRC and MAJA algorithms have fluctuating performances in cloud detection when tested with different datasets (Skakun et al., 2022). In the assessment of five masking algorithms that included LaSRC and MAJA, the results showed no significant difference among algorithm performances in the detection of clouds or shadows (Tarrío et al., 2020). Nevertheless, the use of MAJA on Sentinel 2 images revealed a more balanced cloud and shadow masking compared to LaSRC (Tarrío et al., 2020).

The final parameter in this comparative assessment was the reflectance band values, which were based on clear or cloud- and shadow-free, pixels within the SALAMIX paddocks (Figure 18). Overall, the reflectance values of the visible (BLUE; GREEN, and RED) and NIR bands were highly correlated with R^2 values of 0.98 and 0.91, respectively. These were accompanied by a mean slope of 1.09 and an absolute mean intercept of 0.005 for all four bands. While the SWIR 1 and SWIR 2 bands were correlated still highly with R^2 values of 0.88 and 0.87, respectively, accompanied by a mean slope of 1.025 and a mean intercept of 0.005. Apart from the individual bands, three vegetation indices were derived to determine the correlation of transformed reflectance bands. These indices were the NDVI = $(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$; EVI = $2.5 * ([\text{NIR} - \text{RED}] / [\text{NIR} + 6 * \text{RED} - 7.5 * \text{BLUE} + 1])$; and NMDI = $(\text{NIR} - [\text{SWIR1} - \text{SWIR2}]) / (\text{NIR} + [\text{SWIR1} - \text{SWIR2}])$. The obtained vegetation index

correlations were high with an average R^2 of 0.95. The slope and intercept remained close to 1 and 0, respectively.

The data source assessment used and compared the parameters of data acquisition and quality (Table 1). Although conclusions were uncertain for some parameters, the obtained insights were used for practical consideration.

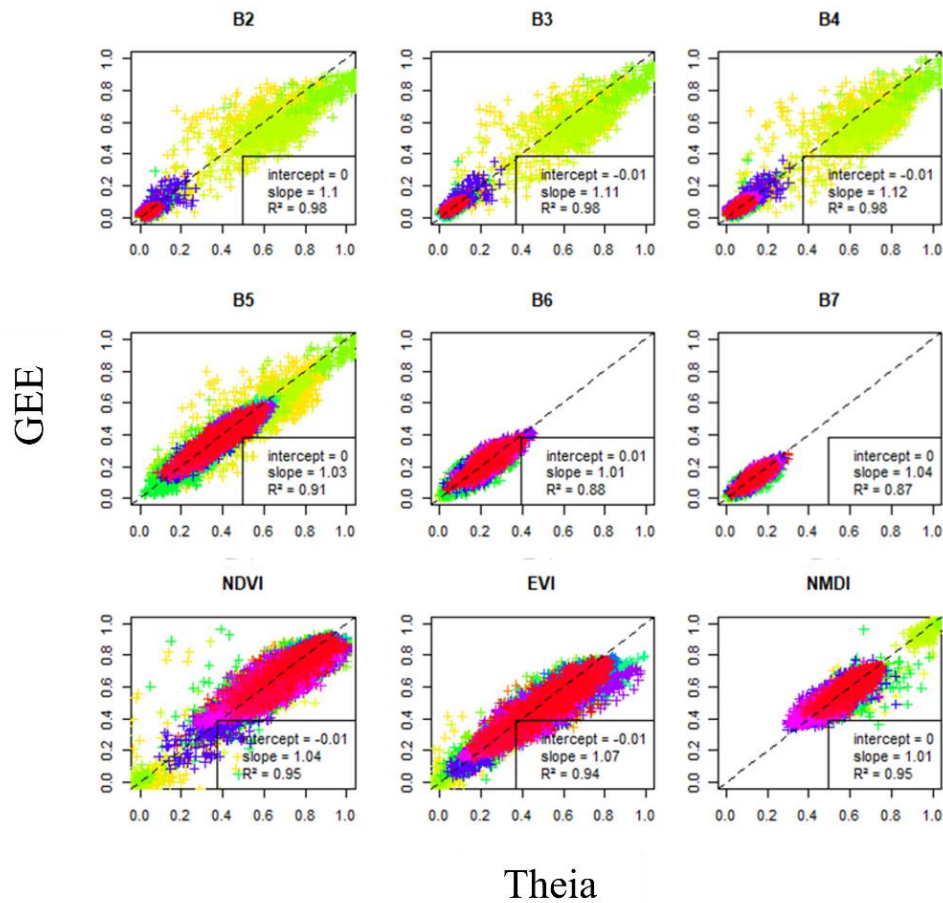


Figure 18. Correlation of the GEE- and Theia-obtained Landsat visible and infrared bands (B2: BLUE; B3: GREEN; B4: RED, B5 = NIR, and B6 = SWIR1 and B7 = SWIR2) and vegetation indices. Observations within the plots were clear pixel values from multiple dates. The colors correspond to the clustering of observation dates. Where the red and yellow corresponds to the most and least amount of data, respectively.

Table 1. Summary of the parameters used in the comparison of GEE and Theia data sources. The assessment used images covering the SALAMIX paddocks from 2015 to 2020.

Parameter	Results
Download Time on a single personal computer	GEE (less than 10 minutes) < Theia (approximately two weeks)
Storage requirement	GEE (cloud processing / 0.01 gigabytes) < Theia (22.4 gigabytes)
Image availability (2015 to 2020)	GEE (106 images) > Theia (66 images)
Temporal coverage	GEE (since 1972) > Theia (since 2009)
Cloud and shadow masking	LaSRC: cloud > shadows // MAJA: cloud = shadow
Spatial agreement	Inconclusive result due to inherent error and lack of proper reference
Reflectance bands	Reflectance values were highly correlated

For Chapter 2, the regional study of 143 grassland parcels required multiple image scenes and long temporal coverage, which was provided by the Landsat collection in GEE. The download and storage parameters were related to the Landsat scene file size. GEE provides Landsat in its original coverage, which is larger than Theia Landsat. The Theia Landsat scene is resized based on Sentinel 2 spatial coverage (Skakun et al., 2017). About five Landsat scenes were needed to characterize all the grassland parcels distributed in the region. Then from 1985 to 2019, about 1,900 Landsat images of unique dates were available for the Chapter 2 study. The majority of the Landsat images were found during the growing season (March to November). Accordingly, the wide spatial (Figure 19. a) and long temporal (Figure 19. b) coverages, together with the short download time of Landsat images, which are without strong consequences on data quality, led to the selection of GEE.

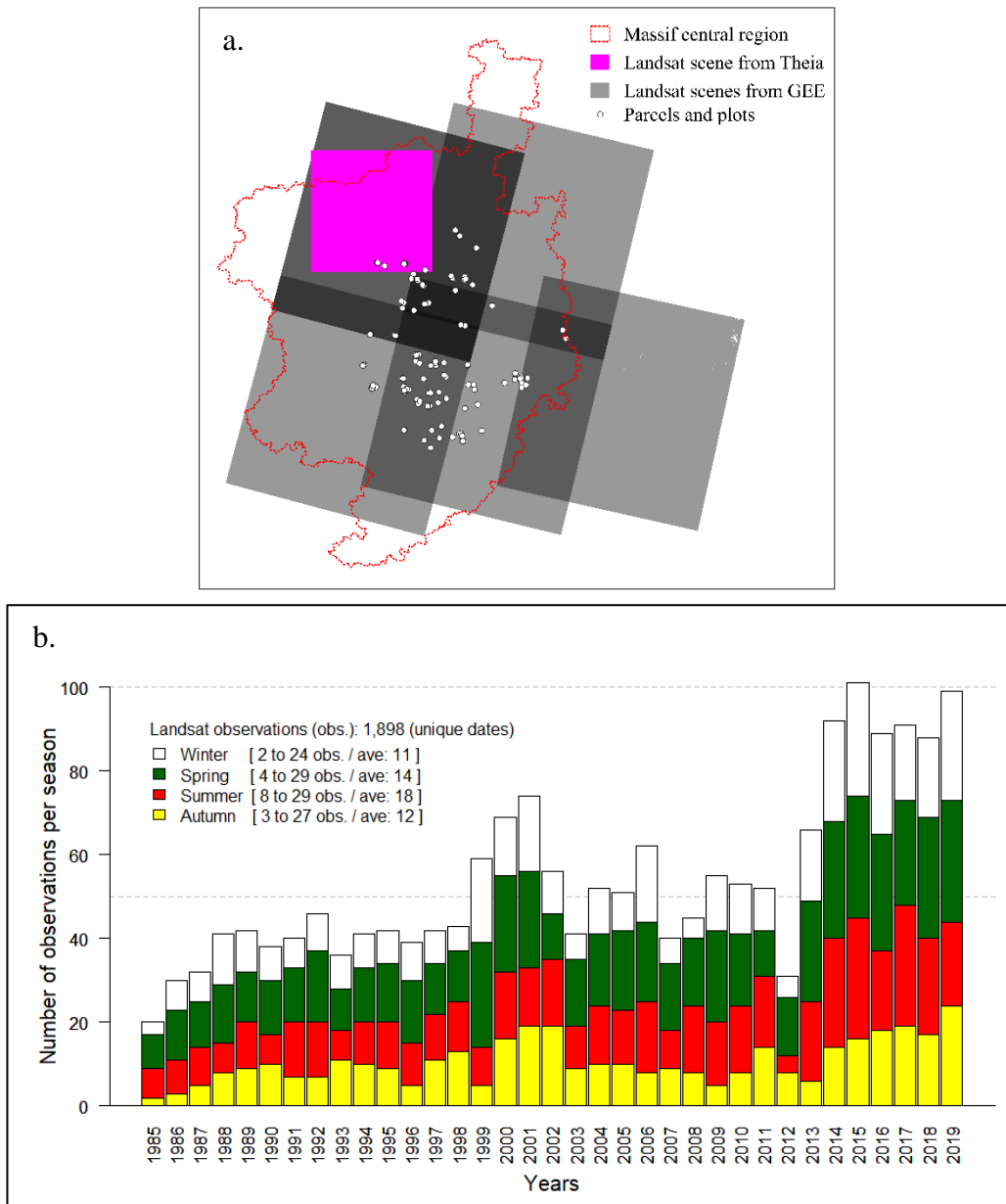


Figure 19. Comparison of the spatial coverage of Theia and GEE Landsat scenes (a) and availability of Landsat observations per season (b) from 1985 to 2019.

The Theia Data and Service Center was considered the data source for Chapter 3. The delay in the download time was manageable when the connection to the Theia server was closely monitored. The local study site was covered by one small scene of Sentinel 2 and VEN μ S. But most of all, VEN μ S images were unavailable in GEE. In terms of data quality, there was an overall equal detection of clouds and shadows with the MAJA (Hagolle et al., 2017) when used on Sentinel 2 (Tarrío et al., 2020).

At the end of the comparative assessment, further investigations were needed to provide a clear distinction between GEE and Theia as sources of satellite data and products. Unfortunately, said investigation is not part of the scope of this thesis. Nevertheless, both data sources were used based on their contributions to Chapters 2 and 3.

3. Vegetation properties from reflectance bands

Optical satellite images are composed of reflectance bands, which are correlated to vegetation properties based on the radiative energy from the sun or artificial sources reflected by objects and received by satellite sensors. For this thesis, the use of vegetation indices and the inversion of a radiative transfer model were used to determine the vegetation properties of temperate managed grasslands in Chapters 2 and 3.

Chapter 2 generated and tested a total of 24 vegetation indices (Appendix D). Specific vegetation indices are based on the transformation of selected reflectance bands that highlight vegetation properties. The Global Vegetation Moisture Index (GVMI) incorporates the SWIR2, which is responsive to the moisture in leaves, at the 1,500 to 2,500 nanometer (nm) wavelength range (Ceccato et al., 2002).

Chapter 3 used the PROSAIL model and the Look-Up Table (LUT) inversion technique to estimate the Leaf Area Index (LAI) of managed grasslands. The PROSAIL model has exhibited high performance among existing RTMs when implemented in homogenous and heterogeneous grassland and cropland covers (Atzberger et al. 2015; Darvishzadeh et al., 2008; Jacquemoud et al., 2009). It is the combination of two radiative transfer models, namely the PROSPECT, a leaf optical properties model, and the Scattering by Arbitrary Inclined Leaves (SAIL), a plant canopy reflectance model (Figure 20). Overall, PROSAIL requires a total of 14 input parameters (Table 2). The PROSPECT model yields an estimate of the leaf's radiative reflectance and transmittance based on the functions of the leaf's biophysical and biochemical properties. Accordingly, the output leaf optical property estimation serves as a direct input for the SAIL model component. Meanwhile, SAIL estimates the radiative transfer in the vegetation canopy, or simply the canopy reflectance, based on leaf-based parameters, soil reflectance, and the pathway of the electromagnetic radiation – by the satellite viewing angles.

Several methods are available for the inversion RTM results. Iterative optimization, LUT, artificial neural networks, and support vector machine regression are some of the available inversion methods (Darvishzadeh et al., 2008; Weiss et al., 2000). Each method aims to maximize the fit between the simulated and observed reflectance trajectories of a given biophysical or biochemical property. The

LUT was determined to be a fast, simple, and robust inversion method (Darvishzadeh et al., 2008; Weiss et al., 2000). It is a computational simple minimization technique that aims to generate a reference table of leaf parameter combinations that best fit the reflectance signature (Berger et al., 2018; Jacquemoud et al., 2009).

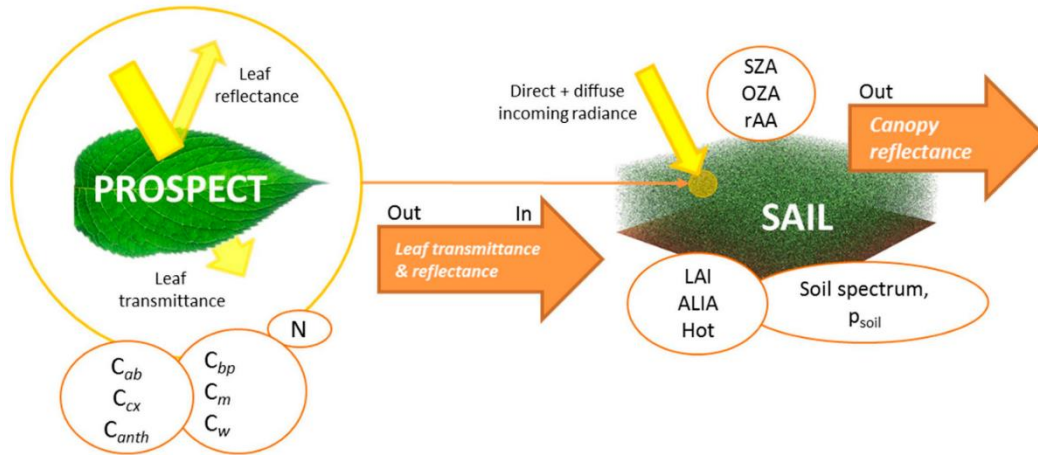


Figure 20. Illustration of the relationship between the PROSPECT and SAIL model. It shows a visual description of each model, and the inputs (Table 2) necessary to perform the simulation. The image was from Berger et al., 2018.

Table 2. Summary of the specific inputs for the PROSAIL model (PROSPECT + SAIL models).

Specific model	Input parameter	Annotation	Unit
PROSPECT (Leaf optical properties model)	Brown pigment content	C_{brown}	unit less
	Dry Matter Content	C_m	g cm^{-2}
	Equivalent Water Thickness	C_w	Cm
	Leaf chlorophyll a + b content	C_{ab}	$\mu\text{g cm}^{-2}$
	Carotenoid content	C_{ar}	$\mu\text{g cm}^{-2}$
	Leaf structural coefficient	N	unit less
SAIL (Canopy reflectance model)	Dry/Wet soil factor	P_{soil}	unit less
	Leaf Area index	LAI	$\text{m}^2 \text{m}^{-2}$
	Leaf angle distribution type	TypeLidf	unit less
	Leaf angle distribution function	lidfa	unit less
	Leaf angle distribution function	lidfb	unit less
	Hotspot parameter	hspot	m m^{-1}
	Solar zenith angle	tts	degrees
	Observer zenith angle	ttp	degrees
Relative azimuth angle	psi	degrees	

Various authors have demonstrated the use of PROSAIL inversion with available satellite images. For instance, the model inversions with Landsat 8, Sentinel 2 and 3, MODIS, and VEN μ S resulted in the estimation of chlorophyll content, leaf area index (LAI), above-ground biomass as leaf dry matter

content, canopy moisture content, and the fraction of vegetation cover of croplands, wheat, grasslands, and saltmarsh (Darvishzadeh et al., 2008; He et al., 2019; Jiao et al., 2021; Upreti et al., 2020; Verrelst et al., 2012, 2015; Yin et al., 2016).

For Chapter 2, grassland sensitivity was based on the most responsive vegetation property proxy from the evaluated 24 Landsat-derived vegetation indices. The available field measurements of the three regional projects were insufficient to perform multiple PROSAIL model inversions of the heterogeneous parcels.

Chapter 3 successfully used the PROSAIL inversion with the LUT method to estimate the LAI of each paddock. The PROSAIL inversion was performed for both Sentinel 2 and VEN μ S images. However, the inversion with VEN μ S showed inconsistencies in the estimated LAI, which was depicted by the large standard deviation compared to Sentinel 2 during processing (Figure 21). One hypothesis for the erroneous estimation of LAI is related to the multiple viewing angles for the respective VEN μ S reflectance bands. These multiple angles were not incorporated in the initial VEN μ S angle extraction script of this thesis. Nevertheless, the available Sentinel 2 trajectories were sufficient enough for use with a process-based model. Vegetation indices were considered also for Chapter 3, however, there was a low correlation between the vegetation indices and available ground measures of biomass and height.

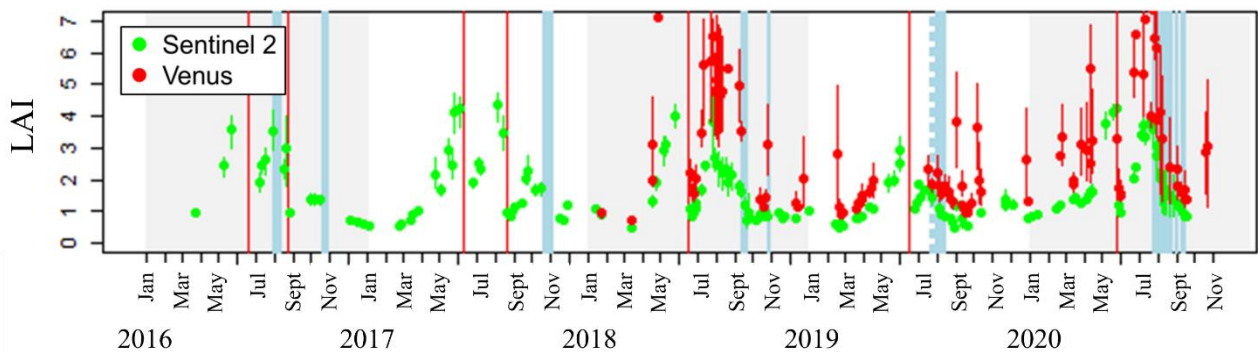


Figure 21. LAI observations derived from the PROSAIL inversion of Sentinel 2 and VEN μ S images covering one sample mowed parcel under the SALAMIX project. The vertical red lines are mowing dates, while the blue shades are grazing events.

H. Summary of selected data

Presented here in the General data and methods were the selected input data associated with Chapter 2 or the regional assessment of the variability and drivers of grassland sensitivity to drought using long-term time series of vegetation indices, and Chapter 3, or the local evaluation of managed grassland resistance and resilience to drought impact, based on a process-based model of vegetation

growth with the assimilation of Sentinel 2-derived LAI. Essentially, Chapters 2 and 3 were conducted with contrasting site spatial coverage, temporal range, and management data details; different sources of climate and satellite data; and remote sensing techniques (Table 3); but similar drought severity measures and objectives to determine grassland response to drought.

Table 3. Summary of the respective field, climate, and remote sensing data inputs for Chapters 2 and 3.

General Inputs	Chapter 2		Chapter 3	
	Regional empirical analysis of variability and drivers of grassland sensitivity to drought		Local-scale process-based modelling for analyzing grassland response to isolated drought impacts	
Sites :	Massif central		Herbipôle experimental site	
Field data	Source/s	Scale	Source/s	Scale
Management	Prairies AOP	Parcel (600 to 366,100 m ²)	SALAMIX (HerbValo)	Paddock (15,200 to 85,500 m ²)
Soil	Prairies AOP and AEOLE	Parcel (600 to 366,100 m ²)	-	-
Biodiversity	Prairies AOP, ATOUS, AEOLE, and plant databases	Plot (2 to 100 m ²)	-	-
Climatic data	SAFRAN	Daily	Meteorological station	Daily
Remote Sensing data	Source/s	Resolution	Source/s	Resolution
Landsat mission (1985 to 2019)	Google Earth Engine	30 m (spatial), 16 days (temporal)	-	-
Sentinel 2 (2015 to 2020)	-	-	Theia Data and Service Center	20 m (spatial), 5 days (temporal)
Vegetation property quantification method	Vegetation indices	-	PROSAIL inversion	-

Chapter 2 was the regional study conducted within the Massif central. It used multiple field measurements, related to the soil, climate, and topographic factors; vegetation diversity; and herbage use. Data were obtained from the completed Prairies AOP, ATOUS, and AEOLE projects. Chapter 2 assessed drought severity using the modified SPEI based on the SAFRAN climate data model and quantified the vegetation conditions of 143 parcels using the vegetation indices from Landsat observations. Both SAFRAN and Landsat were selected due to the large spatial and long-term temporal coverages.

Chapter 3, on the other hand, was conducted within the local scale Herbipôle experimental site. The parsimonious process-based model of grassland LAI benefited from the detailed herbage usage calendar, grazing animal records, and homogenous environmental conditions of the SALAMIX project. Chapter 3 generated the modified SPEI based on the field-collected climate records. Lastly,

the high spatial and temporal resolution of Sentinel 2 supported the calibration of the grassland LAI model.

Lastly, amidst the lack of description regarding Chapter 1, presented in Figure 22 are the input data for all three research chapters of this thesis. The selected field, climate, and satellite data for Chapters 2 and 3 were summarized to highlight the contrasting, different, and similar parts of each research.

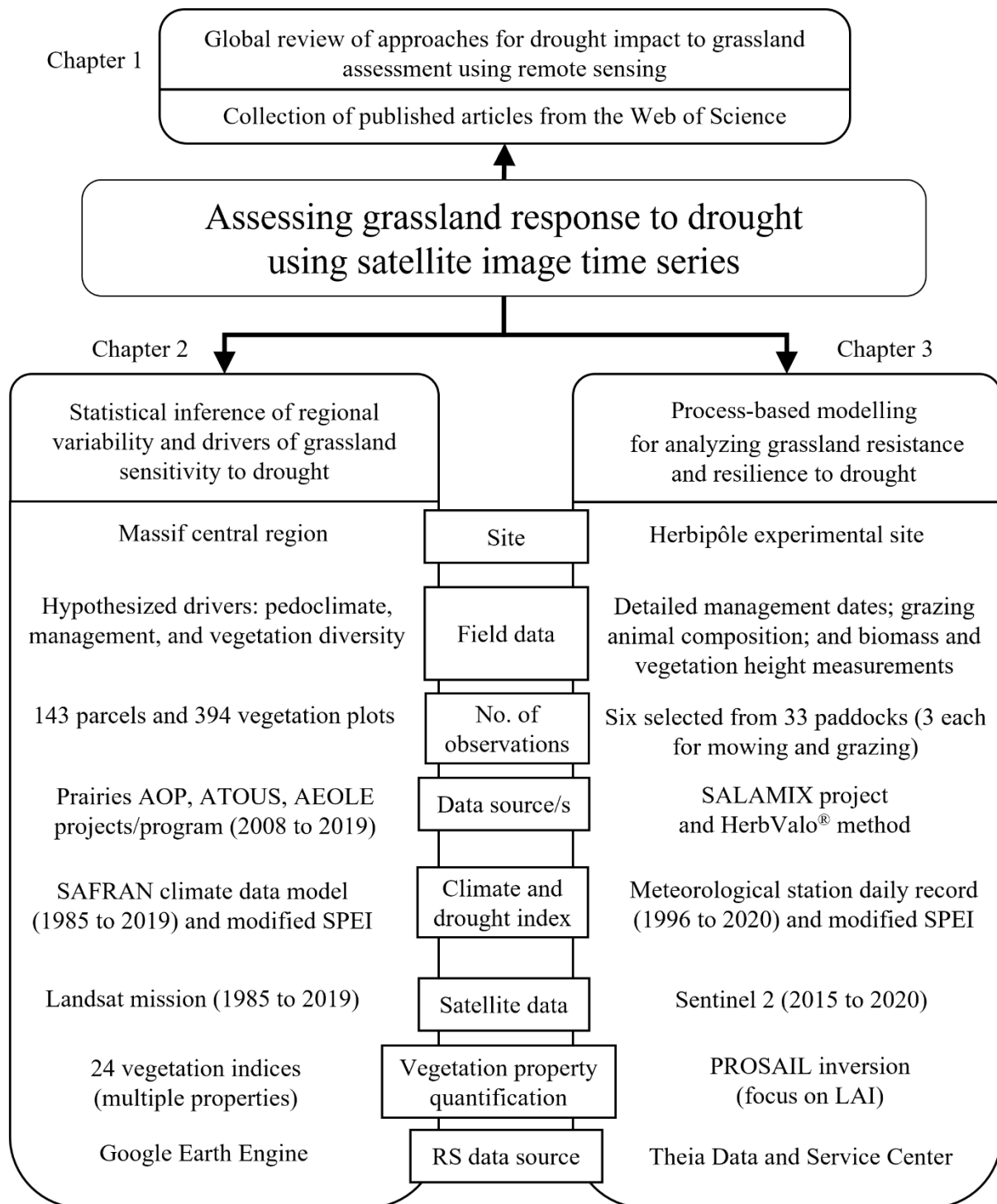
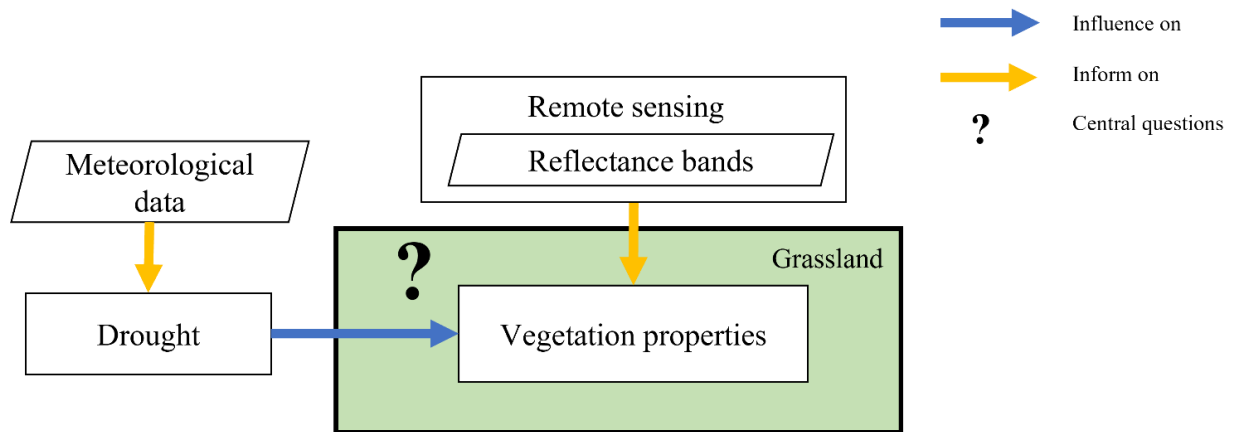


Figure 22. Summary of inputs for the respective research objectives.

ASSESSMENT OF DROUGHT IMPACT ON GRASSLANDS USING REMOTE SENSING TECHNIQUES. A REVIEW



From the conceptual diagram, Chapter 1 focuses on the central question of how drought impacts or influences on grassland vegetation properties were assessed so far. It considers studies that estimated grassland properties based on satellite data and quantified the meteorological type of drought.

CHAPTER 1. ASSESSMENT OF DROUGHT IMPACT ON GRASSLANDS USING REMOTE SENSING TECHNIQUES. A REVIEW

Abstract

Droughts are expected to occur more frequently and severely because of climate change. The impacts of drought are felt in almost all regions of the world. Unfortunately, drought threatens grasslands and its associated ecosystem services. Understanding grassland response to drought provides opportunities to improve grassland resistance and resilience. Ground-based experiments provide key knowledge on how grasslands respond to drought. However, these methods are limited in replicating real-life conditions at larger spatial coverage and longer durations. In this literature review, we highlight the potential of remote sensing technology in assessing grassland response to drought. We focused on articles that investigated drought impacts on grasslands by using remote sensing data. We classified the response assessment approaches into five categories, underline the gaps and bias in the global distribution of assessment studies, and call for a more specific use of “response”. The assessment of grassland response to drought integrates satellite reflectance, as a proxy, and drought severity. Challenges arise with the mismatch in data scales and observation lengths. Uncertainties also exist within the satellite reflectance due to confounding field factors and multiple disturbances. Finally, avenues for future research regarding grassland response to drought are related to the infrequently studied grassland types and regions. Then compared to grassland monitoring, the list of utilized RS data and monitored grassland properties for response assessment thus far is limited.

Keywords: response; satellite data; statistical inference; biomes; time series; vegetation index

1.1. Introduction

Grasslands are ecosystems dominated by graminoid plant species with limited presence of tall – above 5 meters – woody perennials and shrubs (Suttie et al., 2005; White, 1983; Xu and Guo, 2015). They provide key ecosystem services for food production that accounts for billions of employment opportunities (Jiang and Wang, 2022; O'Mara, 2012), carbon regulation and storage of about 34% of the terrestrial carbon (Bai and Cotrufo, 2022; Jones and Donnelly, 2004), biodiversity as habitats, cultural and recreational activities (Bengtsson et al., 2019; Pellaton et al., 2022; Zisenis et al., 2011), and energy source as biomass fuel (Tilman et al., 2006). Grasslands cover approximately 35 to 40% or 52.5 M km² of the Earth's terrestrial areas (Bardgett et al., 2021; Dixon et al., 2014).

Although many grassland types are maintained by certain levels of disturbance regimes (e.g., agricultural activities, fire, etc.), extreme disturbances are detrimental to the maintenance of ecosystems (Newbold et al., 2016; Strömberg and Staver, 2022). More specifically, drought, which is a natural phenomenon experienced by almost every climatic region of the world (Carroll et al., 2021; Dai, 2011; Mishra and Singh, 2010; Zargar et al., 2011), is expected to have more extreme and frequent occurrences along with climate change (IPCC, 2021).

Drought negatively impacts grasslands (Howden et al., 2007), and results in a decrease in the quantity and quality of grasslands, their ecosystem services (Chang et al., 2021; Hofer et al., 2016; Zwicke et al., 2013) and associated biodiversity (Doležal et al., 2022; Tilman and Haddi, 1992). Understanding how grasslands respond to drought can help in mitigating and anticipating adverse drought impacts. So far most of the knowledge on drought impacts on grasslands is inherited from controlled experiments and field observations (De Boeck et al., 2015; Gilgen and Buchmann, 2009; Kröel-Dulay et al., 2022; Volaire, 2018; Wellstein et al., 2017).

Pot, mesocosm, and field drought experiments provide focus and close monitoring of changes in grassland properties in response to manipulated water availability to the plants, which induce drought-like conditions (Knapp, Hoover, et al., 2015; Stampfli et al., 2017). Drought experiments improve our knowledge of the influence of soil properties, plant biodiversity, and management practices on response to drought at the population and community organizational levels (Buttler et al., 2019; Deléglise et al., 2015; Isbell et al., 2015). It reveals the ecophysiological and strategic response mechanisms from the individual to community level induced by drought (Voltaire, 2018; Zwicke et al., 2015) However, grasslands are open systems that experience heterogeneous drought effects across space and time. To account for these spatio-temporal variations, long-term coordinated networks of rainfall manipulation experiments, such as the Drought-Net (Knapp et al., 2017), are conducted in grassland plots in different ecoregions. However, despite the numerous and widely distributed experimental sites over the world, coordinated experiments still face a lack of standardized spatio-

temporal coverage and real-life natural complexities due to constraints of the imposed set-ups. Furthermore, experimental studies underestimate the impact of drought on grassland biomass compared to observational studies (Kröel-Dulay et al., 2022).

As an alternative, remote sensing (RS) expands beyond the spatio-temporal limitations of controlled experiments and permits the recognition of a wide range of biogeographic and agronomic situations. RS is a technology that measures the properties of any objects without physical contact by using sensors that are mounted on satellites; manned or unmanned aerial vehicles; and ground-based setups (McVicar and Jupp, 1998). One simple application is the visualization, interpretation, and comparison (Ali et al., 2016; Svoray et al., 2013) of vegetation greenness using satellite images and vegetation indices (Figure 1– 1) covering an area of interest.

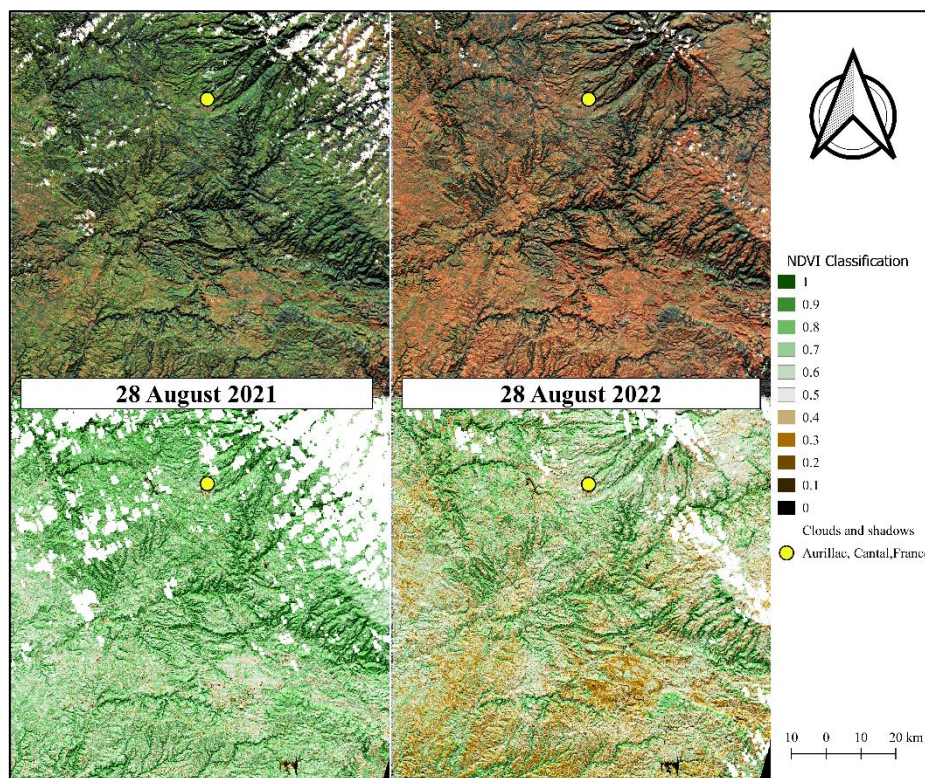


Figure 1– 1. Comparison of years with the absence (2021 – left) and presence (2022 – right) of drought using Sentinel 2 images covering the southern portions of the Massif central region, France. The top images are True Color Image Composite, while the bottom images are the Normalized Difference Vegetation Index (NDVI), where values close to 1.0 are healthy vegetation cover and below 0.3-0.2 are dry vegetation and bare soils or water bodies. The map relief information was extracted from a 25m x 25m Digital Elevation Model (DEM; <https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1>). The Sentinel 2 data were obtained from <https://www.theia-land.fr/en/product/sentinel-2-surface-reflectance/>.

Under drought conditions, plant physiological changes occur at the gene and tissue levels with consequences on higher organizational levels (e.g., organ and individual). The impacts from long or

severe droughts decrease the water available in the soil for plant use. This leads to the dehydration of leaves, which negatively affects leaf chlorophyll contents, and leads to a loss in canopy greenness (Ommen et al., 1999; Sanchez et al., 1983). At the same time, stomatal apertures close to maintain moisture, but prevents entry of carbon dioxide (CO₂; Taylor et al., 2012). The limited water, CO₂, and decreased chlorophyll performance due to drought hinder and halt the photosynthetic activity (Abbasi et al., 2014; Taylor et al., 2012). At prolonged durations and depending on the plants' inherent drought tolerance capacity, the productivity of grasslands is expected to critically decrease. At the same time, the rate of plant senescence is expected to increase with drought (Volaire et al., 2009).

The RS application of optical images for vegetation monitoring is based on the connection of the plant's physiological condition introduced above and the reflected radiative energy (Turner et al., 2003). Indeed, sensors receive the reflected energy, which contains the reflectance measures of specific wavelengths (Drusch and Crewell, 2006; Turner et al., 2003) related to the vegetation moisture content, leaf chlorophyll contents, biomass, and leaf area index (LAI) among other vegetation properties (Gitelson et al., 2003; Sims and Gamon, 2002). The chlorophyll contents, which relate to the greenness of leaves, are detected in the visible light spectrum (400 to 700 nm). Then the leaf area index (LAI) and plant structure properties can be retrieved in the NIR (range 800-2500 nm). While the influence of leaf moisture on vegetation reflectance is strong in the shortwave infrared (SWIR; 1,400 to 3,000 nm) and to a lesser extent in the near-infrared (NIR; 700 to 1,400 nm) wavelengths.

Therefore, the combination and transformation of selected bands can be used to generate reflectance spectra or vegetation indices (VI) that estimate grassland properties from space and across time. Among the variety of VI (Andreatta et al., 2022; Bajgain et al., 2015; Zhou et al., 2014), one commonly used VI is the Normalized Difference Vegetation Index (NDVI), which is a proxy for vegetation greenness, productivity, cover, and biomass (Wang et al., 2022). More specific indices were developed to monitor moisture content, like the Normalized Difference Water Index (NDWI; Gao, 1996; Xiao et al., 2004) and Global Vegetation Moisture Index (GVMI; Ceccato et al., 2002) among others.

The potential of optical remote sensing data has encouraged the development of a tremendous number of ecosystem monitoring studies over the last decades. To synthesize their findings, several reviews have underscored the importance of RS for monitoring different types of terrestrial ecosystems (Shoshany, 2000), such as forests (Gleason and Im, 2011; Masek et al., 2015), savannas (Fundisi et al., 2022), mangroves (Kuenzer et al., 2011), peatlands (Minasny et al., 2019), wetlands (Guo et al., 2017), and agroecosystems (Atzberger, 2013; Bégué et al., 2018; Huang et al., 2022; Kuenzer and Knauer, 2013; Ozdogan et al., 2010; Weiss et al., 2020). Other reviews focused on the general assessment of ecosystem health in response to environmental changes (Li et al., 2014; Soubry et al., 2021; Xu and Guo, 2015; Yi and Jackson, 2021) or specific disturbances. For instance, the use of RS

in the assessment of forest ecosystem responses to fire (Chu and Guo, 2013), hurricanes (Lugo, 2008), insect infestation (Senf et al., 2017), and deforestation (Gao et al., 2020) were reviewed. Closer to our topic, other authors synthesized the knowledge of data and techniques for monitoring grassland ecosystems (Ali et al., 2016; Reinermann et al., 2020; Svoray et al., 2013; Wang et al., 2022), in response to management practices (Reinermann et al., 2020), shrub and woody plant invasion (Cao et al., 2019; Soubry and Guo, 2022), or climate changes (Li et al., 2018; Wang et al., 2022). Reviews on the use of remote sensing for the monitoring drought and water stress on terrestrial ecosystems were conducted for forests (Deshayes et al., 2006; Konings et al., 2021; Zhang et al., 2013) and croplands (Gerhards et al., 2019). Then instead of the use of RS on specific ecosystems, authors focused on the RS techniques and indices related to drought impacts (AghaKouchak et al., 2015; Alahacoon and Edirisinghe, 2022; Hazaymeh and Hassan, 2016; Inoubli et al., 2020; Jiao et al., 2021)

According to this collection of reviews of RS applications for environmental sciences, there is currently no specific synthesis of the remote sensing researches conducted, so far, on the assessment of drought impacts on grasslands. We filled this gap and specifically aimed to (i) identify and classify the different approaches used to achieve the assessment goals, the associated inputs, their advantages, and limitations; (ii) summarize key findings emerging from these studies; and (iii) highlight challenges and opportunities for future studies.

To do so, this study initially started with a collection of 304 articles from the Web of Science on 31 January 2022 based on the search criteria of [(“remote sensing” OR “earth observation” OR satellite) AND (grassland* OR pasture* OR meadow* OR steppe* OR rangeland*) AND (impact OR effect OR response OR resilience) AND drought NOT forest NOT wetland]. Then a three-stage screening process was implemented to obtain 64 preliminary articles. The screening retained meteorological drought studies that identified or quantified drought events and trajectories and investigated studies on grassland response to drought. Essentially, the articles used RS as the main source of data or complements the determination of grassland response to drought.

1.2. Classification of the assessment approaches

Assessing grassland response to drought is a process that involves the monitoring of conditions of grassland properties and determining its connection to the trajectory of drought severity. We identified five different approaches, classified into (i) vegetation index threshold, (ii) year comparison, (iii) time series analysis, (iv) statistical inferences, and (v) mechanistic modelling.

1.2.1. Vegetation index threshold

Vegetation indices (VIs) are the transformation of selected reflectance bands contingent on the vegetation property being monitored (Bajgain et al., 2015; Sishodia et al., 2020; Zhou et al., 2014). The use of the VI threshold is the most basic approach to assessing grassland response to drought. It aims at comparing various grassland sites that experience the same meteorological drought event. Drought is considered to impact vegetation when site-specific VI thresholds or ranges are exceeded. Usually, independent information on drought is discarded except for defining the VI threshold. For instance, Nejadrekabi et al. (2022) determined that MODIS-extracted NDVI values from 0.12 to 0.18 correspond to drought-affected vegetation based on spatial statistic techniques and multiple vegetation sites in Khuzestan, Iran. Vanegas et al. (2014) and Bajgain et al. (2015) determined that a negative Land Surface Water Index (LSWI) value indicates drought impact on the grasslands of Oklahoma, USA. To strengthen the drought impact identification, they added a short temporal criterion that the negative LSWI should last for at least 8 days.

The quantified grassland response from the use of VI thresholds presents two main concerns. First, VI values can be under the influence of other natural or anthropogenic disturbances like pest infestations, plant diseases, or herbage use. For instance, the simplified detection of mowing events follows the same application of the VI threshold (Bégué et al., 2018; Garioud et al., 2019; Reinermann et al., 2022) making hard the attribution of an extremely high or low value (depending on the VI being considered) to one or the other source of disturbances. Second, VI values are region- or site-specific, restricting their application to the global scales.

1.2.2. Year comparison

This approach is based on the comparison of vegetation reflectance of at least two different or contrasting years. The independent information on drought is here only used to identify drought years or sometimes to quantify drought severity for a given year with dedicated indices. The RS-based assessment of drought impact is done by computing the difference between the RS signal recorded for a reference – normal or wet year – and for the drought year (Twumasi et al., 2003; Wagle et al., 2019). Generally, the years compared are either discontinuous years, resulting in the analysis of independent drought events, or short consecutive years, illustrating immediate changes between reference and drought years.

The main drawbacks of this approach lie in (i) the definition of a proper baseline of grassland status under normal conditions, which cannot be properly estimated from the selection of one year or one growing season; (ii) the uncertainty on the level of drought severity for the selected drought year in connection to the unaccounted years; (iii) the comparison of discontinuous years may hide the delayed

or lingering impacts of drought (De Boeck et al., 2018; Müller and Bahn, 2022; Wu et al., 2017); and (iv) the comparison of adjacent years may not adequately represent the dynamics of vegetation in response to drought, including the resistance and recovery phases.

1.2.3. Time series analysis

The time series analysis accounts for the dynamic nature of grasslands. This approach uses RS signal trajectories instead of state comparison as the previous approach, and information on drought as continuous observations of climate variables or drought severity indices. The analysis of grassland response to drought is based on the disruptions in the paired grassland long-term satellite reflectance and drought trajectories. For instance, an abrupt decline in the satellite-based VI is generally interpreted as a consequence of stressful conditions (Brookshire and Weaver, 2014; Kowalski et al., 2022; Wei et al., 2022). The magnitude of this decline is used also as an indicator of ecological resistance. As drought impacts persist after the end of the drought event, the slope of a gradual increase in reflectance trajectory is used as an indicator of resilience.

As examples of the time series approach, in the Mongolian plateau, Bao et al. (2014) highlighted that after an increasing phase of NDVI values from 1982 to 1994 in steppes, alpine steppes, and desert steppes, vegetation greenness declined between 1995 and 2012 due to a significant decline in precipitation. Consistently, Tong et al. (2017) identified an increase in drought impacts in the mid-90s, in Xilingol, China, which was adjacent to the Mongolian plateau.

The time series analysis approach allows the determination of the ecosystem reference conditions, which is usually defined as the overall mean of the dynamic long-term reflectance observations (Garbulsky and Paruelo, 2004; Pollock et al., 2012; Stoddard et al., 2006), typically 30 years, as adapted from climatic studies (Marchi et al., 2020; Rigal et al. 2019). Other authors have defined ecosystem reference conditions as pristine or slightly disturbed conditions free from anthropogenic influences (Hess et al., 2020; Pollock et al., 2012; Stoddard et al. 2006). But basic levels of anthropogenic influence are recognized as components of agroecosystems (Rendon et al., 2020).

The time series data provides additional extractable grassland parameters. Kang et al. (2018) extracted the start of season (SOS), length of season (LOS), and end of season (EOS) matrices based on the NDVI time series to study drought impacts on grassland phenology and productivity. Long time series of satellite images have also been used to generate new indices measuring vegetation response to drought. For instance, the Vegetation Health Index (VHI; Kogan, 2006) is derived from the time series of NDVI or EVI. It follows the formula $VHI = a*VCI + (1-a)*TCI$. Where the coefficient represents the contribution of VCI or Vegetation Condition Index (a) and TCI or Temperature Condition Index ($1 - a$) to the total vegetation health (Kogan, 2006). The VCI follows the formula VCI

$= 100 * (\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min})$ and estimates the vegetation condition (Kogan, 1990). The NDVI minimum (min) and maximum (max) values are based on the time series observations under investigation. Essentially, VCI reflects the impact of weather on vegetation. Then following a similar formula of $\text{TCI} = 100 * (\text{BT}_{\max} - \text{BT}) / (\text{BT}_{\max} - \text{BT}_{\min})$, the TCI estimates the drought condition based on the weather stress (Kogan, 1995). The BT or brightness temperature is based on thermal infrared bands and established conversion tables (Kogan, 1995). Both the VCI and TCI are standardized indices based on historic minimum, maximum, and observed NDVI values from satellite image time series observations.

A limitation of this approach is the need for a long and continuous time series with sufficiently frequent records. Generally, various meteorological data meet this requirement with very few gaps. But for satellite images, the number of usable observations is greatly dependent on the temporal resolution and percent of clear pixels that may prevent the implementation of this approach in some parts of the world or some periods of the year.

1.2.4. Statistical inference

The statistical inference refers to the interpretation of drought effects on grassland vegetation from the statistical relationship (usually linear) between vegetation indices and drought indicators (e.g., precipitation, temperature) or severity index [e.g., Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), or Palmer's Drought Severity Index (PDSI)] or standardized measures (e.g., anomalies or Z-score; Wilcox et al., 2017; Zhang et al., 2017). The inference can be based on a coefficient of correlation (r), the slope, or the coefficient of determination of a linear model (Byrne et al., 2017; Hermanns et al., 2021; Li et al., 2016). Therefore, a high correlation or slope is interpreted as the high sensitivity of grasslands to drought severity (Han et al., 2018). Key to the statistical inference is the number of paired observations of vegetation reflectance and drought indicators. As an example, Wang et al. (2019) revealed a 0.58 coefficient of determination between the global net primary production (NPP), derived from MODIS, and the self-calibrating Palmer drought severity index (scPDSI) from 1982 to 2008, with a decrease of NPP while drought severity increased.

Together with the slopes and correlations, the use of standardized grassland reflectance values may provide a further understanding of the origin of the response. Nutini et al. (2010) proposed a scheme that attributes the standardized measures of grassland reflectance and drought severity with climate-driven events based on quadrant clustering (Figure 1– 2). Observations located in quadrant 3 (+, +) and quadrant 1 (-, -) can be associated with climatic influences, while observations in quadrants 2 and 4 can be associated with abnormal conditions unexplained by climate events.

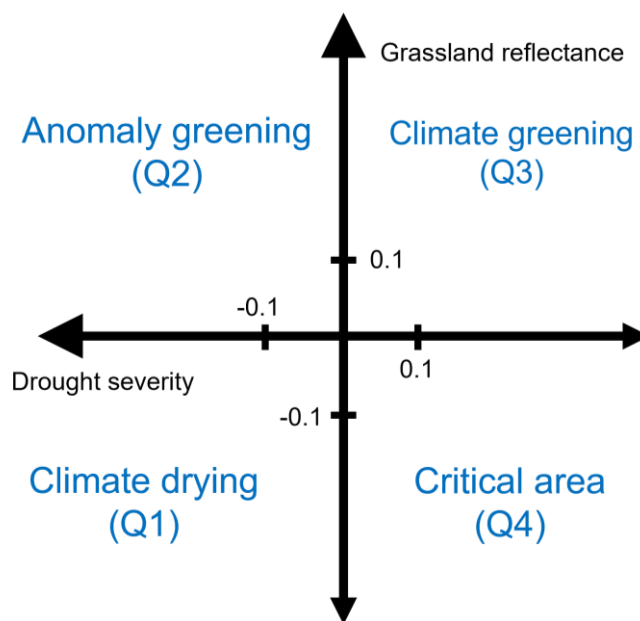


Figure 1–2. Grassland response scheme adapted from Nutini et al. 2010.

A further step in the use of the quadrant location is the analysis of their temporal changes. Washington-Allen et al. (2008) and Kowalski et al. (2023) observed the movement of grassland properties across time in the quadrant scheme. Movements towards climate drying Q1 from the normal condition depict grassland resistance to drought. Before the end of a drought, grassland resilience is portrayed by the movement to the anomaly greening Q2. At the end of a drought and the start of more favorable climatic conditions, grasslands positioned in the quadrant are expected to move toward recovery (Q3). In some cases, the inability to demonstrate resilience and recover from climate drying leads to mortality, which is a critically negative outcome (Q4).

The statistical inference approach underlines the development of a new class of vegetation indices. Brown et al. (2008) created the Vegetation Drought Response Index (VegDRI), which combines the NDVI values and drought severity indices like PDSI and SPI. Zhang et al. (2019) evaluated similar indices but combined MODIS products of greenness indices and temperature or photosynthetically active radiation as a proxy of vegetation and drought conditions, respectively.

Although statistical inference is the most used approach (Figure 1– 3), it suffers from three main limitations. First, it requires large datasets for the best estimation of the relationship between VIs and drought indices or proxies. Second, this relationship is usually noisy because of the influence of other stress factors (Bao et al., 2014; De Keersmaecker et al., 2015; Zhu et al., 2020). Third, it assumes a

linear relationship between grassland reflectance and drought variables, which is likely not a general case (Griffin -Nolan et al., 2018).

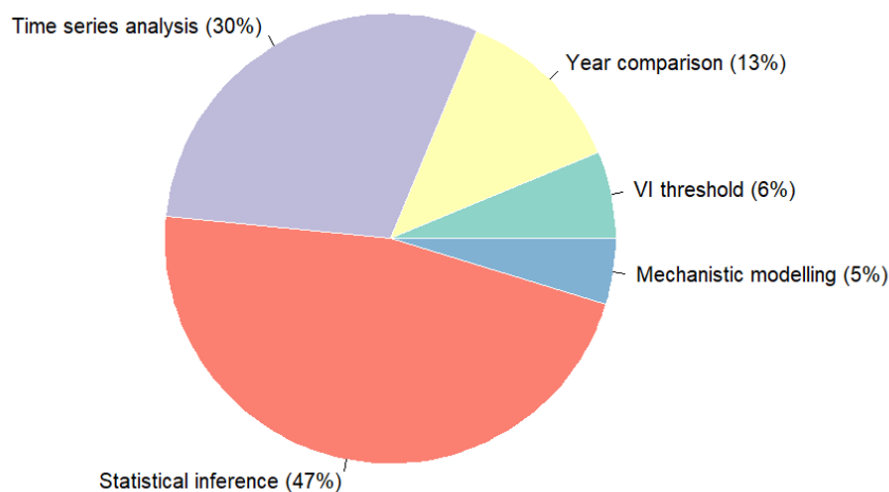


Figure 1– 3. Distribution of studies among the five approaches identified for assessing grassland response to drought based on the article collection (n= 64).

1.2.5. Mechanistic modelling

Mechanistic models can be used to simulate the dynamics of grasslands properties (i.e., gross primary productivity or GPP; leaf area index or LAI; etc) and their responses to environmental changes. Assimilated with RS data, they can be applied in a wide range of situations and may provide a comprehensive assessment of drought impacts.

We found only a few examples of the implementation of such an approach to analyze drought impacts on grassland. These studies differ in the assimilation method of RS data into their vegetation model. First, Bayat et al. (2018) derived several grassland properties like LAI, leaf chlorophyll contents, leaf water content, leaf dry matter content, leaf inclination distribution function, and senescent material content, from images (MODIS) with the inversion of several radiative transfer models. They used these parameters as input for the Soil-Canopy Observation of Photosynthesis and Energy fluxes (SCOPE) for predicting drought effect on GPP and ET. Second, Hermance et al. (2015) directly used NDVI (MODIS) and daily rainfall to simulate the biomass of semi-arid shortgrass steppes of North America. The phenomenological model considered the temperature, at the start and end of the season, and the efficiency of water use as parameters. The simulated grassland biomass trajectory is then assessed with the time series analysis approach.

Zhang et al. (2019) demonstrated the benefit of RS assimilation into vegetation models by comparing the performance of three satellite-based light-use efficiency (LUE) models, against five statistical models based on RS data only, under the presence and absence of drought conditions in the temperate steppes of northern China. They showed higher performance of process-based models than statistical models and interpreted it as a consequence of explicit modelling of effects.

Although RS data assimilation in the vegetation model provides a comprehensive assessment of drought impacts, they also face severe limitations, which may explain the low contribution of this approach in our article collection. The use of mechanistic models is data-demanding, especially when complex processes are being simulated. Contrastingly, excessive model simplification threatens the accuracy of simulated output (Vogeler et al., 2023). Since models are often designed according to certain environmental conditions and time periods, a consequence is that they require constant parameter recalibration when implemented on other sites at different conditions and time periods (Pogačar et al., 2022; Siehoff et al., 2011).

The approaches for grassland response to drought assessment were summarized in Figure 1–4. The use of VI in monitoring grassland response is common to all approaches. The subsequent analyses increase in complexity, as well as data requirements, from the year comparison to the mechanistic modelling approaches. As RS-based methodologies, the application to large spatial extents is inherent to each approach and is mainly limited by the availability of input data and computation time, which is typically the case when assimilating RS products into mechanistic models.

1.3. Key findings from grassland response to drought assessments

RS has consistently supported the assessment of grassland response to drought by providing local regional and global historic estimates of grassland reflectance data together with drought indices and indicators. In connection to the classified approaches, key collective points from the conducted studies can be highlighted.

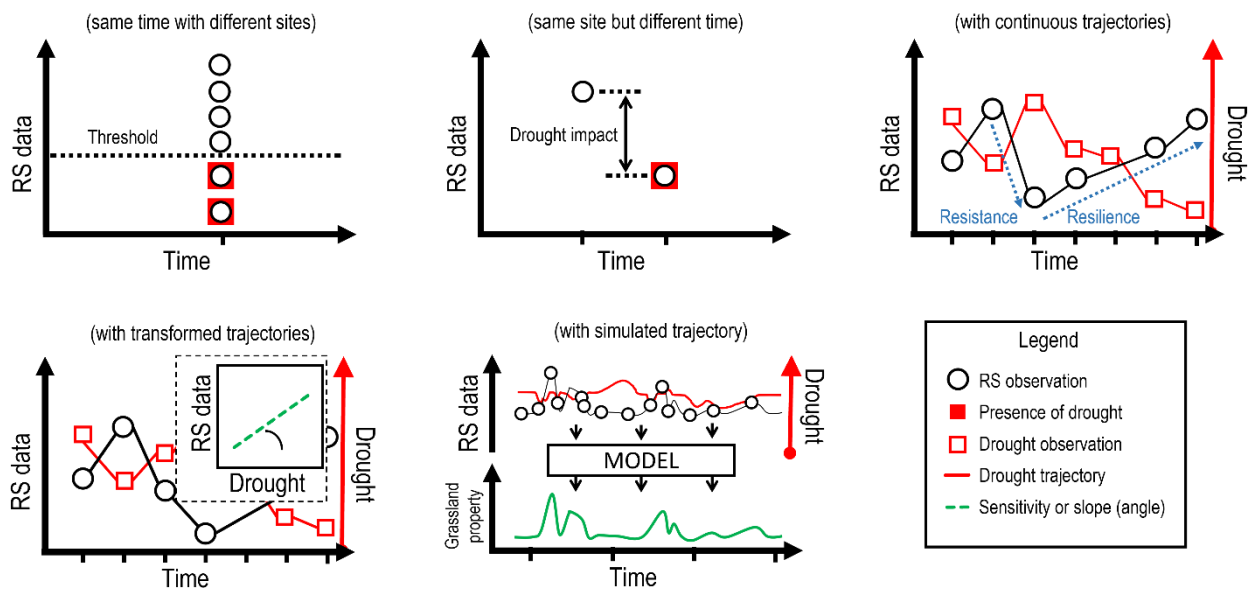


Figure 1– 4. Schemes of the classified approaches for grassland response to drought assessment showing the respective inputs and complexities. Specifically, these approaches are a) VI threshold; b) year comparison; c) time series analyses; d) statistical inference; and e) mechanistic modelling.

1.3.1. How grassland “response” to drought is used?

Very few authors explicitly defined what represents “response” in their studies. Common to all approaches is the assessment of response as a change in vegetation state after drought. For the use of the VI threshold, the response to drought is a numeric index variable representing the presence or absence of drought impact on the vegetation. While for the year comparison, the gap in grassland reflectance between the reference and drought year is often interpreted as an indication of resistance – rather than of resilience. The time series analysis and mechanistic modelling approaches allow the extraction of both resistance and resilience components as analyzed trajectories across years (e.g., Y. Liu et al., 2021). Moreover, the use of mechanistic modelling provides gap-free trajectories and detailed drought impact assessments – based on simulations under normal climatic conditions and drought – of grassland properties (e.g., LAI, biomass, GPP). Lastly, the statistical inference approach acknowledges the rate of change in reflectance due to a unit of decrease in the climatic water balance or precipitation (Knapp, Carroll, et al., 2015). Thus, such an estimate can be interpreted as an indication of grassland “sensitivity” to drought. In case the study is conducted with data of low temporal resolution it is usually difficult to know whether each estimate corresponds to the resistance or resilience phase. However, when the temporal resolution of the dataset increases and with the known chronological trajectory of grassland reflectance. Some authors have moved beyond the sole

interpretation of the sensitivity and proposed a mixed framework with the time series approach such as with the interpretative scheme of Nuttini et al. (2010). The direction of the slope indicates resistance when subsequent observations cluster toward the climate-drying quadrant (Figure 1 - 2). Then it indicates resilience when subsequent observations cluster toward the climate-greening quadrant.

1.3.2. Unequal geographical distribution of study sites

Grasslands are distributed in various topographic and climatic regions of the world, where the majority are in temperate and arid biomes (Dixon et al., 2014; Godde et al., 2020; Xu and Guo, 2015). From the article collection, studies on grassland response to drought were conducted in sites distributed in 30 countries globally (Figure 1– 5).

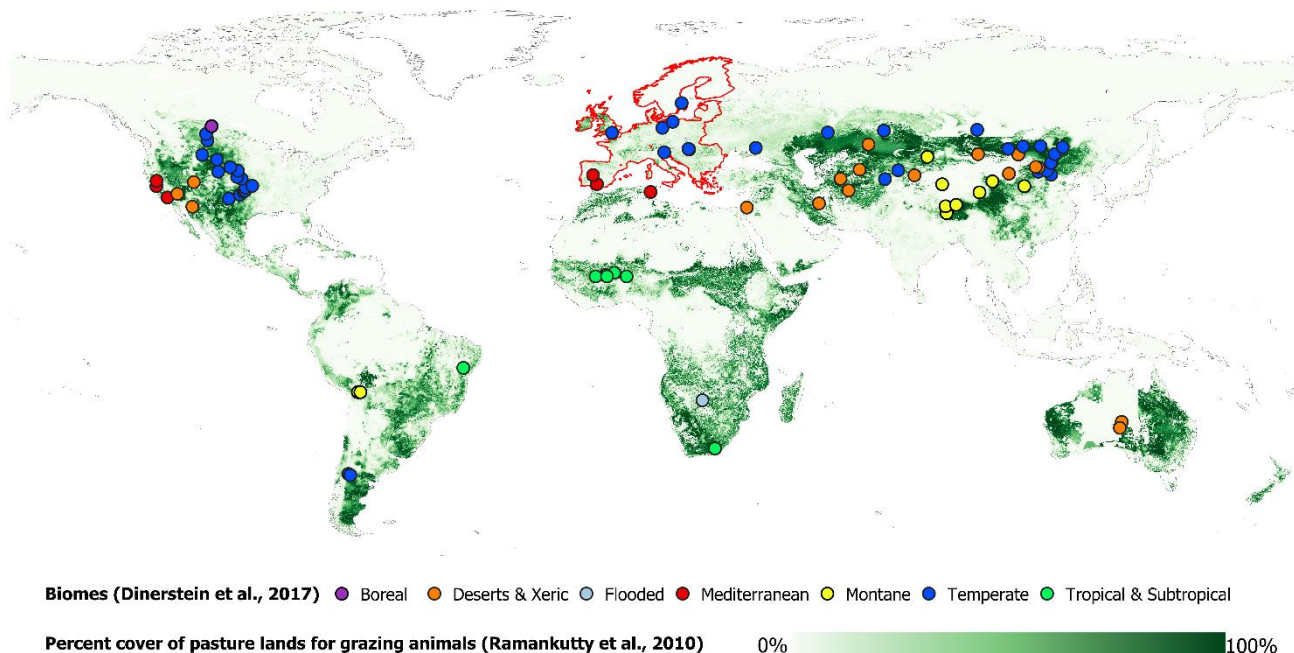


Figure 1– 5. Distribution and coverage of study sites extracted from the selected article collection. Some studies considered multiple sites, explaining a total number of 85 sites for 64 articles.

Most of the studied grassland sites were found in the United States of America (USA) and the People’s Republic of China. This corresponds to the large grassland cover in these respective countries (Dixon et al., 2014; Xu and Guo, 2015). In addition, these two countries are highly exposed to drought hazards (see Carrão et al., 2016) and both have experienced multiple droughts (see Meza et al., 2020). Similarly, other countries in the article collection, such as Australia, Argentina, Northeast Brazil,

Southern Europe, and Southern Africa region, have high exposure and have experienced multiple drought events.

In terms of biomes, the study sites were located in temperate (48%), desert and xeric (20%), montane (13%), tropical and subtropical (10%), Mediterranean (7%), boreal (1%), and flooded (1%) grassland regions. The global biome classification was based on the works of Dinerstein et al. (2017), who updated the terrestrial ecoregion map of Olson et al. (2001) using various papers at that time.

The biogeographic distribution of the study sites, where RS-based assessments of grassland response to drought were conducted, reflects the global distribution of grasslands. However, this leads to several understudied grassland types. Among the biogeographic gaps, the temperate managed grasslands of Western Europe may require particular attention. Indeed, the agricultural management, composition, diversity, and lifecycle of the associated vegetation largely differ from arid grasslands and the Great Plains of the USA and Canada. The knowledge emerging from the current collection of studies can hardly be transposed to anticipate/mitigate drought impacts in temperate regions of Europe.

If compared to rainfall manipulation experiments, the concentrations of experiments on grassland response to drought are largely found in the USA, and in the central European region, which remains understudied using RS-based approaches (see Matos et al., 2020).

1.3.3. Varied responses of grasslands to drought

As presented in the previous section, grasslands are globally distributed in various regions with heterogeneous conditions. Thus, responses to drought or climatic variations are expected to be different with other ecosystems and among grasslands, depending on the specific grassland type and biome.

1.3.3.1. Comparison of responses between grasslands and other ecosystems

All the approaches developed so far to assess the response of grasslands to drought are deemed applicable to other ecosystems. Such transferability of the methods has encouraged some authors to compare the impacts of drought between grasslands and other ecosystems, mostly crop systems.

In the southern portion of the Great Plains, Ji and Peters (2003) found that NDVIs of croplands were better related to precipitation than of grasslands (with R^2 of 0.67 and 0.58, respectively) based on the 3-month SPI. However, the slope of this relationship was steeper for grasslands, indicating greater sensitivity. In the northwestern portion of the Great Plain, Tollerud et al. (2018) confirmed that grasslands were more affected by drought than croplands (commonly wheat) based on the VegDRI. Similarly, in Eastern Cape, South African, Graw et al., (2017) demonstrated the same pronounced response of grasslands than commercial and communal managed croplands during a drought year.

In northern China, Kang et al. (2018) demonstrated that anomaly measures of grassland phenology and productivity using the NDVI from 1982 to 2012, were significantly correlated with specific measures of the Standardized Precipitation Evapotranspiration Index (SPEI). Specifically, these were the EOS anomaly and autumn SPEI ($r = 0.19$), the LOS anomaly and annual SPEI ($r = 0.41$), and integrated growing season NDVI (iNDVI) and annual SPEI ($r = 0.54$). They confirmed the high sensitivity of grassland compared to other land covers dominated by shrublands, barren vegetation, and cropland. Xu et al. (2021) supported the high response of grasslands to drought compared to croplands, forests, deserts, and wetlands using solar-induced fluorescence (SIF) and SPEI. They further revealed the greater sensitivity of grasslands in arid and semi-arid regions of northern China,

All comparisons from different studies concluded the high responsiveness of grassland to drought compared to other agroecosystems. However, these comparisons were mostly conducted against the general land cover of croplands and in arid or semi-arid regions of Asia. In a global meta-analysis of manipulative experiments in terrestrial ecosystems, grasslands were consistently more responsive to drought than croplands, shrublands, and temperate forests based on parameters like the soil carbon pool, plant carbon pool, aboveground and below-ground plant carbon pool, and aboveground net primary production (Zhou et al., 2016). When grasslands were compared to shrubs and forests, the response ratio changes depending on the measured parameters (Deng et al., 2021). Grasslands were most responsive in 9 out of 22 parameters that include root biomass, dissolved organic carbon, nitrification, and nitrogen mineralization (Deng et al., 2021).

1.3.3.2. Responses among grassland types

Different grassland types are expected to have varying responses to drought (Wilcox et al. 2015). Grasslands can be classified based on their specific locations (e.g., climatic regions) and management. In eastern Inner Mongolia, Liu et al. (2012) confirmed that meadows were more sensitive ($r = 0.53$) to drought than the steppe ($r = 0.45$), and desert grasslands ($r = 0.48$) based on NDVI and SPI correlations from 2006 to 2010. Along an elevational gradient, He (2014) showed that Canadian upland grasslands were more sensitive than lowland grasslands to accumulated precipitation ($R^2 = 0.41$ and 0.09), to climate moisture index ($R^2 = 0.45$ and 0.14) and to modified Palmer drought severity index ($R^2 = 0.53$ and 0.21).

As for management, Thoma et al. (2016) revealed that grazed grasslands exhibit an earlier response to drought than abandoned grasslands, which were previously grazed for the last 14 years. Wagle et al. (2019) recommended the burning of grasslands to obtain better forage harvest compared to the absence of burning. However, during drought, burning provided the opposite effect due to the loss of available water in the soil.

The results of remote sensing studies are consistent with the field experiments. Lei et al., (2022) used field flux measurements and the Biome-BGC model to determine that meadows have a higher NPP decline rate than desert grasslands due to drought in the Inner Mongolian temperate grassland region of China from 1964 to 2012. However, steppe grasslands have the highest NPP decline rate than meadows and desert grasslands, which was attributed to their northern geographic distribution (Lei et al., 2022).

There are expected differences between grazed and mown grasslands due to factors such as herbage uptake method and timing (Moinet et al., 2019). Bütof et al., (2012) found that mown pastures have higher resilience to climate change, while pasture or grazed grasslands have lower survival during low precipitation levels (Bütof et al., 2012). Consistently, Deléglise et al. (2015) found that grazed grasslands were more sensitive to induced drought than mowed grasslands. While for mown grasslands, cutting frequency affects the speed of recovery for permanent grassland, with high-frequency cutting showing lower recovery than low-frequency cutting after drought events (Zwicke et al., 2013; Vogel et al., 2012).

Despite the agreement with the results of ground-based drought experiments, RS-based studies, sometimes, fail to account for detailed experiment conditions and treatments. For example, mapping and quantifying the number of species within the grassland community faces accuracy concerns due to vegetation and spectral uncertainties (Rapinel et al., 2018) and the presence of other factors within the grassland area of concern. Accordingly, the continuous development of satellite sensors provides an avenue for further research.

1.4. Challenges and opportunities

1.4.1. Challenges

Among the various challenges in the assessment of grassland response to drought with RS, we here focus on (i) the mismatch between the spatial resolutions of reflectance data and those of drought indicators, (ii) the limited length of time period of assessment, and (iii) the mixed impacts of drought and other types of disturbances.

1.4.1.1. Mismatch in the data units and resolutions between reflectance and drought

Inconsistencies in the spatial and temporal resolutions of grassland reflectance and drought indicators or indices are usually addressed by data transformations or changes in the temporal units. For instance, the commonly used SPEI and SPI are expressed with a monthly temporal unit. To perform analysis, the RS signals are transformed from daily to monthly, or annual, temporal units using

procedures such as the maximum-value composite (MVC) and extraction of the mean. The decrease in temporal units prevents the consideration of daily changes in the grassland condition. Similarly, possible inaccuracies are present in the spatial resolution mismatch of grassland reflectance and climate data. The commonly used satellite images ranged from 30 m to 1 km, while gridded climate data models, such as the Climate Hazard Group InfraRed Precipitation with Station (CHIRPS), usually have lower resolutions (i.e., 5.6 km). Climate data from field measurements are generally interpolated to better present a given region, however, this procedure is prone to uncertainties from the influence of local topographic features. Climate-related studies perform either upscaling or downscaling of the spatial resolution of climate data models to address the need for the analyses (e.g., Dong et al., 2019; Hofmann et al., 2022; Nutini et al., 2010). In contrast to the climate data models, field meteorological stations are expected to provide site-specific measurements.

1.4.1.2. Limited length of time period of assessment

Most of the studies from the article collection, except those implementing the VI threshold and year comparison approaches, used two data sources: the reflectance data for grassland conditions and the climatic data upon which drought indices are computed, coming as time series. The length of the time period considered is a crucial aspect of the analyses, first to assess the variability of drought impacts in time by having robust observations in the statistical inferences of grassland sensitivity, and second to determine the vegetation reflectance under normal conditions or the reference state. The assessment of grassland response to drought is mostly limited by the temporal range of the RS data, and rarely by the climate data (Figure 1– 6). The temporal range of grassland reflectance data depends on the lifespan and launch date of the sensor and satellites. For example, despite the important spectral and optical properties of Sentinel 2 data for vegetation monitoring, it was launched in 2015. This limits its use for assessing drought impact compared to the Landsat missions that started in 1972. Such data requirement also explains the predominant use of satellite data compared to airborne or Unmanned Aerial Vehicle (UAV) images which usually offer at best very short time series.

Future studies on grassland response to drought should consider a standardized temporal range or time unit. A minimum time length requirement would allow for better comparisons among studies, leading to efficient use in meta-analyses. For instance, the WMO recommends a 30-year climatic data time series for determining normal climatic conditions (Marchi et al., 2020; Rigal et al. 2019; WMO, 2012). Such recommendations may be extended to the statistical inference approach.

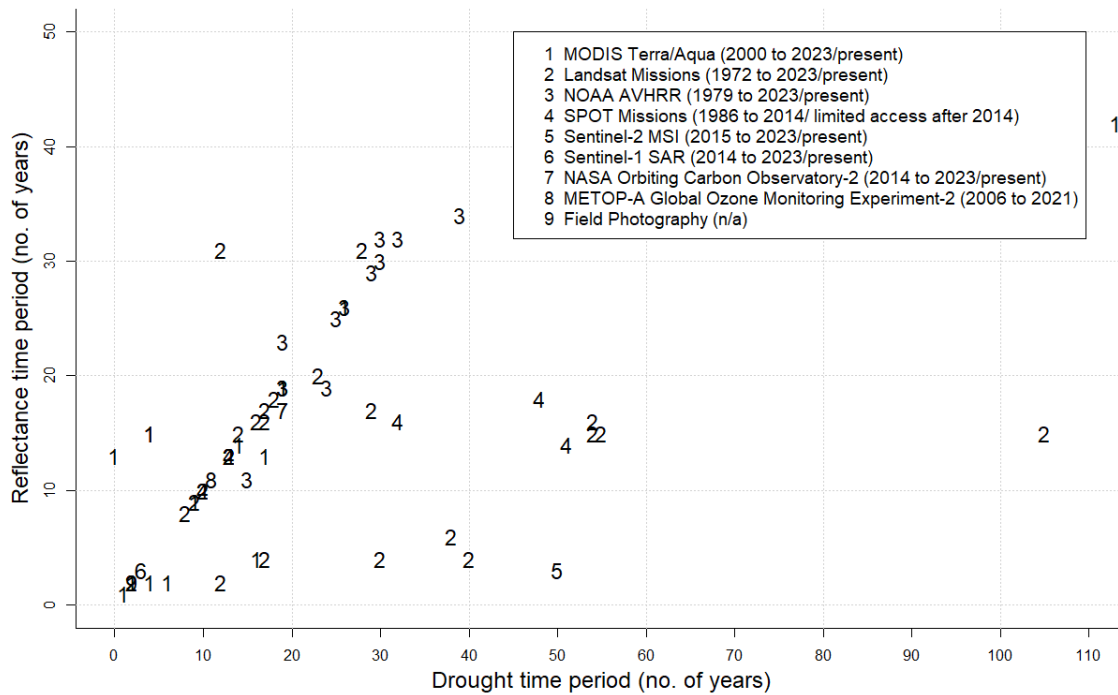


Figure 1–6. Length of grassland reflectance and drought time periods in response assessment studies. Data were extracted from the article collection of this review.

1.4.1.3. Mixed impacts from drought and other disturbances

One key issue in the RS-based assessment of drought impact is that vegetation reflectance may be influenced by various anthropogenic and environmental factors at the same time. Thus resulting in confounded RS signals. For instance, an abrupt decrease in reflectance value in some parts of the light spectrum may be due to drought, as well as the impact of mowing events (Kolecka et al., 2018) or phenological senescence. Dube and Pickup (2001) used spatial assumptions of grazing locations to quantify the anthropogenic and drought impacts of rangelands in Botswana, Africa. Then, only two other studies assessed the impact of multiple sources of disturbance and focused on drought and fire in the tallgrass prairie (Villarreal et al., 2016; Wagle et al., 2019). Liu et al. (2017) suggested the need to account for water management activities to better explain the increasing vegetation cover reflectance despite more frequent drought from 1961 to 2012 in Qinghai Province, China. However, these studies did not quantify the specific impact contributions of each disturbance.

Drought impact assessment is prone to uncertainties that partly result from the confounding effects of multiple sources of disturbance (Wagle et al., 2019). The availability of models and the use of multiple data sources can provide the means to detect the specific influences of these confounding factors.

1.4.2. Opportunities

1.4.2.1. Need for further comparison between grassland types and regions.

In this review, grasslands were considered synonymous with rangelands, pastures, meadows, steppes, and prairies. Several studies in the article collection have stressed the variability of grassland responses among several grassland types. However, these pertained mostly to grassland types found in arid regions and, in a lesser proportion, in temperate regions. Possible reasons for the limited remote sensing studies in the tropical and subtropical biomes are the low probability of drought occurrence (Bhaga et al., 2020) and the limited number of RS data observations due to cloud cover (Carter et al., 2000). Nevertheless, drought impacts are expected to be different due to climatic factors (e.g., seasons) and environmental conditions (e.g., presence of trees). With the influence of climate change, drought frequencies are expected to increase in tropical grasslands, while drought events are expected to occur during the summer in temperate and boreal grasslands (Long and Hutchin, 1991). The establishment of baseline studies would be crucial for future assessments. This review highlights that within one type of grassland and/or biogeographic regions, the variability of drought impacts between different grassland management regimes remains to be unassessed.

1.4.2.2. Exploration of new and existing RS data and techniques

Various RS data and products are continuously being developed with the advancement in sensor technologies and algorithms (Masek et al., 2020). The RS data used so far mainly focused on optical satellite images from the MODIS Terra/Aqua, Landsat missions, NOAA AVHRR, and SPOT missions. The spatial resolution of these sensors ranges from 30 m to about 1,000 m, while the temporal resolution ranges from daily to 16 days. Despite these resolution ranges, none of these satellite products have both high spatial and temporal resolutions. Accordingly, each emphasizes trade-offs between the two resolutions.

In the last decade, Sentinel 2 – composed of two satellites – was launched to monitor Earth systems with new optical satellite images of 10 m and 5-day, spatial and temporal resolutions, respectively. These higher resolutions allow for a better assessment of grassland heterogeneity and temporal changes. However, as with any optical satellite product, it still faces the reduction of image availability due to cloud cover. Sentinel 1, a microwave RS product that collects Synthetic aperture radar (SAR) images can address this issue (Clementini et al., 2020). Abdel-Hamid et al. (2020) demonstrated its potential with the correlation of backscatter coefficients with the Landsat NDVI of grasslands of Eastern Cape, South Africa. NDVI and the VH backscattering correlation yielded R^2 of 0.79 and 0.89, under the presence and absence of drought conditions, respectively. Sentinel missions have for now

been underexploited because of their lack of historical depth but will become a key source of data for future studies.

The solar-induced fluorescence (SIF) is another rarely used RS data in grassland response to drought assessment. SIF reflects chlorophyll fluorescence based on a narrow range in the electromagnetic wavelength. A low SIF reflects the high absorption of radiation by healthy chlorophyll contents of leaves.

None of the studies of this review used satellite hyperspectral images, which was consistent with the previously conducted reviews on RS application for grassland monitoring (Ali et al., 2016; Reinermann et al., 2020; Wang et al., 2022). This was probably due to hyperspectral images being expensive to acquire and having high computational needs when processing large and complex data (Wambugu et al., 2021). Then the available products (e.g., CHRIS-PROBA, PRISMA, HysIS) show limited spatial and temporal coverage (Filchev, 2014; Qian, 2021).

Instead, Hermanns et al. (2021), used airborne RS – with the HySpex VNIR-1800 sensor – in 2018 and 2019 to determine grassland response to drought in Saxony-Anhalt, Germany. Together with the additional value from multiple narrow wavelengths, this study brings to light the potential of determining the spectral signature of drought-stressed grasslands.

Shafran-Nathan et al. (2013) have demonstrated that vertical photography, with mounted cameras on the field, can estimate vegetation cover of 1 m x 1 m grassland plots at very high spatial and temporal resolution during successive drought years. They concluded that herbaceous plants prioritize productivity over spatial plant cover during the two-year drought in a dry environment by applying a finer and more detailed scale.

The RS products that have been used so far for assessing drought impacts on grassland show the trade-off between spatiotemporal coverage of the images and resolutions (spectral, temporal, and spatial). Recent developments in data fusion may allow assessments to move beyond these limitations. For example, merging images from different missions can generate long and fewer gaps time series of RS data (Bao et al., 2014; Clementini et al., 2020). Most importantly, recent data fusion techniques have allowed to generate NDVI images of 30 m spatial resolution with daily frequency from Landsat and MODIS products with the use of the spatial and temporal adaptive reflectance fusion model (STARFM; Gao et al., 2006; H. Liu et al., 2021).

The approaches identified in this review use parametric methods. The recent development of machine learning techniques opens new avenues for assessing the non-linear response of grasslands to drought and understanding complex influences of driving factors to drought response. Zhou et al. (2022) used a linear and non-linear approach to account for the combined impact of climate change and anthropogenic activities in determining the vegetation response to drought. Their results revealed

that vegetation response was highly variable in space. The use of machine learning in grassland response to drought assessment is limited still for now. But it has been used in ecosystems of similar structure to grasslands. Hendrawan et al. (2023) demonstrated the use of a machine learning (random forest) algorithm in understanding the sensitivity and drivers of cropland productivity to drought. For grasslands, Schucknecht et al. (2022) confirmed the improvements of machine learning algorithms (i.e., Gradient Boosting Machine and Random Forest) in estimating grassland biomass using airborne hyperspectral data.

1.4.2.3. Expansion of monitored grassland properties

Studies on grassland response to drought have mostly monitored changes in grassland properties related to primary productivity. Greenness-based indices are used directly or as inputs to other indices and models. However, many other VIs, RS products, and reflectance bands can represent other grassland properties such as moisture content, and phenology. Bajgain et al. (2015) demonstrated the higher sensitivity of LSWI to drought compared to NDVI and EVI, while Kang et al. (2018) completed their analyses with phenological metrics like the start of season, end of season, and length of season, which were highly correlated to drought severity.

Different grassland properties are expected to have different responses to drought. For example, Han et al. (2018) revealed that aboveground biomass (AGB; $R^2 = 0.80$) was more responsive than leaf area index (LAI; $R^2 = 0.56$), to the ratio of transpiration and evapotranspiration (T/ET). Thus, monitoring multiple properties at the same time can improve our understanding of grassland responses to drought. However, RS-based assessments of the response of key grassland properties are still missing such as soil carbon stock, and nitrogen content. Carbon storage in the soil is among the ecosystem services provided by grasslands. However, this service is under threat due to the impact of drought on plant processes and soil conditions. Vegetation diversity is recognized to influence the response to drought (Wagg et al., 2017; Xu et al., 2022) but although to modulate the effect of drought on productivity (Craven et al., 2016; Grange et al., 2021; Isbell et al., 2015). Unfortunately, the mitigating effect of vegetation diversity is sometimes absent (De Boeck et al., 2018; Grace et al., 2007) or negatively impacts resistance to drought as exhibited by aboveground productivity (Vogel et al., 2012; Weisser et al., 2017). RS-based studies should thus consider biodiversity as another grassland property to relate to spatio-temporal differences in RS signals during and after droughts. Remote sensing has the capacity to estimate grassland properties aside from productivity. Existing RS products and techniques allow the determination of soil carbon (Angelopoulou et al., 2019; Ayala Izurieta et al., 2022) and vegetation diversity (Fauvel et al., 2020; Thornley et al., 2023). These two factors are

among the important grassland parameters that can help understand grassland response to drought (Lei et al., 2016; Lüscher et al., 2022; Reinthaler et al., 2021).

Finally, we once again emphasize the importance of disentangling the drought impact from other disturbances with the use of RS and multiple data sources. A detailed understanding of the response of multiple grassland properties to drought should increase our scientific knowledge for mitigating or anticipating drought impacts.

1.5. Conclusion

This literature review synthesizes the use of remote sensing in the assessment of grassland response to drought. We highlighted five different assessment approaches with their basic principles, required inputs, and concerns. This also indicated the preference for RS optical images, in contrast to microwave images. We identified several knowledge gaps that may guide the future of remotely sensed assessments of grassland response to drought. The uneven global distribution of studies stresses the need to put more attention to tropical and subtropical grasslands, as well as temperate grasslands in Western Europe, compared to the arid and semi-arid grasslands of Asia and temperate grasslands of North America. Despite several RS studies comparing drought responses between different types of ecosystems (including grasslands) or between broad classes of grasslands, additional investigations are needed to confirm or contradict field experiment results comparing similar grasslands but with different management regimes or biodiversity levels. One key limitation of current studies stands is the disentanglement of drought impacts from confounding factors within RS signals. We recognized that the use of existing and new RS product developments opens new avenues for addressing this.

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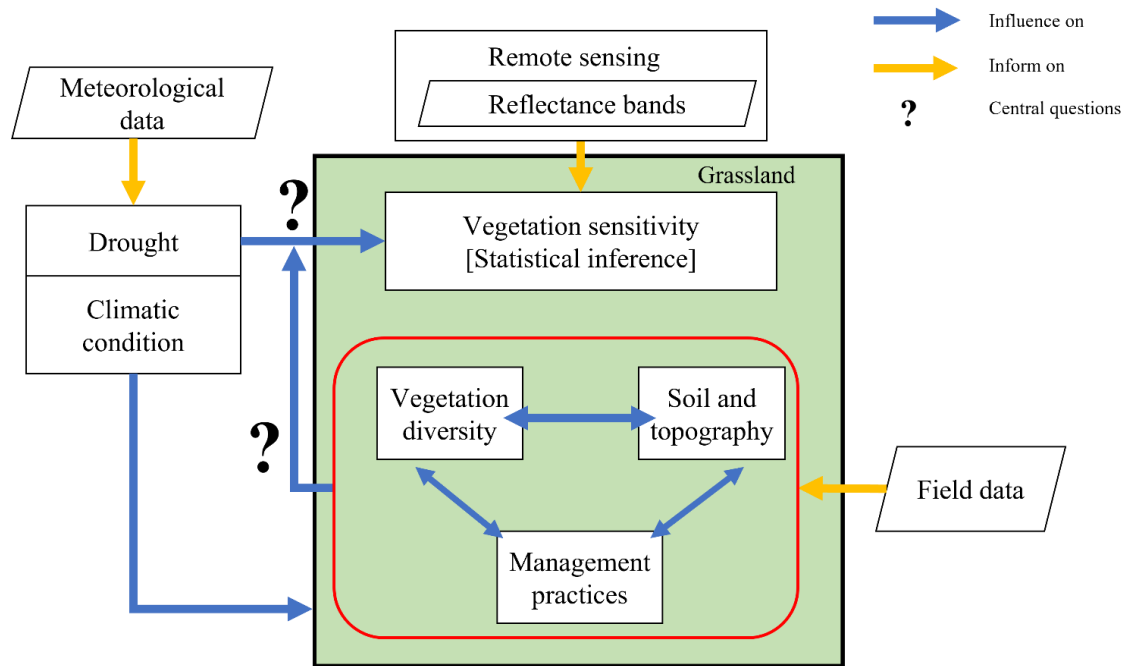
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VARIABILITY AND DRIVERS OF GRASSLAND SENSITIVITY TO DROUGHT AT DIFFERENT TIMESCALES USING SATELLITE IMAGE TIME SERIES



Chapter 2 is the core research of this thesis. It aims at assessing the grassland sensitivity to drought in the Massif central and most importantly identify the drivers of such sensitivities. Three categories of drivers were considered ranging from vegetation diversity, management practices, and soil and topography.

CHAPTER 2. VARIABILITY AND DRIVERS OF GRASSLAND SENSITIVITY TO DROUGHT AT DIFFERENT TIMESCALES USING SATELLITE IMAGE TIME SERIES

Abstract

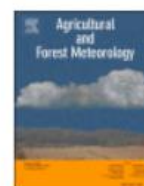
Drought is expected to increase in frequency and severity with climate change, leading to more intense impacts on grasslands and their associated ecosystem services. Complementary to ground experiments, remote sensing technologies allow for the study of drought impacts with large spatio-temporal coverage in real-life conditions. We aimed to quantify the variability of grassland sensitivity to drought using a long-term satellite image time series of 394 temperate permanent grassland plots to identify factors influencing these sensitivities. Accordingly, we assessed the slope of the linear relationship between satellite-based vegetation status, using the standardized anomalies of the vegetation indices (VIs), and drought severity, using a modified version of the Standardized Precipitation Evapotranspiration Index (SPEI), from 1985 to 2019. The process was repeated for 24 VIs and five SPEI timescales. We then conducted a linear model selection procedure, using the grassland sensitivity derived from the most responsive VIs (i.e., VIs for which anomalies indicated a tighter linear relationship with the modified SPEI), to identify which grassland properties influenced sensitivity to drought. A total of 29 properties, grouped into pedoclimate, agricultural management, and vegetation diversity factors, were derived from ground measurements. Overall, we demonstrated that the influence of predictors on grassland sensitivity to drought varied across the drought integration timescales. Our results highlighted the significant mitigating effect of soil water holding capacity on sensitivity to drought for short timescales of fewer than 30 days. The date of first herbage use by farmers was positively related to grassland sensitivity to drought across all timescales. We also demonstrated that higher vegetation diversity significantly reduced sensitivity to drought. However, for the long timescales of drought integration, such influence was mainly redundant with management (i.e., the shared partition of variance) suggesting complex cascading effects between agricultural practices and plant community structure that still need to be addressed comprehensively in future studies.

Keywords: Meteorological drought; Remote sensing; Time scales; Grassland response; NDWI; GVM



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Variability and drivers of grassland sensitivity to drought at different timescales using satellite image time series

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ABSTRACT

Drought is expected to increase in frequency and severity with climate change, leading to more intense impacts on grasslands and their associated ecosystem services. Complementary to ground experiments, remote sensing technologies allow for the study of drought impacts with large spatio-temporal coverage in real-life conditions. We aimed to quantify the variability of grassland sensitivity to drought using a long-term satellite image time series of 394 temperate permanent grassland plots to identify factors influencing these sensitivities. Accordingly, we assessed the slope of the linear relationship between satellite-based vegetation status, using the standardized anomalies of the vegetation indices (VIs), and drought severity, using a modified version of the Standardized Precipitation Evapotranspiration Index (SPEI), from 1985 to 2019. The process was repeated for 24 VIs and five SPEI timescales. We then conducted a linear model selection procedure, using the grassland sensitivity derived from the most responsive VIs (i.e., VIs for which anomalies indicated a tighter linear relationship with the modified SPEI), to identify which grassland properties influenced sensitivity to drought. A total of 29 properties, grouped into pedoclimate, agricultural management, and vegetation diversity factors, were derived from ground measurements. Overall, we demonstrated that the influence of predictors on grassland sensitivity to drought varied across the drought integration timescales. Our results highlighted the significant mitigating effect of soil water holding capacity on sensitivity to drought for short timescales of fewer than 30 days. The date of first herbage use by farmers was positively related to grassland sensitivity to drought across all timescales. We also demonstrated that higher vegetation diversity significantly reduced sensitivity to drought. However, for the long timescales of drought integration, such influence was mainly redundant with management (i.e., shared partition of variance) suggesting complex cascading effects between agricultural practices and plant community structure that still need to be addressed comprehensively in future studies.

2.1. Introduction

Meteorological droughts – in other words, deficits in the climatic water balance – of varying severity, frequency, and duration affect several components of agroecosystems, with serious consequences for agricultural production and environmental health (Howden et al., 2007). Similar to other agroecosystems, managed grasslands are influenced by drought impacts. The increasing frequency and severity of drought threaten the multiple ecosystem services – provision, regulation, and cultural – provided by grasslands and their associated biodiversity (Bengtsson et al., 2019; Chang et al., 2021; Hofer et al., 2016; Zwicke et al., 2013). Grasslands contribute significantly to milk and meat production (O'Mara, 2012) and provide an estimated one billion jobs around the world (Buisson et al., 2022). In addition to provisioning services, grasslands securely store an estimated 30.6% of terrestrial carbon below ground in the roots and soil (Bai and Cotrufo, 2022; Lei et al., 2016) and host a large number of species, some of which are endangered (Dengler et al., 2014). Unfortunately, extreme drought events are well recognized to be detrimental to grassland biodiversity and ecosystem function (Newbold et al., 2016; Strömberg and Staver, 2022). One of the most evident consequences is the reduction of net ecosystem productivity, which reduces agricultural production but also converts grasslands from sinks to sources of carbon (Ciais et al., 2005; Lei et al., 2016; Nagy et al., 2007; Zhang et al., 2020).

Knowledge of grassland sensitivity to drought and its determinants has emerged from field experiments and, more recently, from Earth surface observations. Field observations and semi-controlled experiments have provided, thus far, the most comprehensive insights regarding grassland properties that either promote or suppress vegetation sensitivity to drought. The most obvious properties, or drivers, are related to pedoclimatic conditions. Higher sensitivity to drought has been found in grasslands that are topographically exposed to solar radiation (Yang et al., 2020), situated at low elevations (Catorci et al., 2021; Gharun et al., 2020), and found on soils with low water retention capacity (Buttler et al., 2019). Additionally, grassland management practices, which refer to the modalities of fertilizer application and herbage usage by mowing and/or grazing, have been tested partially and sometimes have revealed mixed effects. High fertilizer addition can either increase sensitivity to drought (Bharath et al., 2020; Klaus et al., 2016; Rose et al., 2012) or have no effect (Vogel et al., 2012; Weisser et al., 2017). More frequent mowing events have been related to stronger negative effects of drought (Vogel et al. 2012; Weisser et al., 2017; Zwicke et al., 2013), and grazing has been associated with greater sensitivity to drought than mowing (Deléglise et al., 2015). Finally, experimental studies have further highlighted the mixed influences of grassland diversity. Higher taxonomic or functional diversity has often been associated with lower sensitivity to drought (Grange et al., 2021; Griffin-Nolan et al., 2019; Isbell et al., 2015; Kreyling et al., 2017), but some studies have

indicated an opposite effect of species richness (Vogel et al., 2012; Weisser et al., 2017) or the absence of effect (De Boeck et al., 2018). According to these findings from drought experiments conducted in managed grasslands, the properties influencing vegetation sensitivity to water deficit can be categorized into pedoclimatic, management, and biodiversity drivers.

Despite their incontestable scientific value, the results provided by semi-controlled experiments conducted at the field level reveal some limitations. These experiments are, in essence, restricted in their design (e.g., limited combinations of rainfall regimes, levels of diversity, type of soils, etc.) and geographic coverage. These limitations hinder the analysis of complex combinations of potential drivers that prevail in real-life conditions (Fraser et al., 2013; Matos et al., 2020) and prevent the generalization of the results to all biogeographic contexts on Earth. In addition, those experiments usually report limited temporal coverage of grassland responses to drought over one or a few successive growing seasons (Hoover and Rogers, 2016). Although coordinated and long-term observations and experiments (Fraser et al., 2013; Knapp et al., 2017a, 2017b; Lemoine et al., 2016) push those limitations, spatially and temporally wider analyses of existent grasslands are needed.

The rapid development of Earth observation techniques tremendously increases both spatial and temporal coverage of agroecosystem monitoring (Ali et al., 2016; Anderson, 2018; Arun Kumar et al., 2021; Reinermann et al., 2020). Therefore, recent studies have assessed the response of natural ecosystems and agricultural lands to drought severity using satellite images at a wide range of spatial scales (Jiao et al., 2019; Maurer et al., 2020; Vicente-Serrano, 2007; Vicente-Serrano et al., 2013). Such assessment is based either on the quantification of the relationship between the local satellite reflectance and climatic variables (Cabello et al., 2012; Graw et al., 2017; Nanzad et al., 2019), or it is based on the satellite product anomalies and the computed standardized drought indices (e.g., Li et al., 2015; Li et al., 2022; Ye et al., 2020). Consequently, these relationships depict the sensitivity of vegetated surfaces to drought events (Vicente-Serrano, 2013). Afterward, remotely sensed sensitivity can be related to geographic variations of a set of environmental parameters, considered to be the hypothetical drivers of vegetation response to drought.

Remote sensing (RS) analyses of drought effects on vegetated surfaces are based on various methodological choices. Regarding drought estimates, studies frequently used the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI). From here, the standardized precipitation indices can be used to determine drought severity at different timescales (Vicente-Serrano et al., 2010; Nanzad et al., 2019), but are seldom considered in studies (Almeida-Ñauñay, et al., 2022; An et al., 2020; Dong et al., 2019; Zhao et al., 2018). Research that considered multiple drought timescales has identified grassland and cultivated vegetation response to drought to be best correlated at a timescale of one to three months

(e.g., Almeida-Ñañay et al., 2022; An et al., 2020; Zhao et al., 2018). However, these studies used monthly meteorological data. Finer climate data resolution, such as weekly or daily, is needed to reveal more accurate impacts of meteorological variations on vegetation property changes (Salehnia et al., 2018; Wang et al., 2015). Regarding RS-based vegetation condition estimates, studies generally used the Normalized Difference Vegetation Index (NDVI) or the Enhanced Vegetation Index (EVI), or their derivatives, such as the Vegetation Condition Index (VCI), and the Vegetation Health Index (VHI; Graw et al., 2017; Kogan et al., 2004; Picoli et al., 2019; Vicente-Serrano, 2007). Aside from these greenness-based satellite proxies, indices related to the hydric status of vegetation, such as the Normalized Difference Water Index (NDWI) or Land Surface Water Index (LSWI), have emerged in other studies (Bajgain et al., 2015; Picoli et al., 2019). However, vegetation indices (VI), such as the NDVI, are used to represent multiple vegetation properties and do not always perform well in the assessment of drought when implemented in other ecoregions (Bajgain et al., 2015; Ebrahimi et al., 2010; Maurer et al., 2020). These discrepancies in methodological choices between studies limit the generalization of the published results and their comparison.

Thus far, the RS studies have attempted to identify the drivers of vegetation sensitivity to drought through a focus on specific categories of drivers, namely, the abiotic environment, land management, and vegetation properties, usually in isolation. Some of these categories have been understudied in grasslands. The investigated drivers are topographic factors for forests and shrublands (Cartwright et al., 2020), and soil properties, such as the soil water holding capacity for different land covers (Ji and Peters, 2003; Thoma et al., 2019). Some studies further considered the influence of land use (Burrell et al., 2020; Munson et al., 2016; Tollerud et al., 2020) and, in the case of grasslands, the type of agricultural management (Burrell et al., 2020; Catorci et al., 2021; Graw et al., 2017; Wagle et al., 2019). A final group of studies has highlighted the importance of vegetation cover (De Keersmaecker et al., 2015) and vegetation diversity (De Keersmaecker et al., 2016; van Rooijen et al., 2015) through the lens of taxonomic diversity rather than functional diversity. These studies have contributed to a better understanding of why some types of vegetation are more sensitive to drought than others, although the influence of abiotic factors in grassland deserves more attention. However, an important gap of knowledge remains in the assessment of the relative influences of these different drivers – classified as pedoclimatic, agricultural management, and biodiversity factors – at the same time.

In this study, we pursued two main objectives. First, we aimed to quantify the sensitivity of managed grassland to drought at various timescales using satellite-based VI anomalies that were best related to irregularities of climatic water balance (i.e., SPEI). This was conducted over 34 years for a vast geographic region predominantly covered by typical Western European grasslands managed for cattle and sheep breeding. Second, we aimed to assess the relative influence of pedoclimate, agricultural

management practices, and vegetation diversity factors on grassland sensitivity to drought. To do so, RS-based assessments of sensitivity to drought were analysed against 29 grassland descriptors measured at the ground level for the 394 vegetation plots of the study area.

2.2. Material and methods

2.2.1. Study area

The Massif central is a mountainous region ranging from 300 to 1,885 metres above sea level in France. It exhibits four climatic zones: mountainous and semi-continental in the major center areas, with influences of oceanic climate in both the northern and western parts and of Mediterranean climate near the southeastern part (Joly et al., 2010). The mean annual cumulative precipitation, between 1985 and 2019, was 1,067 millimetres (mm) with a standard deviation of 348 mm, while the mean annual temperature was 9.3 °C with a standard deviation of 1.96°C. The 85,000 square kilometres (km²) region is covered mostly by managed perennial grasslands representing 60% of agricultural areas, which comprise one-third of the French permanent grasslands.

Our analyses included a total of 143 grassland parcels. These parcels were homogenous areas of management with heterogeneous vegetation, topography, and soil characteristics. An average of three vegetation plots were distributed within each grassland parcel (minimum of one and maximum of 10 plots). The subsequent analyses, therefore, were based on the 394 vegetation plots distributed among the 143 parcels (Figure 2– 1). These plots have an average area of 25 square metres (m²) and range from 2 to 100 m². The sampling design aimed to represent the main types of grassland vegetation within the Massif central region (Galliot et al., 2020; Hulin et al, 2012, 2019; Le Hénaff et al., 2021).

2.2.2. Data

We collected satellite images and meteorological data from 1985 to 2019 for each of the 394 vegetation plots to quantify the temporal changes in vegetation reflectance and drought severity, respectively. We further characterized the pedoclimate, agricultural management practices, and vegetation diversity of these plots from ground observations collected by several projects implemented in the region during the period of interest.

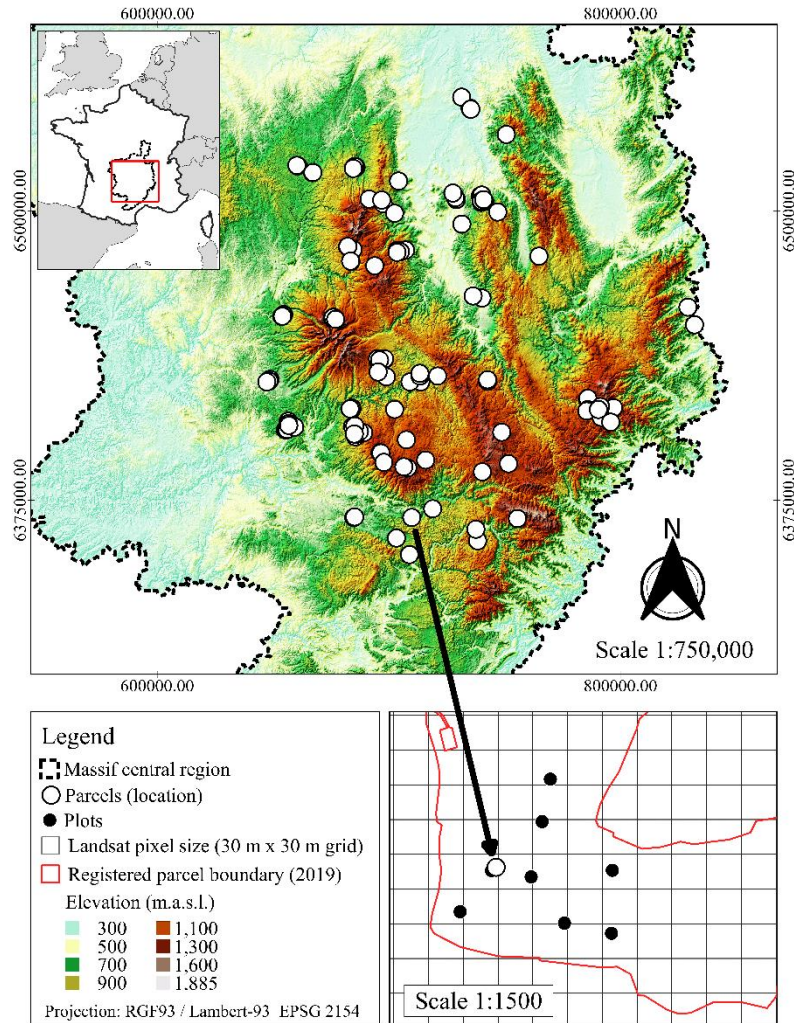


Figure 2– 1. Distribution of the grassland parcels and vegetation plots in the Massif central region (France). The main map depicts the topographic elevation and relief from a 25 m x 25 m digital elevation model of the Copernicus Land Monitoring Service (<http://land.copernicus.eu/pan-european/satellite-derived-products/eu-dem/eu-dem-v1.1/view>). The lower right inset map presents the vegetation plots found with a parcel, together with the Landsat 30m x 30m pixel grid.

2.2.2.1. Drought estimates over the 1985–2019 period

We built the time series of the local climatic water balance, computed as the difference between precipitation and potential evapotranspiration (P-PET), during the 1985–2019 period. To do so, we used the meteorological records from the *Système d'Analyse Fournissant des Renseignements Adaptés à la Nivologie* (SAFRAN) data for France (Durand et al., 1993). SAFRAN provides daily information on a set of meteorological parameters in NetCDF or as a raster with a spatial resolution of 8 km x 8 km. We checked the local uncertainty of the SAFRAN estimates with spatially accurate daily records from a set of 140 local meteorological stations within the Massif central region (Météo-France). Our

comparisons revealed tight linear relationships between the two data sources, validating the use of SAFRAN for assessing local variations of the climatic water balance in the study area ($-A$).

Modified standardized precipitation evapotranspiration index (SPEI)

We then quantified the drought severity with a modified version of SPEI. The original version of this index is based on the long-term time series of the climatic water balance (D_i), which is the difference between the monthly precipitation (P) and potential evapotranspiration (PET) measurements integrated over a given timescale of one, three, six, nine, 12 and 24 months (Beguería et al., 2014; Pei et al., 2020; Vicente-Serrano et al., 2010; Zargar et al., 2011). For example, a seasonal or three-month drought timescale is the integration of D_i at a given month and the two preceding months.

$$D_i = P_i - PET_i \quad \text{where } i = \text{month} \quad \text{Equation 1}$$

To compare the surplus and deficit of the water balance between different sites with different climates or dates, the aggregated D_i values are standardized. To do so, the D time series is fitted into a log-logistic distribution using a three-parameter probability distribution function. The probability distribution of D is standardized to obtain the SPEI using the approximation of Abramowitz and Stegun (1965). The statistical distribution seeks to define the normal expectation. Negative SPEI values indicate a deficit of the water balance with respect to normal conditions, while positive values indicate a surplus of precipitation. Since the SPEI is multi-scalar, we could analyse the effect of different types of droughts (Vicente-Serrano, 2010) and discriminate between short and frequent water deficits (shortest timescales) and long and infrequent water deficits (longest timescales).

To address our objectives, we modified the classic SPEI in two ways. First, changes in grassland growth and conditions due to drought and precipitation occur at daily temporal scales (Salehnia et al., 2018; Wang et al., 2015). Consequently, the impacts of short-duration droughts (i.e., fewer than 30 days) will not be properly estimated by the monthly classic SPEI, especially when such brief drought events are distributed between two consecutive months. Accordingly, we used daily climate data and integrated for a given day the difference between P and PET over the 15, 30, 60, 90, or 120 preceding days. Second, the small number of D observations can lead to a weak goodness-of-fit in the probability distribution step. In climate studies, the World Meteorological Organization (WMO) recommended a 30-year period of climatic data when establishing climatic normal (Marchi et al., 2020; Rigal et al. 2019). However, the climatic water balance across the years rarely exhibits a good and smooth distribution. Thus, instances with the classic SPEI may result in abrupt changes between months or

large differences between two months. For the modification, encouragement was found from Russo et al. (2014) by defining a new set of data, A_d , in the following:

$$A_d = \bigcup_{y=1985}^{2019} \bigcup_{i=d-15}^{d+15} D_{y,i} \quad \text{Equation 2}$$

with d , a given day, and $D_{y,i}$, the water balance of day i in year y . This new set of data A (Equation 2) exhibits an increase in the number of observations, which helps improve the goodness-of-fit of the log-logistic distribution used for the standardization procedure of the SPEI.

2.2.2.2. Standardized anomalies of vegetation reflectance over the 1985–2019 period

Similar to the estimation of drought severity with a modified version of the SPEI, we computed the standardized anomalies of local vegetation reflectance indices. We first extracted the reflectance bands of Landsat 4, 5, 7, and 8 throughout 1985–2019 for each of the 394 vegetation plots from Google Earth Engine (Gorelick et al., 2017) using the *reticulate* package in R (Ushey et al., 2022). Landsat images offer a sufficiently fine spatial resolution (30 m x 30 m) to account for vegetation heterogeneity – in other words, they discriminate between different vegetation plots within the same parcel, as depicted in Figure 2– 1, and temporal resolution (16 days) to monitor vegetation reflectance changes for a growing season. These extractions resulted in a mean number of 519 cloud- and snow-free images per vegetation plot.

We then computed the standardized reflectance anomalies of all 24 VIs (Appendix 2– B) related to vegetation properties, such as greenness, cover, moisture content, and senescence (Bajgain et al., 2015; Davidson et al., 2006; Wu, 2014). Here, we adapted the same standardization procedure of our modified SPEI to quantify the deviation of VIs of a given clear day – in other words, free of clouds or snow cover – to the statistical distribution of VIs of the same day plus the 15 days before and after over the period of 1985–2019. This standardization allowed the spatio-temporal comparisons among plots.

2.2.2.3. Local properties of the grasslands

The local descriptions of the 394 vegetation plots were inherited from several past projects that collected information on management activities, botanical composition, soil properties, and topographic conditions between 2008 and 2019 (Galliot et al., 2020; Hulin et al., 2019).

2.2.2.3.1. Pedoclimate

At the parcel level, the soil properties were assessed with a total of 11 physical and chemical parameters. We considered direct soil measures such as the pH; carbon-to-nitrogen ratio; concentration of phosphorus, potassium, and magnesium; soil organic carbon; and soil organic nitrogen. We further derived variables that are well-recognized to influence the response of vegetation to meteorological drought. First, we computed the soil water holding capacity (SWHC) from the quantified percentage of clay, percentage of sand, and bulk density using a pedotransfer function developed and validated for French soils (Román Dobarco et al., 2019). Second, we derived the aspect (expressed as 0 to 180 degrees from north to south, respectively), elevation (in metres above sea level), and the Terrain Wetness Index (TWI; Beven and Kirkby, 1979; Böhner and Selige, 2006) of the vegetation plots from the 25 m x 25 m spatial resolution digital elevation model from the Copernicus Land Monitoring Service.

2.2.2.3.2. Agricultural management

Management information was collected in two phases; the first was in 2008–2009, then in 2016–2017. This information included the amount of nitrogen (N) fertilization, specific dates of use, and type of use. We assumed from field experience and some farmer interviews that these agricultural practices had seen minimal changes over the past 30 years, especially the use of herbage, and, therefore, may be representative of grassland management for the entire period of 1985–2019. We then summarized these data to obtain: (i) the total amount of nitrogen fertilization from the applied organic and inorganic nitrogen, expressed in kg ha^{-1} ; (ii) the average number of uses per year based on the number of grazing rotations and harvesting dates; (iii) the prominent type of use, computed as the difference between the total number of grazing and mowing events for a two-year period, with positive values indicating the predominance of grazing, negative values the predominance of mowing, and zero equal numbers of grazing and mowing events; and (iv) the date of first use expressed in cumulative growing degree days. This was computed as the sum of the growing degree days of the date of first grazing or mowing event recorded for two years of monitoring and then averaged. Expressing the date of first use in thermal time instead of Julian days allowed the comparison between vegetation plots distributed along a large elevation gradient (Perronne et al., 2019), and minimize the effect of between-year variability of meteorological conditions. Indeed, the farmers manage their parcels according to the grass growth which may lead to variation in calendar dates of management events between years but not in cumulative growing degree days, or at least to a lesser extent.

2.2.2.3.3. Vegetation diversity

Botanical surveys were conducted at the level of vegetation plots, in which all species were identified, and their local abundances were estimated visually. From these *relevés* (surveys), we first derived taxonomic diversity indices: species richness, the Shannon diversity index, and Simpson's diversity index. Then, we used a trait database compiled for 1,300 plant species of open habitats of the Massif central (Baseflor in Julve, 1998; DIVGRASS in Carboni et al., 2016; Choler et al., 2014), together with the plot botanical records, to assess local functional indices. We considered plant traits associated with growth syndromes (specific leaf area [SLA] and plant height), phenology (first flowering and length of flowering periods in months), and reproductive ability (seed mass). We computed the community weighted mean (CWM) of each trait, which is recognized to be associated with ecosystem functions (Garnier et al., 2004; Grime, 1998) and grassland response to drought (Pérez-Ramos et al., 2012). We further assessed the functional diversity, which has been linked to the ecosystem stability (Hallett et al., 2017), of each vegetation plot. We used the functional dispersion index (Nunes et al., 2017) of each trait, plus a two-dimensional functional space composed of plant height and SLA to summarize plant growth syndromes.

2.2.3. Statistical analyses

The simplified workflow indicating the various analytical stages needed to quantify grassland sensitivity to drought and to identify its drivers is presented in Figure 2– 2. It includes variable inputs and the variable selection procedure in the candidate statistical models.

2.2.3.1. Computing remotely sensed grassland sensitivity to drought

Some studies have used statistical inference methods to relate grassland response with climatic variables (De Keersmaecker et al., 2016; Nanzad et al., 2019; Thoma et al., 2019) or drought severity (Jiao et al., 2019; Jiao et al., 2021; Li et al., 2015; Li et al. 2022; Maurer et al., 2020). Similar to these studies, we assessed the grassland sensitivity to drought as the slope of the linear relationship between the standardized VI anomalies and the modified SPEI (Li et al., 2022). As depicted in Figure 2– 3, in the case of vegetation insensitive to drought, we expect this slope to be not significantly different from zero and positive in the case of sensitive vegetation to drought. This was done for each of the 394 vegetation plots using time series data in the period 1985–2019 (Appendix 2– C). The slopes per plot were estimated with a mean number of 519 paired values of the standardized VI anomalies and the modified SPEI falling within the growing season from March to November.

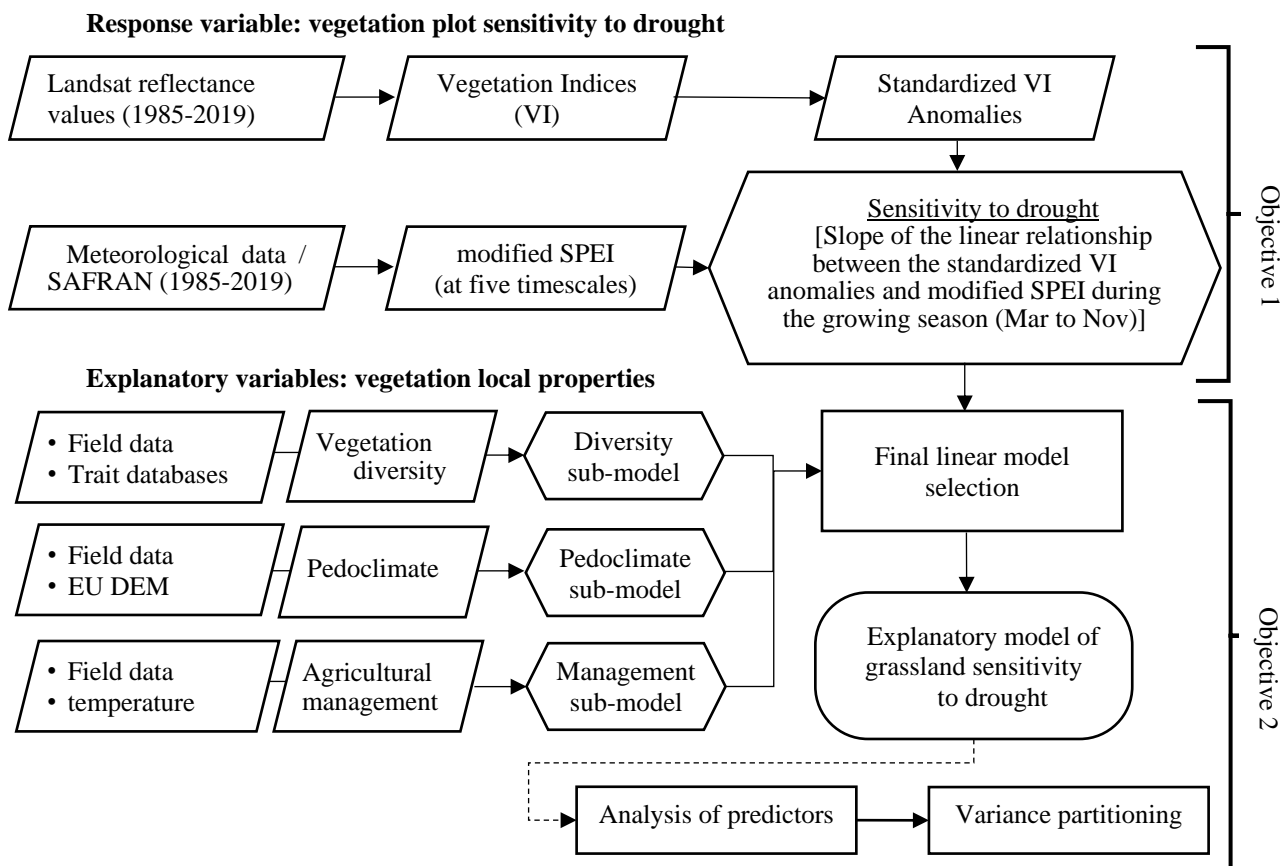


Figure 2–2. Simplified workflow for assessing grassland sensitivity and its drivers. Grassland sensitivity to drought, from Objective 1, was used as the response variable for Objective 2. The selected diversity, pedoclimate, and management factors from the respective sub-models served as the explanatory variables.

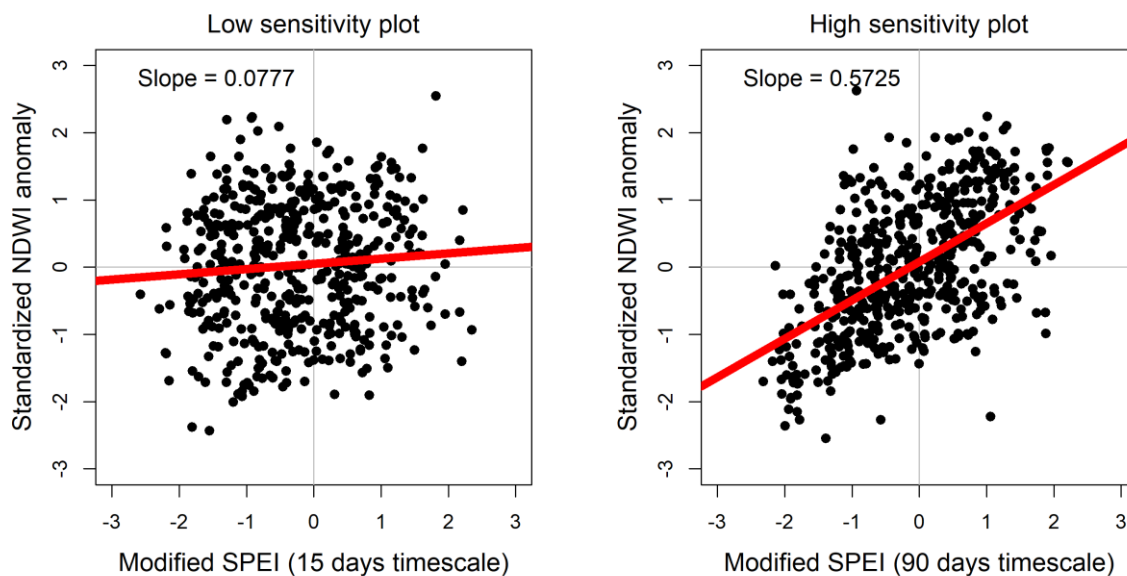


Figure 2–3. Low and high grassland sensitivities to drought for two selected timescales of different sample plots. (The threshold for low sensitivity or insensitivity is 0.1.)

The process described above was repeated for the 24 VIs across the five drought timescales, specifically, for 15, 30, 60, 90, and 120 days. We then assessed how the various VIs and drought timescales affected the estimated sensitivities to drought. To do so, we performed a two-way ANOVA with VIs and timescales as factors. The variance of the residuals, therefore, indicates the fluctuation among plots amid the variation due to methodological choices.

The slope of the linear relationship between the standardized VI anomaly and the modified SPEI, used as an estimate of grassland sensitivity to drought, was assigned as the dependent variable in the subsequent analyses that sought to identify the drivers of grassland response to drought.

2.2.3.2. Statistical modelling of grassland sensitivity to drought

We conducted a linear model selection procedure to quantify the influence of pedoclimatic characteristics, agricultural management, and vegetation diversity on the sensitivity to drought of the 394 vegetation plots. We assigned the grassland sensitivity to drought – in other words, the slope of the linear relationship between the standardized VI anomaly and the modified SPEI – as the response variable and the pedoclimate, management, and diversity factors as the explanatory variables (Figure 2–2). We compiled a total of 29 candidate variables (Table 2–1), all of which were pre-selected based on their biological meaning and possible effect on grassland response to drought, as described in the local properties section (4.2.2.3). To avoid possible multicollinearity, we first computed pairs correlation between the 29 variables. For pairs with a Pearson correlation greater than 0.5, which is more conservative than the recommended 0.7 threshold (Graham, 2003), we removed the variable with the less tangible biological meaning. Then, we conducted a two-stage selection procedure to seek the most explanatory model of vegetation plot sensitivity to drought. The first stage entailed selecting sub-models for each of the three categories of explanatory variables, where vegetation plot sensitivities were also used as the response variable. In doing so, we optimized the inclusion of the best predictors in the final model with similar weights between each category. The second stage consisted of selecting the final linear model with all categories of the previously selected predictors. For both stages, we performed backward and forward stepwise selection based on the Akaike Information Criterion (AIC), which aims to maximize the goodness-of-fit of the final model and minimize its complexity (Venables and Ripley, 2002). Such a procedure may lead to competing models, with similar complexity and close explanatory power but a different combination of predictors. These models have differences in AIC of less than 4 (Burnham and Anderson, 2004). Among these models, we selected the ones with the greatest power of prediction to detect all significant drivers. To compare the effect size of various predictors, we computed the beta coefficients from the selected models. Finally, we partitioned the variance explained by pedoclimate, management, and vegetation diversity factors by partial

regressions of the final model. The partitions explained by the explanatory categories were assessed with the unbiased adjusted R^2 (Peres-Neto et al., 2006).

Note that these analyses were repeated for the most responsive VI-derived sensitivities and at five different timescales of the modified SPEI. Since these analyses were conducted in the linear regression framework, we visually checked for homogeneity of variances and normality of the residuals (Appendix 2– D).

Lastly, all analyses were performed within the R environment (R core Team 2021).

Table 2– 1. List of the 29 grassland local properties used to predict grassland sensitivity to drought of the vegetation plots distributed in the Massif central region, France.

Type	Variable	Unit	Definition	Level of measurement
Pedoclimate	SWHC	cm ³ cm ⁻³	Total water amount that the soil can store for plant use, computed using a pedotransfer function	Parcel*
	C: N	-	Ratio of carbon and nitrogen contents in the soil	Parcel*
	K ₂ O	% of fine dry soil	Soil potassium content available for plants	Parcel*
	MgO	% of fine dry soil	Soil magnesium content available for plants	Parcel*
	P ₂ O ₅	% of fine dry soil	Soil phosphorus content available for plants	Parcel*
	pH	-	Acidity or alkalinity of the soil	Parcel*
	SON	%	Nitrogen content available in the soil organic matter	Parcel*
	SOC	%	Carbon content available in the soil organic matter	Parcel*
	TWI	-	Topographic wetness index was extracted using the SAGA TWI algorithm in QGIS	Plot**
	North- or south-facing slopes (or aspect)	degree	Azimuth direction of land surface exposure	Plot**
Altitude	m.a.s.l.	Vertical distance from the Earth's surface to a point of interest	Plot**	
Agricultural management	Date of first use	degree	Actual date of first defoliation or harvest; variable expressed in cumulative growing degree days	Parcel***
	Type of use	count	Number of uses as either more grazing (+), more mowing (-), or equal number (zero)	Parcel***
	Mean number of uses	count	Mean of the total number of mowing and grazing dates	Parcel***
	Nitrogen fertilization	g.ha ⁻¹	Total organic and inorganic nitrogen applied in the field	Parcel***
Vegetation diversity	CWM length of flowering	month	Community weighted mean of flowering period duration	Plot****
	CWM first flowering	month	Community weighted mean of start of flowering period	Plot****
	CWM seed mass	mg	Community weighted mean of seed mass	Plot****
	CWM plant height	m	Community weighted mean of plant height	Plot****
	CWM SLA	m ² .kg ⁻¹	Community weighted mean of specific leaf area	Plot****
	Fdis length of flowering	-	Functional dispersion of flowering period duration	Plot****
	Fdis first flowering	-	Functional dispersion of start of flowering duration	Plot****
	Fdis seed mass	-	Functional dispersion of seed mass	Plot****

Fdis plant height	-	Functional dispersion of plant height	Plot****
Fdis SLA	-	Functional dispersion of specific leaf area	Plot****
Fdis growth	-	Functional dispersion of growth syndromes	Plot****
Species richness	-	Number of individual species in a community	Plot****
Simpson's diversity index	-	Taxonomic measure relative to abundance within a community	Plot****
Shannon diversity index	-	Taxonomic measure of diversity within a community	Plot****

* Field measurements
** European Union Digital Elevation Model
*** Farmer interview
**** Botanic *relevés* and trait database.

2.3. Results

2.3.1. Variations of grassland sensitivity to drought

The estimated grassland sensitivity to drought differed according to multiple sources of variation, which could be decomposed between (i) the influence of the VI being used to assess vegetation reflectance anomalies, (ii) the timescale of computation of the modified SPEI, and (iii) the variability between vegetation plots, in other words, geographic variability. A two-way ANOVA revealed a significant effect of the VI being used ($F [24, 49,224] = 2,643, p < 0.001$) with a sum of squares of 589.46 and a significant effect of the timescale ($F [1, 49,224] = 4,358, p < 0.001$) with a sum of square of 40.5. The sum of squares of the residuals, corresponding to the geographic variation between vegetation plots, was 454.4. From this analysis, we can conclude that the VI being used was the most important source of variation of the estimated sensitivities to drought in our study, closely followed by geographic variability, while the timescale was a far less important source of variation.

Among the 24 VIs used to quantify grassland sensitivity to drought, the Normalized Difference Water Index (NDWI) and the Global Vegetation Moisture Index (GVMI) exhibited the highest slopes and goodness-of-fit between the standardized VI anomalies and the modified SPEI (Figure 2– 4). This indicates that both VIs were the best to reveal vegetation response to variation in the climatic water balance. The slope values between the NDWI and the GVMI were highly correlated ($r = 0.98$) and ranged between -0.1 and 0.58. However, values between -0.1 and 0.1 were not significantly different from 0. Therefore, slopes below or equal to 0.1 are interpreted as insensitivity to drought. Slope values above 0.1 indicate that negative values of the modified SPEI – in other words, climatic water balance lower than the normal expectation – are associated with negative NDWI or GVMI anomalies – in other words, the NDWI or the GVMI lower than the normal expectation. Therefore, positive slopes above 0.1 are interpreted as a negative response (i.e., sensitivity) of vegetation to drought (Figure 2– 3).

Despite the high responsiveness of the anomalies of these two moisture-based indices with the modified SPEI, their maximum R^2 values were 0.35.

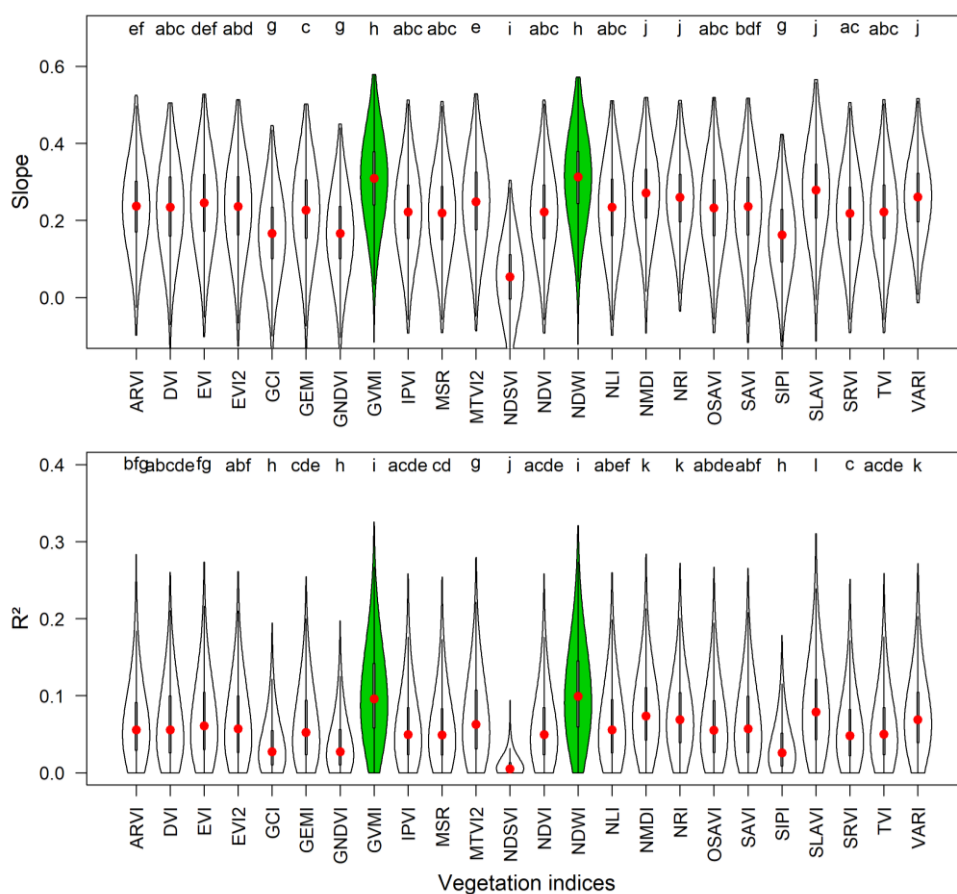


Figure 2–4. Comparison of grassland sensitivity to drought estimated from several satellite-based VIs. The variability represented by the violin plots includes the fluctuation among the 394 vegetation plots and the five drought timescales. The descriptions of the VIs are available in Appendix 2– B. Grouping labels at the top of the graphs are Tukey test results.

The vegetation sensitivity to drought, as estimated with the NDWI or the GVMI, varied somewhat between the timescales of calculation of the modified SPEI (Figure 2– 5). The mean sensitivity increased from 15 to 60 days, and then slightly decreased for 90 and 120 days. Then, the geographic variation of sensitivity to drought (i.e., between vegetation plots) was similar between all timescales with a standard deviation ranging from +/- 0.07 to 0.093.

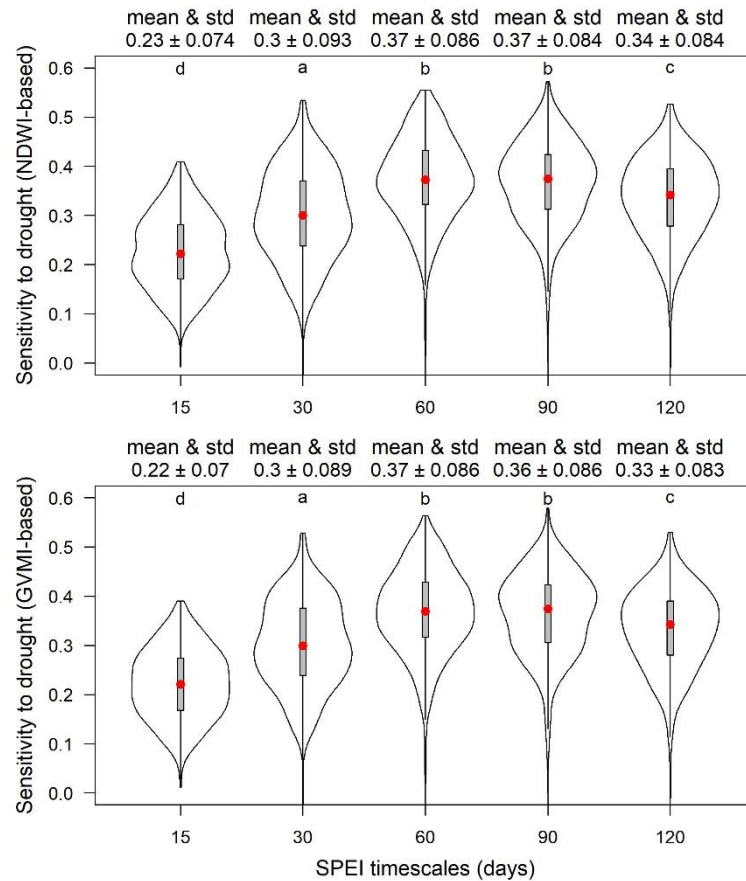


Figure 2– 5. Variability of grassland sensitivity to drought, as estimated from the linear relationship between the standardized reflectance anomaly, using the NDWI (top) and the GVM (bottom), and standardized meteorological water balance index (modified SPEI), compared among the different drought timescales. Variability was measured with the standard deviation (*std*) among the vegetation plots ($n = 394$) per timescale computation. Grouping labels at the top of the graphs are Tukey test results.

2.3.2. Drivers of grassland sensitivity to drought

The best models depicting the effect of the pedoclimatic factors, management, and vegetation diversity on grassland sensitivity to drought estimated either with the NDWI or the GVM were very close (Appendix 2– E). The obtained R^2 for the NDWI and the GVM ranged from 0.35 to 0.62 and 0.37 to 0.59, respectively, depending on the timescale of calculation of the modified SPEI. For both indices, the highest R^2 values were obtained from the short timescales of 30 and 15 days, while R^2 values below 0.5 were obtained for the timescale > 60 days.

Hereinafter, we present the averaged model beta coefficients and averaged variance partitions between the two selected indices in Figure 2– 6 and Figure 2– 7, respectively. Overall, we found different sets of selected explanatory variables and explanatory powers depending on the timescale of calculation of the modified SPEI.

We distinguished among three groups of predictors based on the beta coefficients across the five timescales. The first group included four variables with similar effects, whatever the timescale considered. The date of first use by farmers had a strong (beta coefficient >0.35) positive effect on grassland sensitivity to drought, with delayed use in the growing season associated with high sensitivity to drought. The type of use – dominance of mowing or grazing – had a moderate and positive effect ($0.10 < \text{beta coefficient} < 0.35$), except for the 15 days timescale. This must be interpreted as a greater sensitivity to drought in grazed than in mown grasslands. The nitrogen fertilization had a moderate but negative or mitigating effect ($-0.35 < \text{beta coefficient} < -0.10$) on sensitivity except for the 120 days timescale. It also exhibited a slightly more negative beta coefficient for the 15 days timescale.

The second group included predictors with a stronger effect at short timescales of 15 and 30 days. The most important in terms of effect size was the SWHC, which exhibited the strongest mitigating effect on grassland sensitivity to drought (-0.58 and -0.56). South-facing slopes, a radiation exposure parameter, had a moderate positive effect (0.26 and 0.19), while the CWM seed mass had a moderate but negative effect (-0.17 and -0.14) for the short timescales. Finally, the soil content of MgO had a moderate positive effect (0.25) for the shortest timescale of 15 days and a weak effect (below 0.1) for other timescales.

The third group involved five predictors with higher effects for long timescales. However, these predictors had an overall weak (beta coefficient $<|0.10|$) to moderate effect on grassland sensitivity. Four of them were descriptors of vegetation diversity. In order of importance, the functional dispersion of growth syndromes (Fdis (growth)), had an increasing but moderate negative effect ($-0.35 < \text{beta coefficient} < -0.10$) on sensitivity as the timescale increased. The CWM SLA had constant weak and negative effects from the 60 to 120 days timescales. The CWM plant height also had a weak negative effect (-0.09) but only for the 120 days timescale, and the Shannon diversity index had a weak positive effect (0.08) for the 90 and 120 days timescales. The fifth predictor of this group was the TWI with a weak (-0.07) and moderate (-0.14) negative effect on grassland sensitivity for 60 and 120 days timescales, respectively. Finally, the soil pH revealed an opposite weak effect for long timescales.

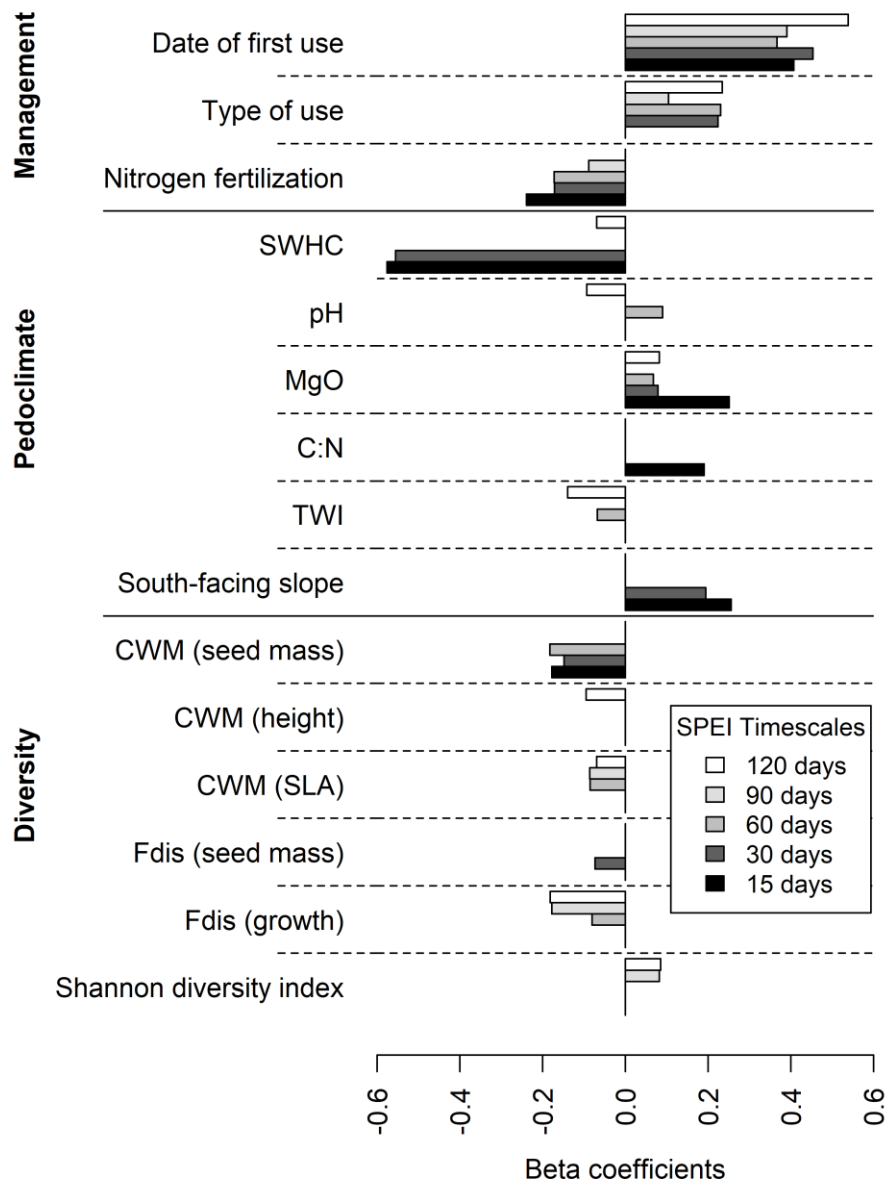


Figure 2–6. Beta coefficients of model predictors of grassland sensitivity to drought averaged between the NDWI- and GVMi-based models at different timescales. Negative beta coefficients reduce sensitivity to drought, while positive values increase sensitivity.

The highlighted variations in effect size with the timescale of the calculation of the SPEI translated into changes in the partitions of variance explained by the pedoclimate, management, and diversity of vegetation plots (Figure 2– 7; Appendix 2– F). The pure partition of the pedoclimate was the most important for the short timescales of 15 and 30 days with 32.59% and 38.02%, respectively. These led to the higher explanatory power of the final models with 57.57% and 68.69% of the variation of sensitivity to drought explained at the 15 and 30 days timescales, respectively, compared with the 36.06%, 22.21%, and 38.22% explained total variances at the timescales of 60, 90, and 120 days. Other

pure partitions did not change noticeably across the five timescales. The pure management effect explained approximately 15% of the total variance for all timescales. Then the partitions associated with diversity effects summed between 10% and 20% over the timescales but were largely shared with the management effect.

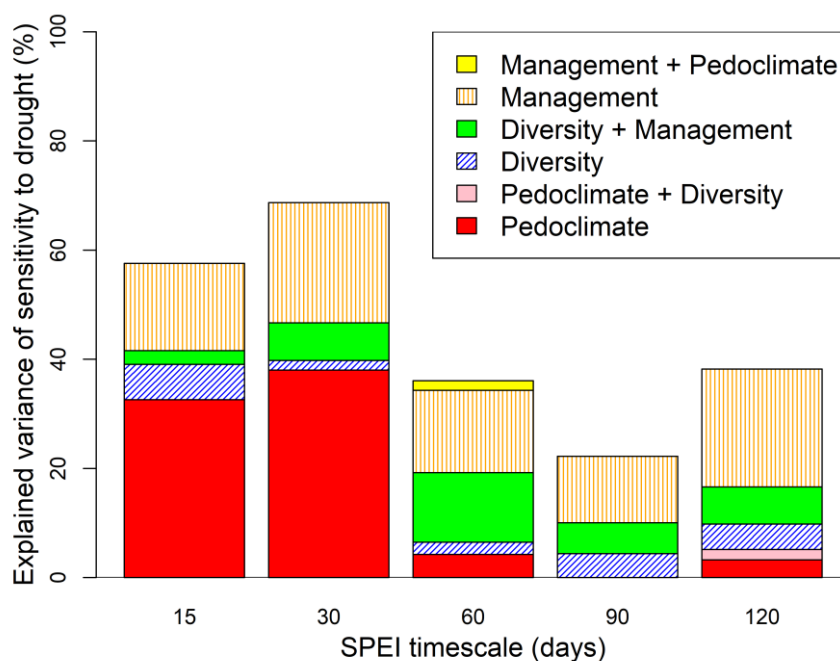


Figure 2–7. Variance partitioning of the model predictors of grassland sensitivity to drought. The average NDWI- and GVMl-based model values at different timescales were used. Model predictors were grouped into pedoclimate, management, and diversity categories.

2.4. Discussion

Using long-term satellite image time series and meteorological data, we demonstrated the significant variability of grassland sensitivity to drought over a vast geographic region dominated by open habitats maintained for cattle and sheep grazing. We further quantified the influence of a set of factors related to the pedoclimate, agricultural management, and vegetation diversity on the assessed vegetation responses. We found that their relative effect and explanatory power varied with the duration and frequency of drought events.

2.4.1. Quantifying geographic variations of grassland sensitivity to drought

We improved the current satellite-based methods of quantification of vegetation response to drought in two ways. First, we demonstrated, based on the comparison of 24 VIs, that indices accounting for SWIR bands (shortwave infrared bands between 1.57 and 1.65 nanometres (nm) for SWIR1 and

between 2.11 and 2.29 nm for SWIR2) outperformed other indices for detecting the effects of meteorological drought on vegetated surfaces. Indeed, indices such as the NDWI and the GVMI were specifically developed for remote sensing of vegetation water content (Ceccato et al., 2002; Gao 1996;) and have an immediate response to moisture changes, while greenness indices – specifically, NDVI – exhibit lagged effects (Liu et al., 2017; Tong et al., 2017) and are not directly related to the hydric status of vegetation, especially during moderate drought intensity (Bajgain et al., 2015; Chandrasekar et al., 2010; Gu et al., 2007). Although many studies have proved the usefulness of greenness indices such as NDVI (Catorci et al., 2021; De Keersmaecker et al., 2016; Ji and Peters, 2003; Nanzad et al., 2019) or EVI (Cabello et al., 2012; Cartwright et al., 2020; Munson et al., 2016; Zhou et al., 2019), these were outperformed by moisture-based indices in this study. Second, we highlighted the importance of the timescale of calculation of standardized drought severity indices such as the SPEI. The estimated sensitivities differed significantly between timescales ranging from 15 to 120 days. Generally, previous studies have considered only one timescale (Horion et al., 2019; Hossain and Li, 2021; Lu et al., 2021; Ma et al., 2016; Maurer et al., 2020). Other studies that scrutinized multiple timescales considered much coarser ones, than we did, with monthly meteorological data (Almeida-Nauñay et al., 2022; Li et al., 2015; Liu et al., 2017; Xu et al., 2021).

Despite recent developments, satellite-based assessments of vegetation response to drought may still suffer from a few limitations. First, the relationships between VI anomalies and the modified SPEI were noisy overall. Indeed, anomalies of grassland reflectance may arise from multiple natural phenomena, including pest attacks (e.g., voles increasing bare soil), vegetation diseases, or compositional changes in the vegetation. Anomalies of the climatic water balance index (SPEI) were computed from the SAFRAN data with fine daily temporal resolution but coarse spatial resolution (8 km x 8 km grid). Despite the high correlation with field meteorological stations (Appendix 2– A), our estimates of the modified SPEI still may not fully capture the fine-scale climatic variations, especially in mountainous regions. Second, our procedure for calculating the long-term normal reflectance of each day and each vegetation plot tolerates the 30-day variation of grazing and mowing events between years. We assumed that management practices were closely similar from 1985 to 2019, however, we cannot guarantee that sporadic changes in management over time have not occurred. Further developments may address this issue in two ways: (i) detection of management events with fine temporal resolution satellite products (e.g., Sentinel 1 and 2; Griffiths et al., 2020; Kolecka et al., 2018; Lobert et al., 2021), although the temporal extents of Sentinel images are currently too short – in other words, eight years for Sentinel 1 and seven years for Sentinel 2 – to estimate the normal vegetation reflectance along the growing season, or (ii) precise recording of the daily sequence of practices along the growing season with the help of farmers. Regarding other sources of disturbance, new RS

techniques should be developed to better discriminate the spectral signature of drought from other natural or anthropogenic disturbances and stresses (McDowell et al., 2015). Despite these methodological limitations, we argue that our procedure provided at least an unbiased, although noisy, estimate of grassland sensitivity to drought. This allowed us to provide a better understanding of its main drivers.

2.4.2. The strong pedoclimatic influence prevails at short timescales

We revealed the buffering effects of the soil water holding capacity (SWHC; Buttler et al., 2019; Thoma et al., 2019) and topographic exposure to solar radiation (Gharun et al., 2020; Jiao et al., 2021; Yang et al., 2020) on vegetation sensitivity to climatic water balance deficit, as demonstrated by previous studies. These were highly expected. However, our findings further indicated that these strong buffering effects hold true only for short and frequent droughts, then completely vanish from the 60 days timescale (Bodner et al., 2015; Finn et al., 2018). Interestingly, for longer timescales, our results revealed the emerging but moderate role of the TWI. This indicates that large-scale hydrological processes related to land surface topography may relay local pedoclimatic buffers when the water deficit becomes too long, which may have implications for the management of agricultural drains. Indeed, such land preparation either hampers or promotes horizontal movements of water in soils. Depending on the topographic context, the removal of an existing drain or the installation of new ones may thus help mitigate the impact of drought on grasslands.

The influence of soil chemical properties also prevailed for the short timescale. High values of MgO and C:N ratio increased sensitivity to drought, especially for the 15-day timescale, but the MgO influence was still significant for longer timescales. Magnesium limitation is recognized to impede several ecophysiological processes that enhance drought tolerance (Shao et al., 2021; Tränkner and Jaghdani, 2019; Waraich et al., 2011). In this respect our results are contradictory. A first alternative explanation is that the selection of soil magnesium (Mg) concentration in our model does not reflect an effect of this chemical component on vegetation sensitivity to drought but is a consequence of repeated droughts in some of the vegetation plots. Indeed, it has been demonstrated that, under water deficit conditions, Mg accumulates in the soil because of a reduced plant uptake (Sardans et al., 2008). A second alternative explanation is the influence of an unknown factor correlated with soil Mg concentration. The soil C:N ratio response is directly modified by N fertilization (Soussana and Lemaire, 2014), and it is expected to mirror fertilization response to drought sensitivity, but in the opposite way because N is the denominator.

2.4.3. On the importance of herbage use

The date of first use by farmers was the primary management factor explaining grassland sensitivity to drought for whatever timescale of SPEI was considered. This was expressed in thermal time (cumulative growing degree days). Doing so, the date of first use better reflects grassland phenology than calendar dates and allows comparisons among plots located at different altitudes while it minimizes the influence of between-year variation of meteorological conditions. Our results indicated that late agricultural uses during the growing season were associated with higher sensitivity to drought. The effect of the date of first use on grassland sensitivity to drought has not been tested in isolation thus far; instead, it is often mixed with cutting frequency (Zwick et al., 2013). We may still interpret our result in light of the timing of herbage use and the occurrence of droughts during the growing season. The timing of drought occurrence has already been highlighted to play a key role in drought impacts on grasslands (Denton et al., 2017; Edwards and Chapman, 2011; Hahn et al., 2021). Although droughts do not have identical occurrences between years, they often occur in late spring and summer in the Massif central. Thus, late uses are more likely to coincide with strong water deficits. However, it is well recognized that defoliation combined with water stress depletes carbohydrate reserves on which plant regrowth and stress tolerance depend (Kahmen et al., 2005; Volaire et al., 1994) and lessens the maintenance of aboveground productivity (Ma et al., 2020). Additionally, the influence of the date of use of farmers may also arise indirectly from its effect on plant community structure, as we discuss in the next section.

We further found strong evidence of greater sensitivity of vegetation to drought in preferentially grazed paddocks than in preferentially mown ones. It should be noted that usually mown grasslands may be grazed early in spring or during the autumn regrowth. Our results confirm previous findings from grassland experiments (Deléglise et al., 2015). The role of repeated defoliation by grazers along the course of the growing season, compared to sudden cuts, tends to maintain grassland vegetation in the vegetative phase (Bloor et al., 2020; Lei et al., 2016). As a result, plants allocate fixed carbon to leaf regrowth at the expense of carbohydrate storage and root growth necessary to ensure soil water and nutrient uptake, which can reduce their tolerance to drought (Amiard et al., 2003; Frank, 2007; Xu et al., 2013). Nevertheless, further research is needed to determine whether grazing pressure has additive or combined effects on the drought response of grasslands (Ruppert et al., 2015).

2.4.4. The joint influence of vegetation diversity and agricultural management

Overall, vegetation diversity explained a substantial part of the variance of grassland sensitivity to drought. Several descriptors had weak to moderate individual effects, but once they were summed together, they had substantial effects, especially for longer timescales. Such effects were largely shared

with agricultural management. In this respect, we interpret the role of vegetation diversity on grassland sensitivity to drought together with the effect of N fertilization and the date of first use.

Our results suggest a complex cascade of effects involving the influence of N fertilization on vegetation diversity and the influence of vegetation diversity on drought tolerance. We found that the Shannon diversity index increased grassland sensitivity to drought, whereas functional diversity and N fertilization had the opposite effect. Regarding taxonomic diversity and N fertilization, our findings seem to contradict those of several grassland experiments (Kübert et al., 2019; Bharath et al., 2020; Meng et al., 2021). However, N fertilization is also recognized to reduce taxonomic diversity (Humbert et al., 2016; Louault et al., 2017; Niu et al., 2014; Socher et al., 2013) but, at the same time, increase functional diversity of growth syndromes and the CWM SLA (Louault et al., 2017; Niu et al., 2014). Nevertheless, greater functional diversity of growth syndromes may result in greater asynchrony of species responses to drought, which has been related to better grassland resilience (Loreau and de Mazancourt, 2013; Muraina et al., 2021). The role of functional diversity has even been suggested to be more important than the potential effect of taxonomic diversity on grassland stability (Valencia et al., 2020). Therefore, the positive effect of the Shannon diversity index that emerged from our results may be interpreted as a spurious effect. We must warn that this conclusion should be taken with caution for management recommendations. Indeed, the effect of N fertilization in other contexts or at much higher levels of application may reduce species richness to a greater extent and result in a reduction of grassland functional diversity and, ultimately, an increase in grassland sensitivity to drought.

Beyond the direct influence of the date of first use on sensitivity to drought, as discussed in the preceding section, the greater sensitivity of late-use grasslands may also be mediated by changes in vegetation. Our results do not allow us to infer the underlying causal relationships. Delays in mowing or grazing have been demonstrated to increase taxonomic diversity when postponed from early to late spring or summer (Humbert et al., 2012). However, taxonomic diversity had only a weak effect in our study and, thus far, the consequences of delaying mowing or grazing on functional diversity remain unknown. Otherwise, delayed mowing or grazing may favor species with late phenology and reduce light use efficiency (Gaujour et al., 2012), which may result in a lower CWM SLA. This is consistent with our finding that lower drought sensitivity was associated with high SLA. However, SLA reduction usually works as a phenotypic adjustment to water stress (Wellstein et al., 2017), which contradicts our results.

Finally, we found that plant communities with heavier seeds were associated with lesser sensitivity to drought. This has already been reported in semi-arid grasslands (Martínez-López et al., 2020) dominated by annual species. Indeed, in stressful conditions, the post-drought establishment and survival of seedlings are more successful for large seeds that contain more reserves. Regeneration in

permanent grasslands is mostly clonal and, in normal conditions, depends more on buds than seeds (Benson and Hartnett, 2006). However, in a long-term drought experiment conducted in mountainous grasslands dominated by perennials, Stampfli and Zeiter (2004) found that post-drought vegetation dynamics were driven largely by recruitment from seeds. We were unable to clearly discriminate how the CWM seed mass was influenced by agricultural practices. Our result highlights the need to conduct new studies on drought mitigation through agricultural management, with an explicit focus on how different practices influence the composition and diversity of the regeneration syndromes of grassland species.

2.5. Conclusions

Our study revealed high variability of satellite-based vegetation sensitivity to drought, at different timescales, across a wide geographic region dominated by permanent grasslands maintained for cattle and sheep breeding, using moisture-based reflectance indices retrieved from Landsat images. Through the indices, vegetation was most responsive to drought for the 60 and 90 days timescales. We demonstrated that variations of satellite-based sensitivity to drought within and between grassland parcels can be explained by pedoclimatic, agricultural management, and vegetation diversity factors. We underlined that the soil water holding capacity (SWHC) worked logically as a strong buffer for meteorological droughts but only for the shortest time scales of fewer than 30 days. Additionally, agricultural management had also a strong influence, either independent or largely shared with vegetation diversity. This suggests complex indirect effects involving changes in functional composition and diversity of the grassland plant communities. Accordingly, such complexity may be disentangled by future experimental studies focusing on the ecological consequences of the timing of herbage use, tests of interactions between several management practices, and analyses of multivariate causal relationships. Finally, a better RS-based assessment of vegetation sensitivity to drought is required to discriminate between drought events and other types of disturbances, whether natural or agricultural.

Appendices

Appendix 2– A. Precipitation, potential evapotranspiration, and mean temperature correlation between the SAFRAN and field meteorological stations within the Massif central region.

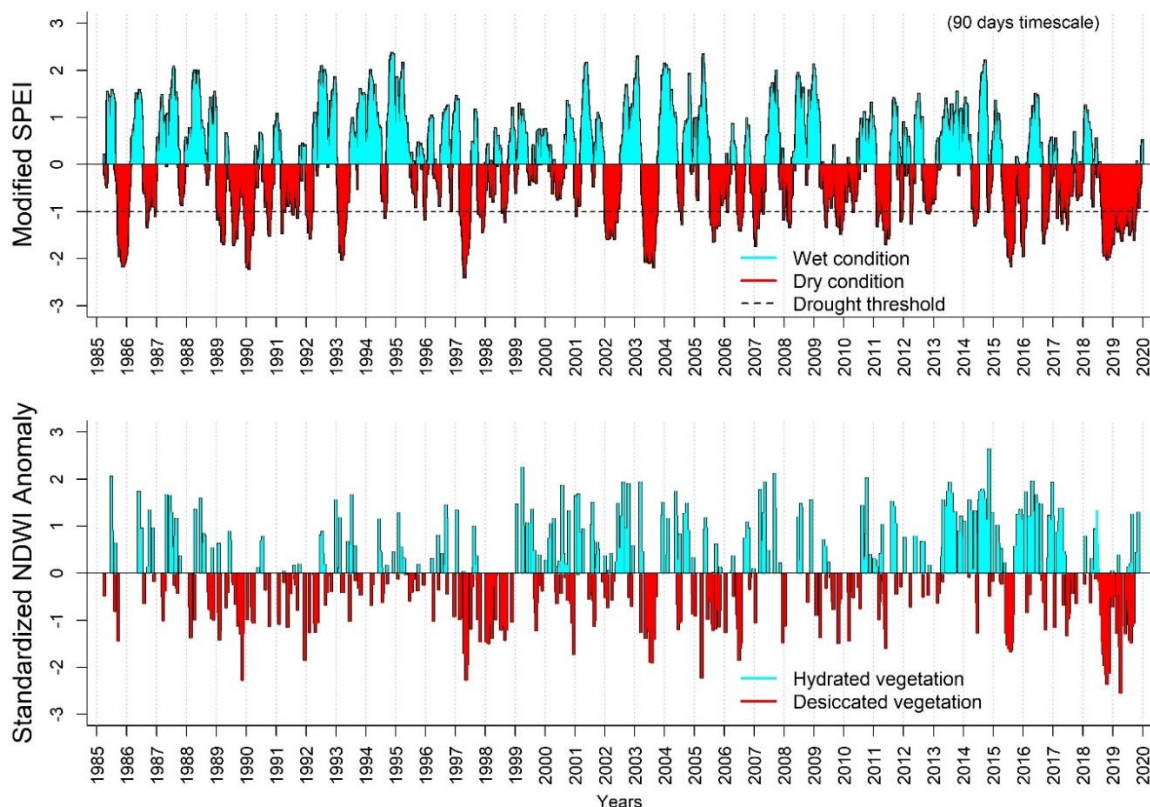
Climatic variables	R ²	Slope	Intercept
Precipitation (P)	0.80	0.84	0.25 mm
Potential evapotranspiration (PET)	0.88	0.90	0.24 mm
Mean temperature	0.96	0.90	-1.33 °C

Appendix 2– B. Satellite reflectance indices used in the study. Input bands were the blue (B), green (G), red (R), near-infrared (NIR), and shortwave infrared (SWIR) 1 and 2.

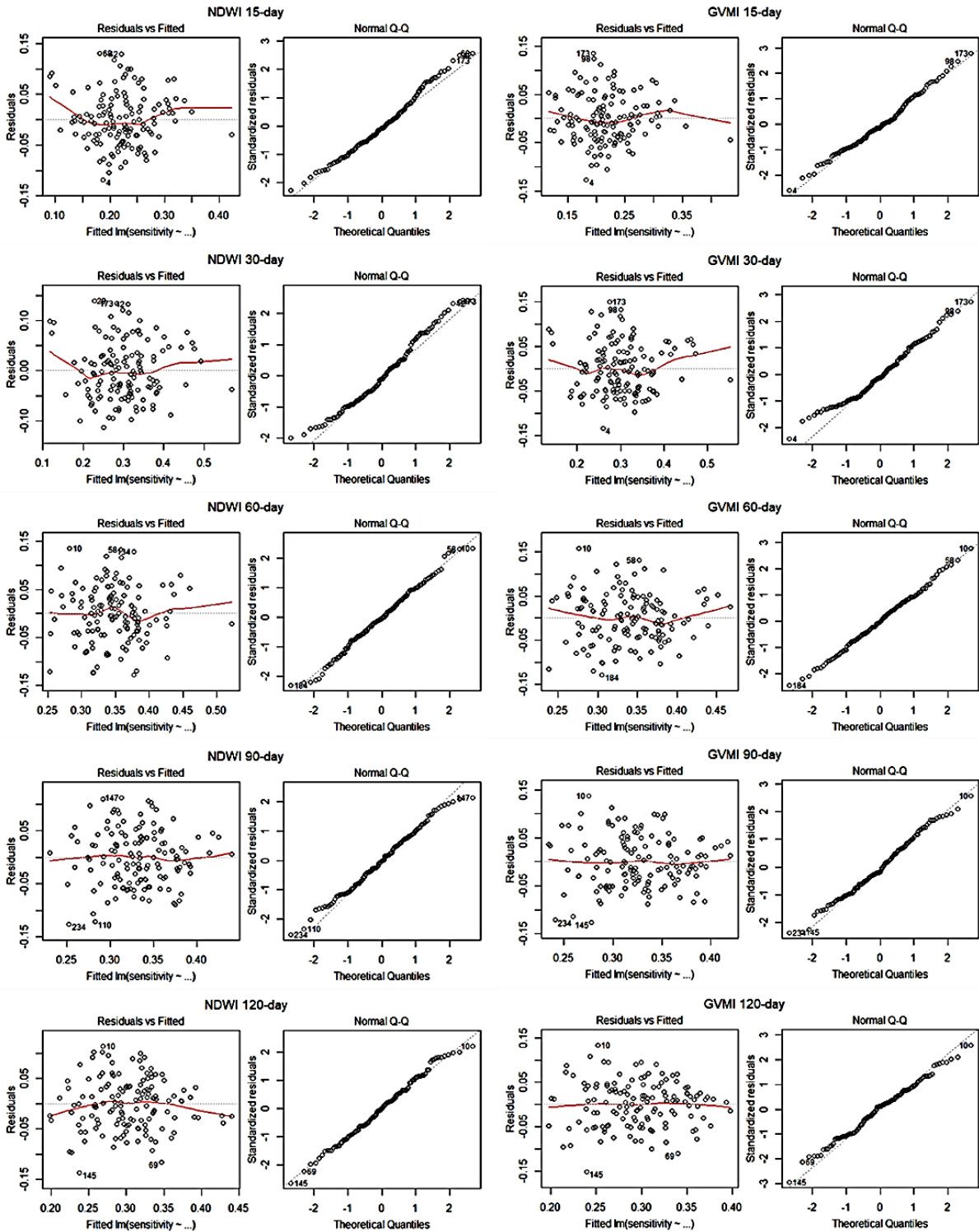
Index	Formula	Purpose / Description	References
NDVI	$(\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$	Commonly used for vegetation biomass (green)	Rouse et al., 1974
ARVI	$(\text{NIR} - [(2 * \text{R}) - \text{B}]) / (\text{NIR} + [(2 * \text{R}) - \text{B}])$	Less sensitive to atmospheric effects compared to NDVI	Kaufman and Tanré, 1992
DVI	$\text{NIR} - \text{R}$	Differentiates vegetation and soil.	Richardson and Wiegand, 1977
EVI	$2.5 * ([\text{NIR} - \text{R}] / [\text{NIR} + 6 * \text{R} - 7.5 * \text{B} + 1])$	For canopy conditions in high biomass areas	Huete et. al., 2002
EVI2	$2.5 * ([\text{NIR} - \text{R}] / [\text{NIR} + (2.4 * \text{R}) + 1])$	EVI without the blue band	Jiang et al., 2008
GCI	$(\text{NIR} / \text{G}) - 1$	For chlorophyll estimation	Gitelson et al., 2003
GEMI	$n * (1 - 0.25 * n) - [(R - 0.125) / (1 - R)]$ where, $n = [2 * (\text{NIR}^2 - \text{R}^2) + (1.5 * \text{NIR}) + (0.5 * \text{R})] / (\text{NIR} + \text{R} + 0.5)$	For vegetation cover; non-linear index	Pinty and Verstraete, 1992
GNDVI	$(\text{NIR} - \text{G}) / (\text{NIR} + \text{G})$	For chlorophyll estimation; NDVI uses the Green instead of Red band	Gitelson et al., 1996
GVMi	$([\text{NIR} + 0.1] - [\text{SWIR}2 + 0.02]) / ([\text{NIR} + 0.1] + [\text{SWIR}2 + 0.02])$	For vegetation water content	Ceccato et al. (2002)
IPVI	$\text{NIR} / (\text{NIR} + \text{R})$	For vegetation biomass	Crippen, 1990
MSR	$([\text{NIR} / \text{R}] - 1) / \text{sqrt}([\text{NIR} / \text{R}] + 1)$	For biophysical parameters	Chen, 1996
MTVI2	$(1.5 * [1.2 * (\text{NIR} - \text{G})] - [2.5 * (\text{R} - \text{G})]) / \text{sqrt}([(2 * \text{NIR}) + 1]^2 - [6 * \text{NIR} - (5 * \text{sqrt}(\text{R})) - 0.5])$	For green leaf area index (LAI) estimation	Haboudane et al., 2004
NDSVI	$(\text{SWIR}1 - \text{R}) / (\text{SWIR}1 + \text{R})$	For senescence detection	Qi et al., 2002
NDWI	$(\text{NIR} - \text{SWIR}1) / (\text{NIR} + \text{SWIR}1)$	For vegetation liquid water content; similar formula with Land Surface Water Index (LSWI)	Gao, 1996; Xiao et al., 2004

NLI	$(NIR^2 - R) / (NIR^2 + R)$	For vegetation cover; accounts for leaf angle distribution	Goel and Quin, 1994
NMDI	$(NIR - [SWIR1 - SWIR2]) / (NIR + [SWIR1 - SWIR2])$	For soil and vegetation moisture	Wang and Qu, 2007
NRI	$(G - R) / (G + R)$	For plant nitrogen status	Filella et al., 1995
OSAVI	$(NIR - R) / (NIR + R + 0.16)$	For vegetation health; minimizes soil effect; standardized vegetation condition of 0.16	Rondeaux et al., 1996
SAVI	$(1 + L) * ([NIR - R] / [NIR + R + L])$ Vegetation: Low (L = 1) Intermediate (L = 0.5) High (L = 0.25)	For vegetation health; minimizes soil effect	Huete, 1988
SIPI	$(NIR - B) / (NIR + B)$	For vegetation phenology (bulk carotenoids to chlorophyll ratio)	Penuelas et al., 2011
SLAVI	$NIR / (R + SWIR2)$	For specific leaf area	Lymburner et al., 2000
SRVI or SR	NIR / R	For leaf area index	Jordan, 1969
TVI	$\text{sqrt}(NDVI + 0.5)$	For green leaf area index (LAI) estimation	McDaniel and Haas, 1982
VARI	$(G - R) / (G + R - B)$	Less sensitive to atmospheric effects; based on ARVI	Gitelson et al., 2002

Appendix 2– C. Time series of drought (top) and vegetation (bottom) conditions from 1985 to 2019 of one sample plot.



Appendix 2– D. Plots for the visual tests of the homogeneity of variances and normality of the residuals of the final NDWI- and GVMI-based models.

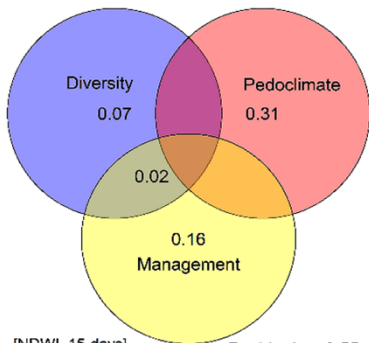


Appendix 2– E. NDWI- and GVMI-based model summaries and beta coefficients.

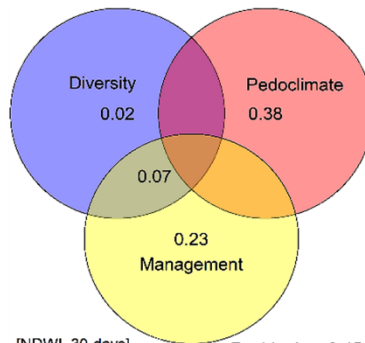
Modified SPEI 15 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.4391	5.546	0	0.3758	5.344	0	
Type of use	0.0989	1.05	0.2956	-	-	-	
Nitrogen fertilization	-0.1905	-2.517	0.0131	-0.2872	-3.953	0.0001	
Mean number of uses	0.1063	1.372	0.1725	0.1226	1.538	0.1267	
SWHC	-0.4728	-6.714	0	-0.6793	-7.757	0	
MgO	0.1673	2.188	0.0305	0.3356	4.189	0.0001	
C:N	-	-	-	0.3815	3.859	0.0002	
TWI	-0.0576	-0.84	0.4025	-0.0885	-1.291	0.1993	
South-facing slope	0.2393	3.562	0.0005	0.2729	3.936	0.0001	
CWM (seed mass)	-0.1614	-1.964	0.0518	-0.1932	-2.422	0.0169	
CWM (height)	-0.1173	-1.404	0.1629	-0.1123	-1.367	0.1741	
CWM (SLA)	-	-	-	0.0736	0.934	0.3523	
Fdis (growth)	-0.0782	-1.003	0.3177	-0.1011	-1.296	0.1974	
Shannon diversity index	-0.1253	-1.522	0.1306	-0.0934	-1.126	0.2625	
	R ² :	0.519		R ² :	0.5235		
	Adjusted R ² :	0.4724		Adjusted R ² :	0.4731		
Modified SPEI 30 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.4628	6.446	0	0.4442	5.803	0	
Type of use	0.221	2.648	0.0091	0.2269	2.434	0.0164	
Nitrogen fertilization	-0.1645	-2.285	0.024	-0.177	-2.388	0.0185	
Mean number of uses	0.1109	1.618	0.1083	0.0774	1.072	0.286	
SWHC	-0.5526	-8.839	0	-0.5577	-8.532	0	
pH	0.0562	0.839	0.4032	0.0729	1.031	0.3044	
MgO	0.1144	1.625	0.1067	0.1579	2.174	0.0316	
South-facing slope	0.2006	3.373	0.001	0.188	3.058	0.0027	
CWM (seed mass)	-0.1538	-2.322	0.0219	-0.1426	-2.079	0.0397	
CWM (SLA)	-	-	-	-0.0841	-1.184	0.2387	
Fdis (seed)	-0.1466	-2.49	0.0141	-	-	-	
Fdis (growth)	-0.0893	-1.341	0.1825	-0.0613	-0.906	0.3669	
Shannon diversity index	-0.0488	-0.684	0.4953	-0.0867	-1.168	0.245	
	R ² :	0.62		R ² :	0.5955		
	Adjusted R ² :	0.5833		Adjusted R ² :	0.5563		
Modified SPEI 60 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.3587	3.971	0.0001	0.3748	4.202	0.0001	
Type of use	0.1982	1.773	0.0786	0.2625	2.362	0.0197	
Nitrogen fertilization	-0.1708	-1.894	0.0605	-0.1732	-1.903	0.0593	
pH	0.1435	1.642	0.1031	0.1798	2.141	0.0342	
MgO	0.1363	1.667	0.0979	0.1086	1.301	0.1957	
C:N	-	-	-	-0.1223	-1.422	0.1575	
TWI	-	-	-	-0.1348	-1.821	0.071	
CWM (seed mass)	-0.2145	-2.469	0.0149	-0.1494	-1.834	0.069	
CWM (SLA)	-0.0817	-0.901	0.3694	-0.1698	-1.868	0.0641	
Fdis lengthflow	0.0711	0.79	0.4312	-	-	-	
Fdis (growth)	-0.1606	-1.819	0.0714	-0.0823	-1.005	0.3169	
Shannon diversity index	0.1009	1.128	0.2615	0.0499	0.55	0.5836	
	R ² :	0.3709		R ² :	0.4039		
	Adjusted R ² :	0.321		Adjusted R ² :	0.3514		

Modified SPEI 90 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.394	4.374	0	0.3875	4.311	0	
Type of use	0.1533	1.355	0.178	0.2089	1.927	0.0562	
Nitrogen fertilization	-0.1206	-1.407	0.1618	-0.1759	-1.94	0.0546	
Mean number of uses	-0.0922	-1.016	0.3118	-0.0876	-0.957	0.3405	
pH	-	-	-	0.0768	0.884	0.3786	
MgO	0.1078	1.263	0.2089	0.1064	1.244	0.2159	
TWI	-	-	-	-0.119	-1.549	0.124	
CWM (seed mass)	-0.0992	-1.058	0.2922	-	-	-	
CWM (height)	-0.1471	-1.547	0.1243	-0.1107	-1.304	0.1946	
CWM (SLA)	-0.1027	-1.204	0.2307	-0.1722	-2.004	0.0472	
Fdis (growth)	-0.2052	-2.353	0.0202	-0.1495	-1.736	0.0851	
Shannon diversity index	0.1652	1.809	0.0729	0.1166	1.25	0.2137	
	R ² :	0.3531		R ² :	0.3755		
	Adjusted R ² :	0.3018		Adjusted R ² :	0.3206		
Modified SPEI 120 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.5767	6.859	0	0.5008	5.793	0	
Type of use	0.2317	2.272	0.0248	0.2372	2.274	0.0247	
Nitrogen fertilization	-	-	-	-0.1021	-1.168	0.2449	
Mean number of uses	-0.0714	-0.807	0.4213	-0.0796	-0.904	0.3676	
SWHC	-0.138	-1.807	0.0731	-	-	-	
pH	-0.1856	-2.302	0.023	-0.115	-1.376	0.1712	
MgO	0.1643	1.975	0.0505	0.123	1.495	0.1374	
TWI	-0.1372	-1.815	0.072	-0.1413	-1.908	0.0587	
CWM (seed mass)	-0.0859	-0.966	0.3362	-	-	-	
CWM (height)	-0.19	-1.943	0.0543	-0.1135	-1.314	0.1913	
CWM (firstflow)	0.0899	1.031	0.3046	-	-	-	
Fdis (seed)	-0.0783	-1.058	0.2919	-0.0416	-0.551	0.5828	
Fdis (growth)	-0.2099	-2.582	0.011	-0.1531	-1.844	0.0676	
Shannon diversity index	0.1714	1.989	0.049	0.113	1.245	0.2154	
	R ² :	0.4541		R ² :	0.4285		
	Adjusted R ² :	0.3965		Adjusted R ² :	0.3732		

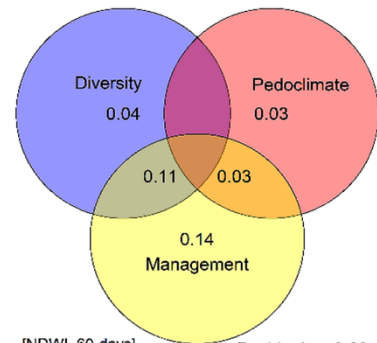
Appendix 2– F. Variance partitioning of NDWI- and GVMI-based models across timescales.



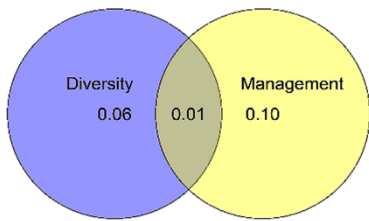
[NDWI, 15-days]
Values < 0.00001 not shown Residuals = 0.55



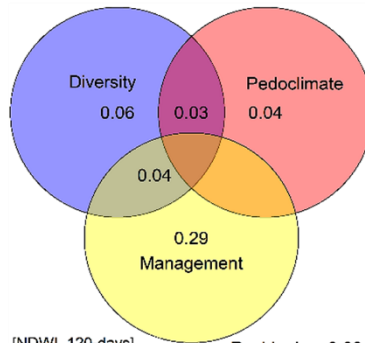
[NDWI, 30-days]
Values < 0.00001 not shown Residuals = 0.45



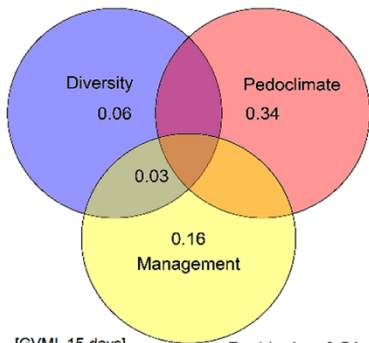
[NDWI, 60-days]
Values < 0.00001 not shown Residuals = 0.69



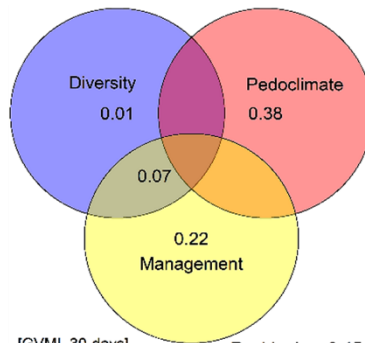
[NDWI, 90-days]
Values < 0.00001 not shown Residuals = 0.84



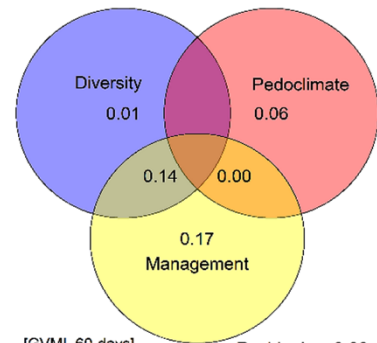
[NDWI, 120-days]
Values < 0.00001 not shown Residuals = 0.60



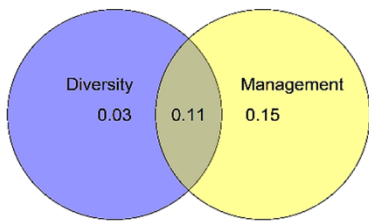
[GVMI, 15-days]
Values < 0.00001 not shown Residuals = 0.54



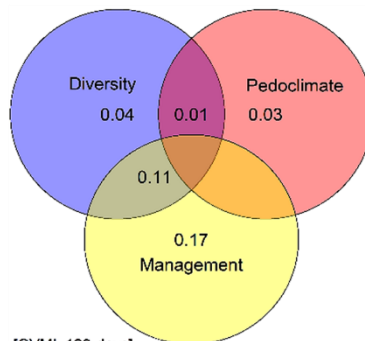
[GVMI, 30-days]
Values < 0.00001 not shown Residuals = 0.45



[GVMI, 60-days]
Values < 0.00001 not shown Residuals = 0.66



[GVMI, 90-days]
Values < 0.00001 not shown Residuals = 0.72



[GVMI, 120-days]
Values < 0.00001 not shown Residuals = 0.67

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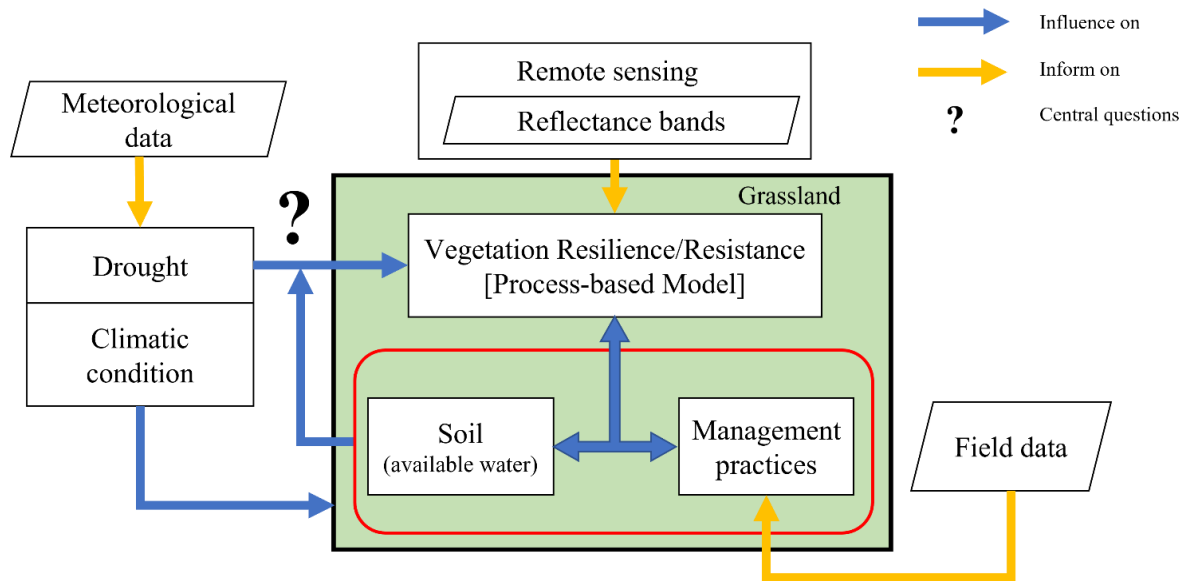
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ANALYZING DROUGHT IMPACTS ON TEMPERATE MANAGED GRASSLANDS BY ASSIMILATION OF SENTINEL 2 IMAGES WITH A PARSIMONIOUS MODEL OF VEGETATION GROWTH



Chapter 3 attempts to move beyond some limitations highlighted in the previous chapter. It used a process-based model assimilated with satellite data to better acknowledge grassland resistance and resilience to drought in mown and grazed grasslands.

CHAPTER 3. ANALYZING DROUGHT IMPACTS ON TEMPERATE MANAGED GRASSLANDS BY ASSIMILATION OF SENTINEL 2 IMAGES WITH A PARSIMONIOUS MODEL OF VEGETATION GROWTH

Abstract

Droughts negatively impact the temperate managed grasslands leading to a decrease in the quality and delivery of ecosystem services. Various studies and drought experiments have provided key knowledge on the eco-physiological response of grasslands to drought and highlighted the role of soil, water, and agricultural practices. However, these experiments have limited spatial and temporal coverages and are constrained by experimental setups. We developed a parsimonious process-based model of grassland green leaf area index (Lg) assimilated with Sentinel 2 time series observations to expand the knowledge on grassland response to drought. Our model is driven by climatic trajectories and management impact. It consists of four parameters related to phenological growth and senescence, and management practices. It features a time-varying parameter that replicates the dynamic growth of managed grasslands across seasons and under the impacts of herbage uptake and drought. We analyzed the grassland resistance and resilience to drought using the log response ratio (LRR) from model simulated normal meteorological and unlimited water supply conditions. The use of the time-varying parameter increased the internal validation of our model. However, the external validation was low possibly due to the scale discrepancy between field and satellite-based measurements. Our model showed that grassland resistance and resilience changed after exceeding a drought event severity of 80. We found no significant difference between the resistance of mowed and grazed paddocks, but we faintly observed that grazed paddocks were more resilient to drought than mowed ones. Overall, our parsimonious model predicted Lg with the assimilation of Sentinel 2. To improve our model, we face the dilemma of prioritizing the ease of use with parsimony or increasing the explanatory power by adding the dynamics of nutrient cycles and vegetation diversity.

Keywords: LAI, PROSAIL, LUT, radiative transfer model, response, resistance, resilience

3.1. Introduction

Droughts threaten temperate managed grasslands and decrease the quality and delivery of their ecosystem services (Craine et al., 2012; Hofer et al., 2016; Jung et al., 2020; Lei et al., 2016; Srivastava et al., 2018). Various studies were conducted in controlled or semi-controlled field experiments to determine how droughts impact managed grasslands (Deléglise et al., 2015; Leuzinger et al., 2011; Vogel et al. 2012; Volaire et al., 2020). These experiments have provided key scientific understandings from the eco-physiological responses driving plant individual responses to the role of plant community structure and the effects of different agricultural practices.

However, drought experiments face two important shortcomings (Fraser et al., 2013; Kröel-Dulay et al., 2022; Leuzinger et al., 2011; Matos et al., 2020a). The first is their inability to cover the large diversity of grassland types and contexts, because of their restricted spatio-temporal coverage and the second is the setup of unrealistic field conditions, due to inherent experimental constraints, leading to misestimated drought impacts (Kröel-Dulay et al., 2022; Leuzinger et al., 2011; Vicca et al., 2012).

Remote sensing products and techniques have the capacity to expand the spatio-temporal coverage of drought experiments (Kerr and Ostrovsky, 2003; Li et al., 2014; Soubry et al., 2021; Xu and Guo, 2015) and focus on the real-life conditions of the managed grasslands in farm systems. Various remote sensing products estimate the biophysical and biochemical properties of vegetation based on the reflectance values received by satellite sensors from the Earth's surface. To determine the grassland response to drought, one approach consists of analyzing the trajectories of long-term satellite image time series (SITS) of vegetation reflectance paired with drought severity measures (Bao et al., 2014; Buras et al., 2019; Ivits et al., 2014; Tong et al., 2017). Within the SITS, the abrupt changes in the reflectance trajectories are explained by the corresponding drought severity. The vegetation reflectance serves as a proxy for vegetation properties, such as productivity, greenness, moisture content, etc., in the form of vegetation indices or other types of information derived from reflectance bands. The statistical inference approach, on the other hand, quantifies the response to drought from the linear relationship between vegetation reflectance and drought severity indices (Nanzad et al., 2019; Smith et al., 2017; Wilcox et al., 2017; Wang et al., 2019). It has been recently used to complement knowledge from controlled experiments on the role of pedoclimatic factors, vegetation diversity, and management practices in enhancing or reducing drought impacts on grassland vegetation at a regional scale (Luna et al., 2023). However, the relationship between vegetation reflectance and drought severity usually suffers from detrimental noise and analysis concerns (Luna et al., 2023). The observed changes in the vegetation reflectance following drought can also be under the influence of other co-occurring disturbances – such as pest or plant disease infections (Terentev et al., 2022; Zhang et al., 2019); fire outbreaks (Dwyer et al., 2000; Rogers et al., 2020; Wang et al., 2004); management

practices of mowing or grazing (Kowalski et al., 2022; 2023; Estel et al., 2018; Reinermann et al., 2020); or the natural phenological development of the vegetation (Reed et al., 1994; Dronova and Taddeo, 2022). In addition, gaps in time series analyses due to clouds (Whitcraft et al., 2015) or satellite temporal resolution (Villarreal et al., 2016), limit the quantification of resistance or recovery to drought due to missed reflectance peaks, and valleys. To improve the understanding of drought impact on grassland with remote sensing, it is thus necessary to isolate pure drought effects from confounding or interacting factors and distinguish between resistance and resilience capacities for different types of grasslands and especially between grasslands managed under different agricultural practices.

Assimilation of RS products with process-based models (Cuddington et al., 2013; Meroni et al., 2019) has the potential to improve model predictions in agroecosystems (Dorigo et al., 2007; Jin et al., 2018). Since better predictions of mechanistic models support our understanding of ecological phenomena (Mouquet et al., 2015), when used together with RS data they may help in isolating drought impacts from other processes like management practices or phenological changes in case they are explicitly considered in the model design.

Numerous mechanistic models of grasslands have been developed (see review in Taubert et al., 2012). They have been successfully used for predicting the vegetation cover, growth, and productivity (GrasProg in Peters et al., 2022; GrazeGro in Barrett et al., 2005; LINGRA in Schapendonk et al., 1998; STICS-Prairie in Di Bella et al., 2004; VISTOCK in Bellini et al., 2023) and nutrient and energy fluxes (DALEC-Grass in Myrriotis et al., 2020; PaSiM in Riedo et al., 1998 and Schmid et al., 2001; SAFY-CO² in Pique et al., 2020) for different management conditions (ORCHIDEE-GM in Chang et al., 2013; PaSiM in Graux et al., 2009) and under the impacts of drought (ModVege in Jouven et al., 2006a; 2006b; Calanca et al., 2016; SCOPE in van der Tol et al., 2009; Bayat et al., 2018). Some of them have already been assimilated with satellite products like SAFY – but for crops – and SCOPE. The SCOPE model has been applied to grasslands and other ecosystems to compare model simulation in drought and non-drought conditions (Bayat et al., 2018). The main drawback of all these models is that they are highly data-demanding. They require time series observations of many input variables and the calibration of dozens of parameters. As a result, these models were mostly applied in grassland observatories, (Chang et al., 2013; Pique et al., 2020), field experiments (Calanca et al., 2016; Myrriotis et al., 2020; Peters et al., 2022) sometimes equipped with flux towers (Bayat, 2018; Graux et al., 2009). This makes difficult the assimilation of these models with satellite data for simulating vegetation growth of many grasslands in farms, where data are usually scarce. More parsimonious models are thus needed. One example of a model of lower complexity is the eco-hydrological model proposed by Choler et al. (2010). It simulates the coupled dynamics of vegetation cover and soil water

content with five parameters only. Estimates of the fractional vegetation cover derived from MODIS-NDVI were used for parameter calibration. This approach successfully predicted the dynamics of semi-arid perennial grasslands, in Queensland - Australia, in response to spatio-temporal variations of water supply. The application of such a low-dimensional model in temperate managed grassland impacted by drought requires two main modifications. First, it should explicitly account for the effect of agricultural practices and especially herbage uptakes. Second, it should simulate phenological changes inherent to temperate perennials.

In this study, we thus aimed to (i) develop a parsimonious model of vegetation growth in temperate managed grasslands, (ii) calibrate and validate it with the use of satellite image time series, (iii) quantify resistance and resilience of grasslands to drought events from model simulations, and (iv) compare the vegetation response to drought between contrasted management practices.

To do so, we first developed a simple process-based model simulating the daily dynamics of the green leaf area index (L_g) and the amount of water available for plants. The green leaf area index (L_g) was chosen as the targeted vegetation state variable because of its role in the use of water by plants (Allen et al., 1998; Chen and Wang, 2012), its response to changes in phenological stages (Corbari et al., 2017), and its signature on vegetation reflectance spectra (Gitelson et al., 2003; Mourad et al., 2020). Then we used Sentinel 2-derived L_g generated from the inversion of the radiative transfer model PROSAIL (Atzberger et al., 2015) to calibrate the model. Finally, we analyzed, from model simulations, the differences in resistance and resilience to drought between mowed and grazed paddocks.

3.2. Data and methodology

3.2.1. Study site and field data

This study focused on the Herbipôle experimental site (45°38'7.64"N, 2°45'4.77"E) of the French *Institut national de recherche pour l'agriculture, l'alimentation et l'environnement* (INRAE) located at Laqueuille within the Massif central region, France. The site covers 560 ha of temperate permanent grasslands between 1,000 and 1,450 m a.s.l. (Prache, 2017; Vazeille et al., 2018) thus exposed to a mountain climate (Joly et al., 2010). The average annual precipitation is about 1,100 mm, and the average minimum and maximum temperatures are 4.63°C and 11.67°C, respectively.

For the SALAMIX project, 118 ha of permanent grassland of this site managed on organic farming are divided into 33 paddocks, which were either dedicated to hay production, hence are mostly mowed

in spring and early summer, or to light grazing with cattle, sheep or cattle and sheep in combination (Prache et al., 2023).

The grassland paddocks were monitored between May 2015 and November 2020. The vegetation biomass (sorted in green and senescent tissues) and height were recorded in each paddock before the start of each grazing rotation or cut. Biomass and height were determined from at least four sampling quadrats in each paddock, which were 70 cm x 70 cm in dimension and with known geographic coordinates. Detailed records of the herbage uptake calendar were done during the entire period and for each paddock separately. It included dates of mowing events, the entry and exit dates of grazing animals, and the type and number of animals.

For this study, we randomly selected three mowed and three grazed paddocks (Figure 3– 1). The selected mowed paddocks have an average area of 4.08 ha and were cut at least once annually during the summer season (June to August). In addition, each mowing was occasionally grazed late in summer and in fall. The selected grazed paddocks have an average area of 2.80 ha and were grazed 1 to 6 times annually with an average of three grazing events.

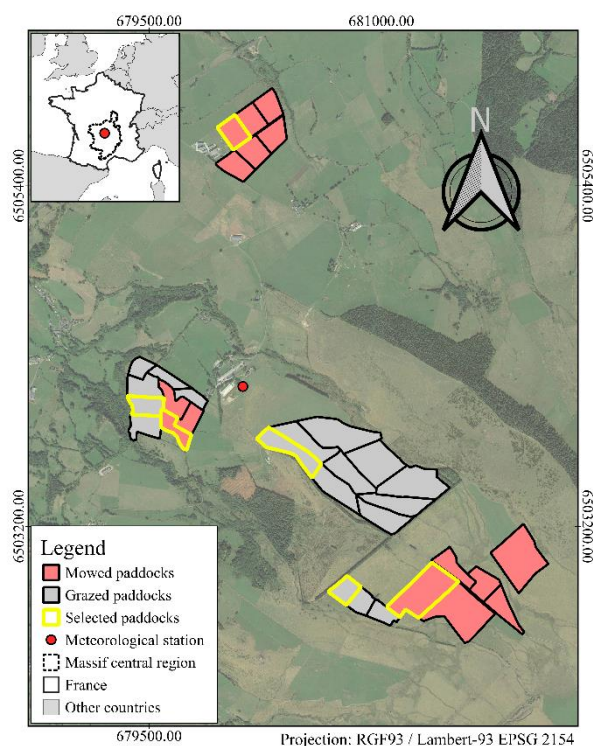


Figure 3– 1. Configuration of the 33 paddocks under the SALAMIX project. Highlighted are the six selected mowed and grazed paddocks used in the model development.

A field meteorological station (45°38'35.88"N; 2°44'3.73"E) was situated in close proximity to the Herbipôle experimental site (Figure 3– 1). The meteorological station provided daily records of climate variables – such as precipitation, temperature, solar radiation, potential evapotranspiration, and humidity – as early as July 1995. For this study, we used the daily climate data as inputs for the model and drought severity assessment. We used the 25-year-long climate data to assess the normal water balance of each day of the year and compute the daily SPEI (Vicente Serrano et al., 2010) as an indicator of meteorological drought.

3.2.2. Assessment of Green Leaf Area Index (L_g) from satellite images

The time series of the green Leaf Area Index (L_g) for each biomass monitoring location (quadrats) of each selected paddock, were derived by the inversion of the PROSAIL radiative transfer model using Sentinel 2 images (Atzberger et al., 2015; Boegh et al., 2013; Darvishzadeh et al., 2008; Wang et al., 2019) downloaded from the Theia Data and Service Center (France). Sentinel 2 MultiSpectral Instrument (MSI) is an optical satellite that provides images with spatial resolutions of 10, 20, and 60 m and a 5-day collection revisit. We used an average of 182 Sentinel 2 images, which range from 177 to 186 snow and cloud-free observations depending on the paddock considered, covering May 2015 to November 2020 time period.

PROSAIL is composed of the PROSPECT (leaf) and SAIL (canopy) models. PROSPECT provides leaf reflectance and transmittance to SAIL. The direct inputs for the PROSAIL are the biophysical and biochemical leaf properties of chlorophyll, dry matter, and brown pigment contents; equivalent water thickness; leaf angles, LAI, and the satellite and sun viewing angles (see Jacquemoud et al., 2009). The output of SAIL is the reflectance signature of the vegetation canopy. Intentionally, the merging of PROSPECT and SAIL allowed for a better inversion of reflectance signature to estimate the leaf properties (Baret et al., 1992; Jacquemoud, 1993; Jacquemoud et al., 2009).

The retrieval of the biophysical and biochemical leaf properties with the inversion of PROSAIL was done with the look-up-table method (LUT; Jacquemoud et al., 2009). The LUT method is a simple minimization technique that requires multiple computations to generate a reference table of leaf parameter combinations and their associated reflectance signature (Berger et al., 2018; Jacquemoud et al., 2009). For this study, we followed the recommended LUT size of 100,000 parameter combinations (Richter et al., 2009; Weiss et al., 2000). The parameter combinations originated from independent random draws of parameter values from uniform distributions (Darvishzadeh et al., 2008). The best 30 parameter combinations were selected using the relative root mean square error (RRMSE) as the cost function. We then averaged the LAI values from this selection (He et al., 2019). The repetition of this

procedure for each date and location allowed to generate time series of L_g for each paddock during the 2016-2020 period.

3.2.3. A simple dynamic model of grassland green leaf area index (L_g)

We developed a simple model of the dynamics of green LAI (L_g) in interaction with the dynamics of the soil available water content (W), considered as a minimum system to represent drought impacts on temperate managed grasslands. At each daily timestep, L_g is updated (Eq. 1) according to the balance between three basic processes: vegetation growth (g), senescence (s), and herbage uptake by mowing or grazing (d).

$$L_g(t + 1) = L_g(t) + g(t) - s(t) - d(t) \quad \text{Eq. 1}$$

The daily increase in L_g [i.e., $g(t)$ in Eq. 1] is modelled as a reduction of the maximum potential growth of the grassland (g_{max}) by three functions (Figure 3– 2. a, b, c) representing (i) temperature limitation (f_1) according to Yan and Hunt (1999), (ii) water limitation (f_2) depending on the product between the actual evapotranspiration (E_a) and the instantaneous water use efficiency ($IWUE$) of the vegetation and (iii) an empirical function of the seasonal pattern of temperate grassland growth (f_3) representing changes in reserve storage and mobilization with the sum of growing degree days (GDD_{Σ}) following Jouven et al. (2006a). Accordingly, $g(t)$ is defined as:

$$g(t) = g_{max} \times f_1(T(t)) \times f_2(E_a(t)) \times f_3(GDD_{\Sigma}(t)) \quad \text{Eq. 2}$$

The calculation of the actual evapotranspiration (E_a) is written as:

$$E_a(t) = \begin{cases} E_{max}(t) & W^* \leq W(t) < W_{max} \\ E_{max} \left(\frac{W(t)}{W^*} \right) & 0 \leq W(t) < W^* \end{cases} \quad \text{Eq. 3}$$

Where E_{max} represents the evapotranspiration under conditions of full water availability. While W is above a given threshold W^* , the evapotranspiration is unlimited. Below this threshold E_a decreases linearly until W equal 0 (Calanca et al., 2016). Note that W represents the soil water content available for plants. Therefore, $W = 0$ means that the soil water content is at its wilting point in the soil layer where plant roots are distributed.

$E_{max}(t)$ is given by the adjustment of the potential evapotranspiration of the reference surface ($E_0(t)$), as provided by meteorological stations, to $L_g(t)$ according to Smith (2012) and following:

$$E_{max}(t) = E_0(t) \left(\max \left\{ 0, \left[\ln(L_g(t) + 1) \right]^{0.4} \right\} \right) \quad \text{Eq. 4}$$

W is modelled as a simple one-layer bucket model (Eq. 5 and 6) where gain in water depends on precipitation (P), and losses depend on actual evapotranspiration (E_a) and runoff (R):

$$W(t + 1) = W(t) + P(t) - E_a(t) - R(t) \quad \text{Eq. 5}$$

with

$$R(t) = \max(0, (P(t) - E_a(t)) - (W_{max} - W(t))) \quad \text{Eq. 6}$$

The senescence $s(t)$ is defined as the product of a senescence rate (s_0), $L_g(t)$, the absolute temperature of the day and an empirical function inherited from Jouven et al. (2006a) depicting the influence of plant phenology (Eq. 7). Accordingly, the senescence is proportional to heat and frost but minimal around 0°C. Along the course of the growing season, the senescence is null until the first cohort of leaves starts to senesce, which depends on the leaf lifespan (LLS) expressed in growing degree days (GDD). Then, the senescence increases linearly until the peak of flowering and remains at its maximum as the GDD_{Σ} further increases (Figure 3– 2. d).

$$s(t) = L_g \times s_0 \times |T^{\circ}(t)| \times f_3(GDD_{\Sigma}(t)) \quad \text{Eq. 7}$$

In our model, the influence of management on the dynamics of L_g lies on the simulation of herbage utilization by mowing or grazing according to:

$$d(t) = \begin{cases} L_g(t) - (L_g(t) - L_{g,lim}) & \text{mowing} \\ L_g(t) - \max(L_g(t) - L_{g,lim}, c \times I(t)) & \text{grazing} \end{cases} \quad \text{Eq. 8}$$

Where $L_{g,lim}$ stands for the remaining L_g after cutting and the limit below which animals cannot graze. Under grazing, decrease in L_g is given by the conversion of animal intake ($I(t)$), expressed in $\text{kgMS}^{-1} \cdot \text{ha}^{-1}$, into L_g with a coefficient c . Animal intake is calculated with the HerbValo method, which

accounts for the animal intake capacity, herbage ingestability, grazing severity, and the potential use of animal food supplements. See Delagarde et al. (2017) for more details.

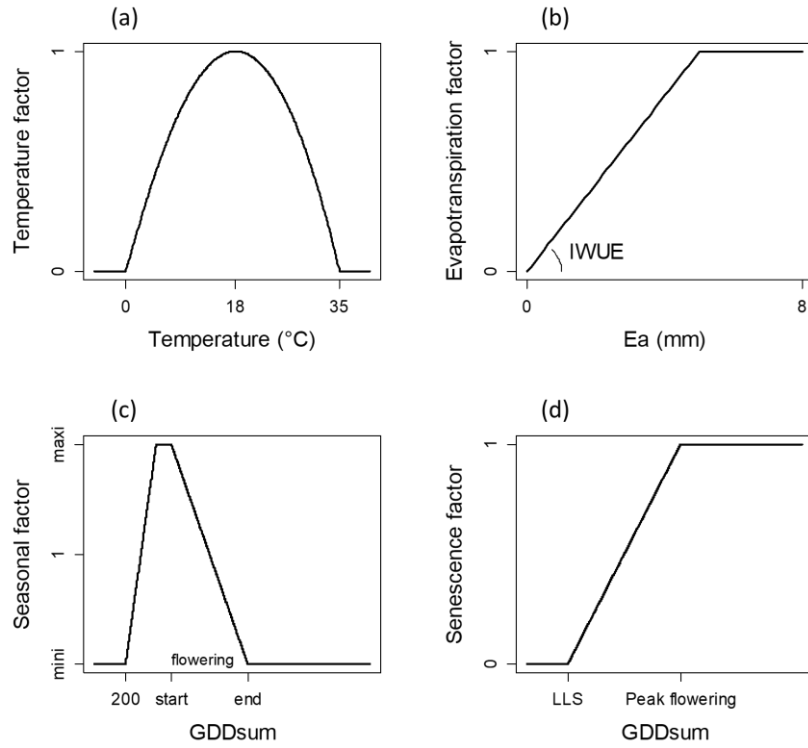


Figure 3– 2. Empirical function modulating growth (a, b, c) and senescence (d). (a) the effect of temperature on growth (f_1 in Eq. 2); (b) the effect of the actual evapotranspiration (E_a) on growth with IWUE representing the instantaneous water use efficiency (f_2 in Eq. 2); (c) the seasonal pattern of growth depending on the sum of growing degree days (f_3 in Eq. 2); and (d) the seasonal pattern of senescence (f_4 in Eq. 7).

Finally, the daily update of the sum of growing degree days (GDD_Σ) is given by:

$$GDD_\Sigma(t+1) = \begin{cases} 200 & \text{mowing} \\ (1-p)(GDD_\Sigma(t) + T_g(t)) + p \times 200 & \text{grazing} \\ GDD_\Sigma(t) + T_g(t) & \text{else} \end{cases} \quad \text{Eq. 9}$$

with

$$T_g(t) = \begin{cases} 0 & \text{doy} \leq 60 \\ \max(0, \min(20, T(t))) & \text{else} \end{cases} \quad \text{Eq. 10}$$

and

$$p = \frac{d(t)}{(L_g(t) - L_{g,lim})} \quad \text{Eq. 11}$$

The GDD_{Σ} represents the temperature-dependent development of plants along the growing season, which depends on the range of efficient temperature for growth, typically between 0°C and 20°C for temperate grasslands (Eq. 10) and reset to 0 during the winter (Cros et al., 2003). After management events, the vegetation starts a new cycle of development and GDD_{Σ} is set to 200 °C for the entire grassland area under mowing (Bossuyt et al., 2018; Kuinchtner et al., 2021; Rivington et al., 2008) or in proportion p to the grassland area that is fully grazed by animals (Eq. 9 and Eq. 10).

3.2.4. Model calibration and validation

We assimilated the observed L_g derived from Sentinel 2 with the model described above using a calibration procedure (Dorigo et al., 2007; Villaverde et al., 2022). To optimize the identifiability of the model and thus the quality of the calibration procedure, we first fixed a set of parameters. The influence of phenology on growth and senescence was inherited from Jouven et al. (2006a) and implied a total of six parameters (the peak of flowering, the leaf lifespan, the start and end of the flowering period, and the minimum and maximum values of the seasonal factor, see Figure 3– 2). Jouven et al. (2006a) used the functional typology of temperate grass species developed by Duru et al. (2007) as a reference for defining those parameters. Using this same typology, we derived simple empirical relationships predicting the value of five of these parameters based on the peak of flowering expressed in growing degree days (GDD) (Appendix 3– A). Then, we fixed $W^* = 0.4$, since Calanca et al. (2006) showed that such an assumption provided a similar result to more complex parametrization of the effect of hydric stress in similar mountainous grasslands. We also fixed the coefficient $c = 0.0012$ (in $\text{m}^2 \cdot \text{m}^{-2} / \text{KgMS} \cdot \text{ha}^{-1}$) of conversion of aboveground biomass into LAI based on previous simulations of the PaSIM model performed for nearby grasslands (Ma et al., 2015). The $L_{g,lim}$ was fixed to 0.36 based on field knowledge of the remaining aboveground biomass after mowing and severe grazing converted into LAI with c . Finally, we further fixed $IWUE = 0.2$ (in mm^{-1}) to control the identifiability of the model. Indeed, several combinations of $IWUE$ and g_{max} values can lead to the same net daily increase of LAI for the same meteorological conditions. $IWUE = 0.2$ results in maximum potential growth for 5 mm of evapotranspiration and allows to keep realistic daily increase of LAI. All these assumptions result in a set of five input variables and four parameters for calibration (Table 3– 1).

Table 3– 1. Input variables and parameters for calibration (underlined) of the dynamical model of LAI.

Inputs/parameters	Description	Unit	Source
E0	Daily potential evapotranspiration of the reference surface	mm	Meteorological stations
T	Daily mean temperature	°C	Meteorological stations
P	Daily precipitation	mm	Meteorological stations
I	Animal intake	KgMS.d ⁻¹	Field data (HerbValo)
Cuts	Binary data of mowing events	-	Field data
<u>g_{max}</u>	Maximum daily increase in LAI	m ² .m ⁻²	
<u>Peak</u>	Peak of flowering	°C.d	
<u>W_{max}</u>	Maximum available water for plants	mm	
<u>s_{max}</u>	Basic rate of LAI decrease (senescence)	m ² .m ⁻² .°C ⁻¹	

The calibration procedure, similar to the LUT method, first consisted in selecting, for each of the 6 paddocks separately, the best parameter combinations from 30,000 random draws of parameter values from prior uniform distributions (Table 3– 3). The ranges for g_{max} and s_{max} were selected from a previous investigation of the model to avoid unrealistic LAI estimates and trajectories. For instance, the maximum LAI observed in European grasslands in Gilmanov et al. (2007) was 7 m².m⁻². Then, the range of *Peak* values covers the phenological attributes of the functional typology of grassland species of Duru et al. (2007). The W_{max} range was estimated for low-water retention soil with a shallow rooting depth (15 cm) and high-water retention soil with a deep rooting depth (60 cm). From the 30,000 model simulations, we selected the best 30 parameter combinations with the lowest mean squared error (MSE) between the observed L_g (Sentinel 2-derived) and the model predictions, used as a cost function. We checked whether the best parameter estimates converged from a visual inspection of their posterior distribution (Appendix 3– B).

The calibration procedure depicted above considers parameter values to be fixed during the 2016–2020 period. However, some of them (i.e., g_{max} , W_{max} and s_{max}) should be viewed as an integrated parameter influenced by the vegetation composition and/or nutrient availability, are not expected to remain constant through time but rather to be influenced by past events from the preceding growth periods. Since the model outputs are mostly sensitive to changes in g_{max} (Appendix 3– C), we focused our attention on this parameter. Indeed, disturbances or physical stresses promote changes in vegetation composition or influence the storage of nutrients and carbohydrates necessary for initiating forthcoming vegetation growth (Cibils and Coughenour, 2001; Pouget et al., 2021; Schmid et al., 2022). The variability of precipitation is also known to modify the soil nutrient supply in time and thus growth potential (Knapp et al., 2008). As these processes were not included in the model for simplicity, g_{max} should ideally be re-calibrated for each growth period. Therefore, we conducted a time-varying

parameter calibration of g_{max} , with all the other parameters set as fixed values, inherited from the previous calibration procedure. Growth periods were based on the changing of seasons or management events that reinitialize the plant life cycle to the vegetative stage. Accordingly, a new growth period starts at the end of each winter or after the occurrence of cuts or heavy grazing. The best parameter combinations were selected using the same procedure as for the fixed parameter calibration except that we used 3,000 random draws of g_{max} .

We assessed the goodness-of-fit between the observed L_g derived from Sentinel 2 and the model predictions, for each paddock, and for both the fixed and time-varying parameter calibration. For such internal validation of the model, we reported the R^2 , intercept (with 95% confidence intervals), and slope (with 95% confidence intervals) of standard major axis regressions (Warton et al., 2006). In addition, we considered the mean absolute error (MAE), the maximum absolute error (MaxAE), the mean relative error (MRE), and the root mean square error (RMSE) of model predictions. For external validation, we further regressed the predicted L_g to field measurements of the vegetation standing biomass, senescent biomass, and height records since ground measurements of LAI were unavailable. Only ten to fourteen measurements were available for each paddock. Therefore, we merged all data and built a mixed-effect model for testing a potential random effect of paddock identity.

3.2.5. Drought response assessment and comparison between mowing and grazing

We used model simulations to assess the response of the studied managed grassland paddocks to the drought events occurring between 2016 and 2020 and to decompose it into its resistance and resilience components.

We first assessed the severity of the drought events. To do so, we used the climatic records from the field meteorological station and computed a modified daily version of the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010; modifications from Luna et al., 2023).

We assessed the start of drought events as the date when the modified SPEI turns negative and the end of drought events as the next date when the modified SPEI became positive again (Table 3– 2; McKee et al., 1993; Vicente-Serrano et al., 2010). This allowed the computation of the duration of the drought events and their severity (DS) following $DS = \sum_{d=start}^{end} mSPEI_d$ (Haile et al., 2020; McKee et al., 1993). Drought events no longer than 10 days, outside the growing season (March to November), and of moderate intensity (no modified SPEI value below -1.5 during the drought) were excluded from the subsequent analyses.

Table 3–2. Modified SPEI rating adapted from SPI (McKee et al., 1993).

Values	Water balance category
≥ 2.0	Extremely wet
$1.5 < \text{modified SPEI} \leq 2.0$	Severely wet
$1.0 < \text{modified SPEI} \leq 1.5$	Moderately wet
$0.0 < \text{modified SPEI} \leq 1.0$	Slightly wet
$-1.0 < \text{modified SPEI} \leq 0.0$	Slightly dry
$-1.5 < \text{modified SPEI} \leq -1.0$	Moderately dry
$-2.0 < \text{modified SPEI} \leq -1.5$	Severely dry
≤ -2.0	Extremely dry

Second, we used the best set of parameter values of each paddock to simulate L_g under two conditions, namely under normal (or observed) meteorological and unlimited water supply (i.e., W is fixed at W_{max}) conditions. The logarithm of the ratio of L_g between these two simulations reflects thus the instantaneous response to drought (Log Response Ratio or LRR; Figure 3–3). From the trajectories of LRR, we computed two metrics reflecting grassland resistance and resilience to each drought event in compliance with the definitions of Van Meerbeek et al. (2021). The resistance was defined as the minimum LRR during the drought event and normalized between 0 and 1, with 0 indicating no reduction of L_g in observed meteorological conditions compared to unlimited water supply and 1 as a reduction of 95% of L_g . The resilience was derived from the slope between the minimal LRR during the drought event and complete recovery or the next drought event (Figure 3–3).

To identify the determinants of grassland resistance and resilience to drought, we fitted linear regression models of the resistance and resilience metrics with drought severity per type of management and their interaction.

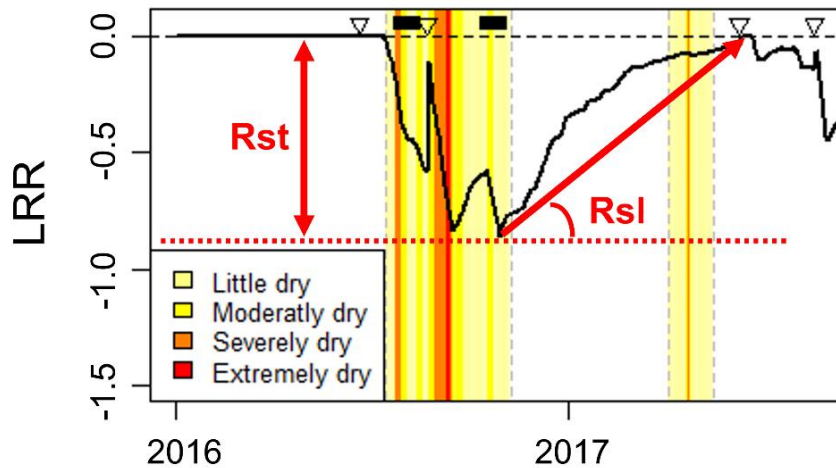


Figure 3– 3. Quantification of the resistance (R_{st}) and resilience (R_{sl}) of the managed grassland based on the logarithm of the drought response ratio (LRR).

3.3. Results

3.3.1. Fixed and time-varying parameter calibrations

A visual inspection of the posterior distribution of the parameter estimates indicates convergence toward one single optimum value for all paddocks (Appendix 3– B). From the 30,000 random draws of parameter values, we used the mean of the best 30 parameter combinations per paddock for the fixed parameter calibration of the model (Table 3– 3).

Table 3– 3. Summary of initial and calibrated model parameters.

	Parameters	FF1 ^a	FR2 ^a	FS1 ^a	PE1 ^b	PR2 ^b	PS1 ^b
g_{max}	prior distribution	$U(0.05, 0.25)$			$U(0.05, 0.25)$		
	posterior mean	0.105	0.121	0.127	0.165	0.233	0.119
W_{max}	prior distribution	$U(15, 90)$			$U(15, 90)$		
	posterior mean	86	88	77	76	81	81
Peak	prior distribution	$U(1000, 1800)$			$U(1000, 1800)$		
	posterior mean	1110	1083	1082	1023	1018	1044
s_{max}	prior distribution	$U(0.001, 0.005)$			$U(0.001, 0.005)$		
	posterior mean	0.00144	0.00146	0.00223	0.00456	0.00475	0.00232

^a Mowed paddocks, ^b Grazed paddocks

The internal validation of the model showed that the two calibration procedures, namely the fixed parameter calibration and the time-varying g_{max} calibration provided unbiased estimates of Lg (Table

3– 4). Indeed, for both calibration procedures, the relationship between the observed and predicted L_g was very close to the 1:1 line (Appendix 3– D). However, regarding the dispersion around the regression line, the time-varying g_{max} outperformed the fixed parameter calibration with a mean R^2 of 0.83, as opposed to a mean of 0.66. This also translated to an average reduction of 0.15 of the mean absolute error; 0.60 of the max absolute error; 0.14 of the mean relative error; and 0.18 of the root-mean-square error between the fixed and time-varying parameter calibration. In addition, the model showed slightly better predictive accuracy for mowed paddocks than grazed ones (Table 3– 4) with a difference of 0.035 mean absolute error; 0.175 max absolute error; 0.07 mean relative error; and 0.06 root mean square error.

Table 3– 4. Assessment of the goodness-of-fit between the predicted and observed L_g for the internal validation of the mowed and grazed paddocks.

Goodness-of-fit measures:	FF1		FR2		FS1		
	Mowed paddocks	Fixed	Time-varying	Fix	Time-varying	Fixed	Time-varying
MAE		0.39	0.25	0.46	0.26	0.44	0.33
MaxAE		1.50	1.14	3.29	1.35	1.66	1.84
MRE		0.33	0.20	0.30	0.18	0.29	0.22
RMSE		0.51	0.33	0.61	0.36	0.56	0.43
R^2		0.74	0.89	0.69	0.89	0.71	0.81
Intercept		0.39	0.01	0.33	0.06	-0.15	-0.01
95% CI for intercept		(0.26, 0.51)	(-0.09, 0.11)	(0.18, 0.48)	(-0.05, 0.17)	(-0.33, 0.02)	(-0.15, 0.13)
Slope		0.79	0.98	0.79	0.96	1.00	0.97
95% CI for slope		(0.73, 0.86)	(0.93, 1.03)	(0.73, 0.86)	(0.91, 1.01)	(0.92, 1.09)	(0.91, 1.05)
	PE1		PR2		PS1		
	Grazed paddocks	Fixed	Time-varying	Fixed	Time-varying	Fixed	Time-varying
MAE		0.48	0.33	0.57	0.41	0.34	0.21
MaxAE		1.93	1.41	2.36	2.74	2.35	1.04
MRE		0.39	0.23	0.33	0.24	0.51	0.25
RMSE		0.61	0.43	0.76	0.59	0.49	0.30
R^2		0.48	0.78	0.61	0.74	0.72	0.90
Intercept		0.04	-0.31	-0.44	-0.33	0.24	-0.08
95% CI for intercept		(-0.16, 0.23)	(-0.45, -0.16)	(-0.7, -0.19)	(-0.51, -0.15)	(0.11, 0.37)	(-0.17, 0.01)
Slope		0.97	1.13	1.21	1.05	0.88	1.02
95% CI for slope		(0.86, 1.08)	(1.05, 1.22)	(1.1, 1.34)	(0.97, 1.14)	(0.81, 0.95)	(0.97, 1.07)

Mean Absolute Error (MAE), Max Absolute Error (MaxAE), Mean Relative Error; Root Mean Square Error (RMSE)

The external validation of the model, where the predicted L_g was compared to ground measurements of biomass and vegetation height, showed mixed results. We built a mixed model of total biomass, senescent biomass, and vegetation height (measured with an herbometer) where the predicted L_g had a fixed effect and paddock ID a random effect on the intercept. The analyses yielded marginal (marg) R^2 values (i.e., the variance explained by the fixed factor) of below 0.40 and

conditional (cond) R^2 values (i.e., the variance explained by both fixed and random factors) below 0.52 for both calibration procedure (Table 3– 5). Among the three field measurements, the total biomass yielded the highest conditional R^2 at 0.515 for the fixed parameters and 0.473 for the time-varying g_{max} . The lowest conditional R^2 of 0.037 was between the predicted Lg of the time-varying g_{max} and vegetation height. Beyond the goodness-of-fit of these mixed-effect models, the signs of the estimated fixed effects (the predicted Lg) were consistent with basic expectations: positive for height and total biomass and negative for the senescent biomass.

Table 3– 5. Summary of the external validation of the model. The p -values of the random intercept effect were assessed.

Calibration	Total biomass			Senescent biomass			Vegetation height (herbometer)		
Fixed parameter									
<i>Fixed effect</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>
	465.53	81.63	5.704***	-57.39	11.09	-5.12***	1.19	0.36	0.0017**
<i>Random effects</i>	<i>sd</i>			<i>sd</i>			<i>sd</i>		
Paddock ID (intercept)	598.9***			44.1			1.929***		
Residual	804.7			80.2			2.893		
<i>Fit</i>	<i>R² marg</i>	<i>R² cond</i>		<i>R² marg</i>	<i>R² cond</i>		<i>R² marg</i>	<i>R² cond</i>	
	0.247	0.515		0.322	0.479		0.13	0.4	
Time-varying parameter									
<i>Fixed effect</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>	<i>b</i>	<i>SE</i>	<i>tvalue</i>
	498.06	81.46	6.114***	-59.16	12.43	-4.76***	1.49	0.38	3.929***
<i>Random effects</i>	<i>sd</i>			<i>sd</i>			<i>sd</i>		
Paddock ID (intercept)	427.2*			44.53			2.426*		
Residual	809.2			82.57			8.051		
<i>Fit</i>	<i>R² marg</i>	<i>R² cond</i>		<i>R² marg</i>	<i>R² cond</i>		<i>R² marg</i>	<i>R² cond</i>	
	0.327	0.473		0.27	0.435		0.181	0.37	

As an additional qualitative assessment of the reliability of the model, the posterior distributions of the parameter (Appendix 3– B) agreed with some general characteristics of the grasslands under study. The W_{max} did not vary much between the paddocks and was overall high, which is consistent with the overall high and homogeneous soil water holding capacity across the site and deep rooting. The senescence and growth rates were slightly higher for the grazed paddocks, which is also consistent with the tendency of grazing to promote compensatory growth associated with the high rate of plant tissue turnover (Järemo and Palmqvist, 2001; McIntyre et al., 1995; McIntyre et al., 1999; McNaughton, 1983; Stowe et al., 2000). However, the estimated peak of flowering was early for all paddock, which is not in accordance with the phenology of the dominant grass species of the site,

namely *Agrostis capillaris*, *Festuca rubra*, and *Anthoxanthum odoratum*, which are expected to flower later in the growing season.

3.3.2. Quantification of severe drought events

We identified eight drought events during the growing season of 2016 to 2020 (Figure 3–4). The top four drought events with DS values above 80 started between July and August until October and November of the early fall seasons (Appendix 3–E). The year 2018 had the most severe drought event (DS=165.5), followed by the years 2020 and 2019 with DS = 146.2 and DS =122.8, respectively. Although the years 2016 and 2017 are also considered as drought years in western and central Europe (García-Herrera et al., 2019) our assessment showed lower DS values compared to 2018 to 2020. Our analysis revealed that the drought event severities were mainly dependent on drought duration and timing (summer) rather than intensity (Appendix 3–F).

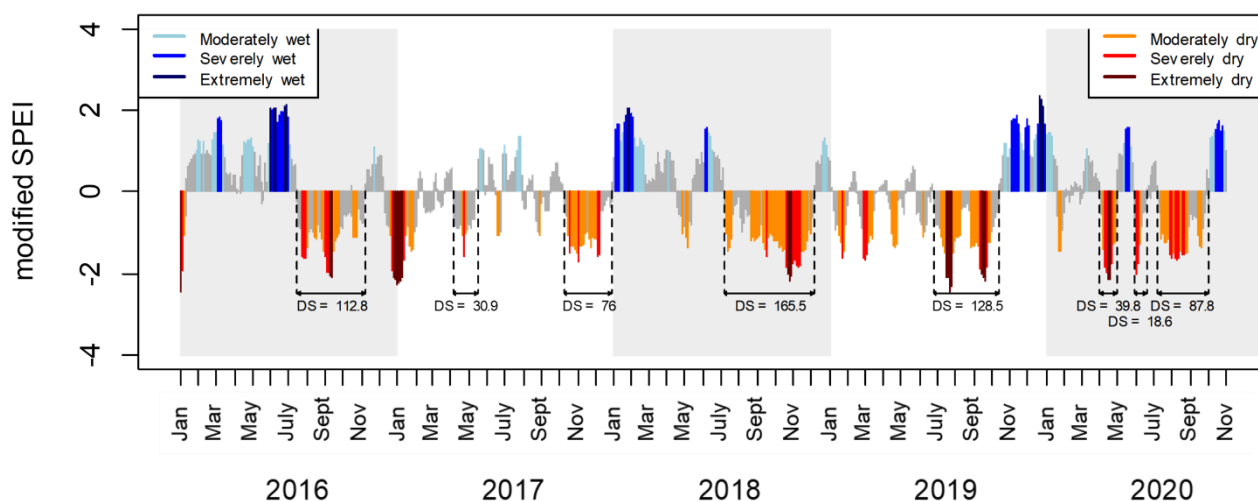


Figure 3–4. The quantified drought severity of the growing season as the sum of the integral area of the drought intensity and duration based on the modified SPEI trajectories from 2016 to 2020.

3.3.3. Managed grassland response to drought

Within expectations, the Logarithm of the drought Response Ratio (LRR) was mostly negative during and right after the severe drought events. The vegetation was not responsive mostly for moderate spring droughts and the light summer drought of 2018. Surprisingly, the LRR became positive (especially in one grazed paddock labeled PE1) after the most severe summer drought of 2016, 2018, and 2019 during the fall and winter, indicating that L_g was greater for simulation with observed meteorological conditions than under an unlimited water supply (Figure 3–5).

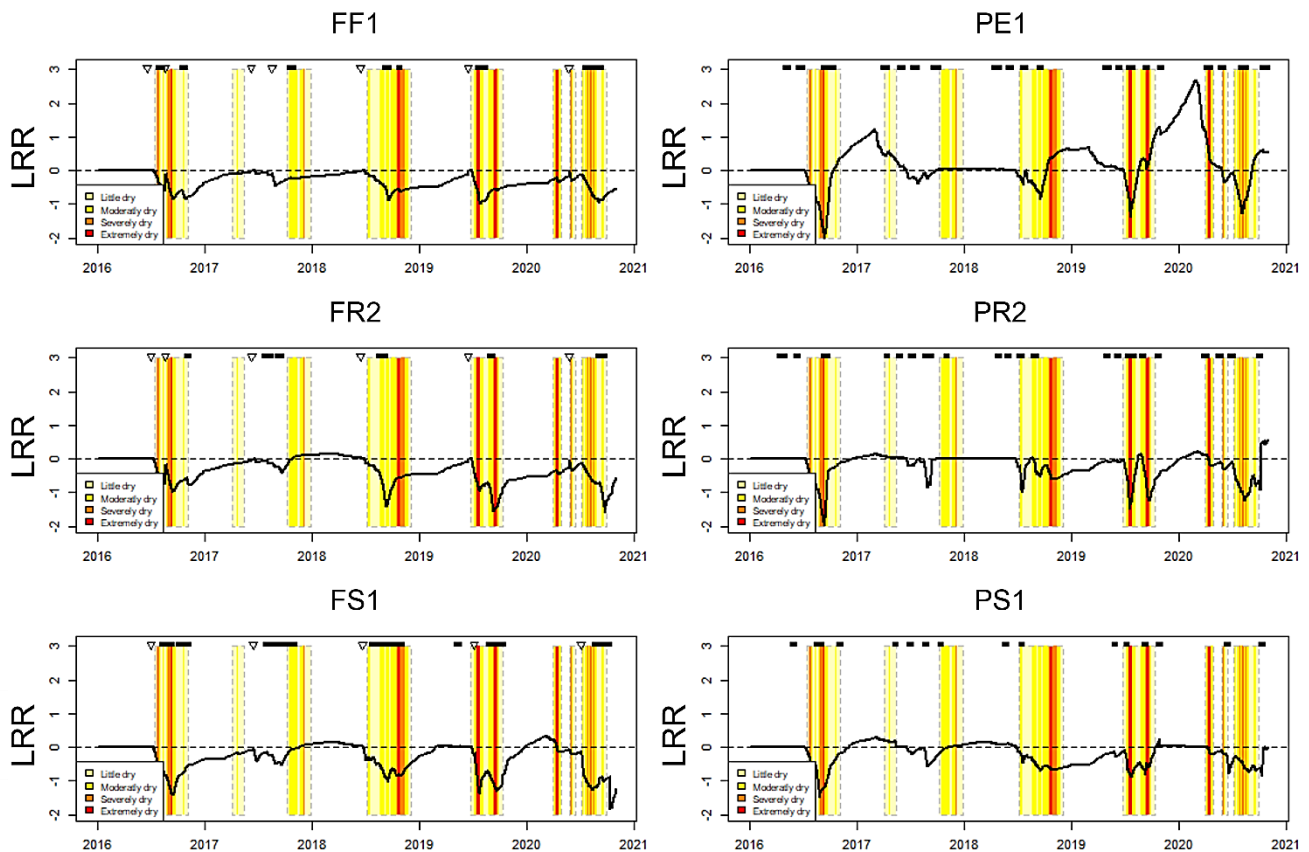


Figure 3– 5. Response ratio of all the selected paddocks. The black solid continuous lines represent the trajectories of the response ratio. The inverted triangles indicate the mowing dates and the short horizontal ticks the grazing periods. The colored areas depict drought intensity according to the modified SPEI.

We found that the resistance (assessed as the normalized minimum LRR during the drought events) was negatively related to drought severity; however, this relationship was not linear (Figure 3– 6), with a clear threshold of drought severity around 80, corresponding to events shorter than 75 days. Below this threshold, the resistance remained high with a mean of 0.93 while above this threshold the resistance was also homogeneously distributed around a mean value of 0.6. We did not find any significant difference in resistance between the two types of management, be it below and/or above the threshold of drought severity of c.a. 80.

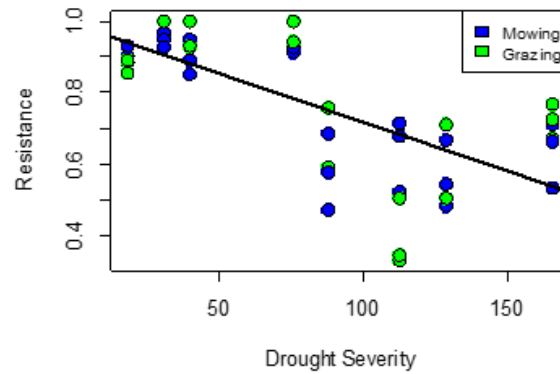


Figure 3– 6. Resistance to drought as a function of drought severity.

Considering the resilience to all drought events, we found no relationship between drought severity and no management effect (Figure 3– 7). However, the pattern was different below and above the same threshold of drought severity (DS = 80). Below it, the resilience was low. Since both resistance and resilience metrics account for the minimum LRR during drought events, this result suggests that even for light drought impacts the vegetation needs a minimum time to fully recover. For drought events of high severity (above the 80 threshold) we found a decrease in resilience with drought severity. Despite a p-value of 0.2 for the interaction between drought severity and management in our analysis, the grazed paddocks were slightly more resilient than mowed ones for drought events, while both management showed the same low level of resilience for the most severe droughts.

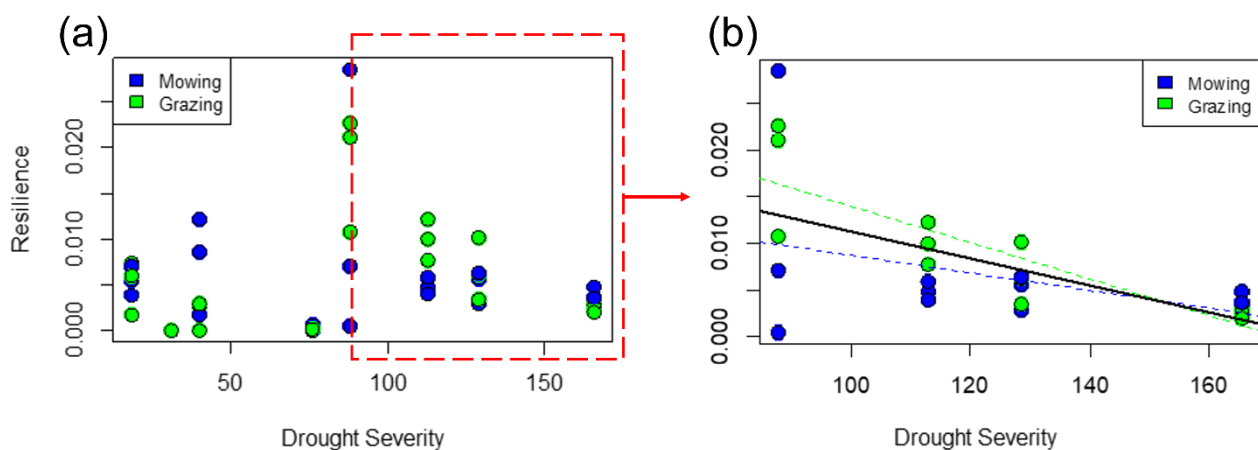


Figure 3– 7. Resilience component of the grassland response to drought (a). The decreasing resilience trend after the threshold of DS = 80 is highlighted (b). The grassland resilience to drought was based on the LRR.

3.4. Discussion

We created a simple dynamic model simulating daily changes in green LAI (L_g) for temperate managed grasslands using inputs from field meteorological stations, Sentinel 2 long-term observations, and management data from the SALAMIX project and HerbValo method. Since the simulated trajectories of L_g were close to the observations derived from Sentinel 2 by inversion of the PROSAIL radiative transfer model, we used our model to assess the resistance and resilience of grasslands facing fluctuating drought severities between 2016 and 2020. Overall, we found insignificant differences in drought responses between mowed and grazed paddocks. However, our results revealed that grazed paddocks were slightly more resilient than mowed paddocks when drought is too severe.

Our dynamic model was able overall to predict the trajectories of L_g derived from Sentinel 2 time series but performed better when calibrating g_{max} as a time-varying parameter, as already highlighted in other contexts (Reyes et al., 2017; Thirel et al., 2015). Such calibration counterbalances the overall simplicity of our model which hinders basic vegetation properties to evolve during the simulation. Indeed, different types of disturbances, like climatic extremes or management practices, or stresses, like heat and frosts, modify the amount of stored carbohydrates in plant tissues (Janeček et al., 2015; Kahmen et al., 2005; Volaire et al., 1994), or the mineralization of soil nutrients and thus their availability for plants (Borken and Matzner, 2009; Deng et al., 2021; Larsen et al., 2011). As a consequence, the rate of daily growth for the next growth period, after drought and other disturbances, is expected to change (Schnyder and de Visser, 1999). In addition to changes in physiological and biochemical processes influencing vegetation growth rate at short time scale, species turnover within the course of the growing season may be high, especially after management events (Pouget et al., 2021). The calibration of time-varying parameters can be logically supported by some ecological arguments. However, we did not find any clear pattern of changes in g_{max} during the season with management or droughts events (Appendix 3–G). This does not necessarily invalidate the calibration approach but reflects the complexity of vegetation changes resulting from the sequence of diverse environmental changes of different natures and magnitudes. However, a potential disadvantage of time-varying parameter calibration is the risk of overfitting. More precisely, grazed paddocks were in our case subject to frequent and short rotations. The g_{max} was repeatedly fitted for short periods with very few L_g observations so that changes in g_{max} may not reflect the role of hidden ecological processes and even possibly flaw the vegetation response to drought intended to be simulated by the model. Other methods of time-varying parameter estimation should be considered to avoid this risk of overfitting (Sawada, 2022).

The external validation of our model did not result in a tight relationship between the predicted L_g and ground measurements of biomass or vegetation height. Such low goodness-of-fit was unexpected. Indeed, LAI is linked to the amount of solar energy captured by the leaves, which allows for a good approximation of photosynthetic activity and productivity (Ruimy et al., 1999; Verrelst et al. 2016), and ultimately of biomass production (Prieto-Blanco et al., 2009; Yu et al., 2018). We attribute our poor external validation to the discrepancy in the scale of ground measurements and Sentinel 2-based estimation of L_g . The total biomass was recorded in quadrats with a 70 cm x 70 cm dimension or about 0.50 m² area. However, L_g estimates of the same location were based on 20 m x 20 m Sentinel 2 pixels amounting to 400 m² area on the ground. Grassland vegetation can be highly heterogeneous within grasslands even at a very fine spatial scale (Adler et al., 2001; Bloor et al., 2020). Thus, biomass estimates over 400m² from half-meter square sampling might be critical. Better validation of the model predictions should ideally include several well-distributed ground measurements of the L_g in the targeted Sentinel 2 pixels. Destructive methods should in this case be preferred to optical ones, which usually underestimate LAI (Brenner et al., 1995; Bréda, 2003) and in order to separate green from dead leaves. Then on the other hand, the SWIR 1 and 2 reflectance bands, which have the 20 m x 20 m spatial resolution, may be excluded as inputs in the PROSAIL radiative transfer model to reduce the represented ground area from 400 m² to 100 m². Indeed, the retrieval of LAI using the inversion of PROSAIL showed no significant improvement with the addition of SWIR bands (Punalekar et al., 2018).

The experimental site experienced extreme drought events from the years 2018 to 2020. These identified years were consistent with conducted drought assessment studies in Europe (Blauhut et al., 2021; Hari et al., 2020; Rakovec et al., 2022). From here, the close link between predicted and Sentinel 2-derived L_g allowed us to analyze the resistance and resilience to drought events of the six paddocks under study, despite the inconclusive external validation of the model.

Normally, in grassland response to drought studies, exceeding a drought intensity threshold results in a change in the ecosystem state or to mortality (Breshears et al., 2016; Matos et al., 2020b). In a multiple ecosystem response to drought study, an SPEI threshold of -1.0 revealed drought impacts (Chen et al., 2022). In our results, we observed changes in grassland resistance and resilience after a given drought severity threshold. Both responses demonstrated a declining trend upon exceeding DS 80. We showed that drought severity was positively correlated with drought duration (Appendix 3–D). For example, we found that the resilience or the rate of recovery decreased with increasing drought severity, intensified by drought duration, from the same threshold. Our result confirms the findings by

Volaire et al. (2009) from a growth chamber pot experiment. More severe senescence and meristem damages occur for longer durations of water deficits (Volaire et al., 2009; 2014). Then the drop in resistance can be related to the function f_2 (in Eq. 2), which has been validated by Calanca et al., 2006, but were unable to reproduce the progressive effect of drought duration or severity found in experimental studies (Gao et al., 2019). In a long-term field experiment, mowing grasslands removes the canopy cover and exposes the soil, thus increasing evaporation rates, removing available water in the soil, and lowering resistance to drought (Vogel et al., 2012). The high number of species in relationship to productivity increases the competition for soil resources (N and water) leading to their depletion under severe drought thus decreasing resistance (Luo et al., 2023; Vogel et al., 2012). Our model was unable to inform which process better explains the low resistance due to the lack of biodiversity and nutrient components.

No significant differences between the two management treatments were detected in our study. Nevertheless, we suspect a slightly higher resilience in grazed paddocks to drought than in mown ones. Bütof et al. (2012) found the same ranking between pasture and meadows but further found that mown pastures had greater resilience to drought. In their case, these grasslands were first grazed and then mown. It was the opposite in our case. Then in terms of the timing, mown pastures are grazed in the late season (Dormann et al., 2017), as opposed to cuts during the first herbage uptake in our mowed paddocks. This big difference in the timing of cuts may support the similarity of our results to Deléglise et al. (2015). In the field experiment they conducted in the Swiss Jura mountains; grazed grasslands have slightly better resilience than mowed ones. At this stage, we cannot classify, with certainty, our mowed paddocks as meadows or mown pastures. We call for further investigation on determining which modalities of mowing and grazing mixtures provide the best resistance and resilience. Finally, our results are unfortunately based on a limited number of paddocks, which considerably reduces the power of the statistical comparisons between the two management regimes. Extending the simulation protocol to the 27 remaining paddocks may lead to different conclusions.

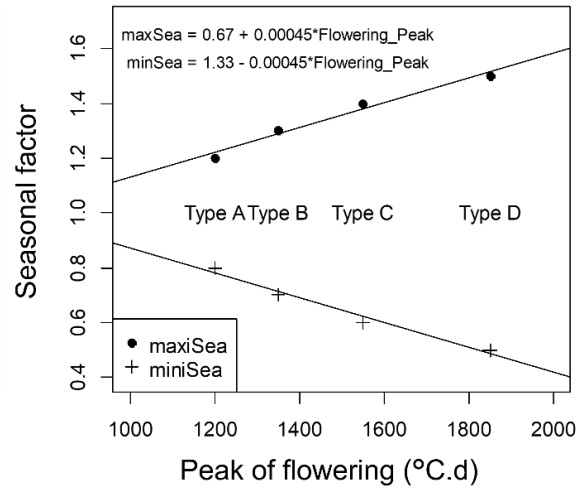
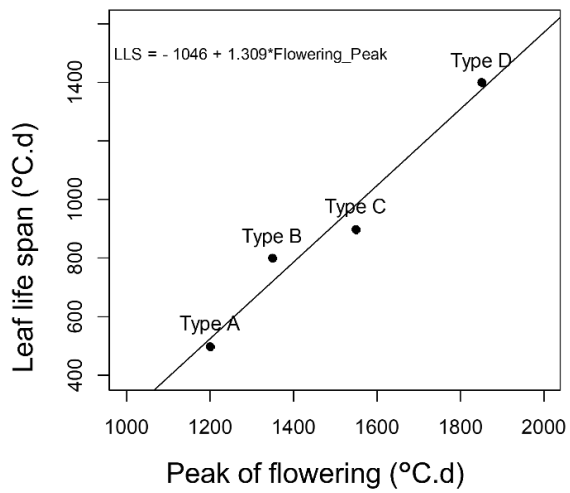
Our assessment of resilience and resistance to drought was based on the dynamics of the log-response ratio between L_g simulation under normal or observed meteorological conditions (i.e., including meteorological drought) and L_g simulation under unlimited water supply. As expected, when severe drought occurred the LRR was negative. More surprisingly, the LRR became positive (greater L_g under drought than under unlimited water supply) in fall and winter following severe summer drought. One possible reason might be related to unrealistic grazing intensities in simulations under an unlimited water supply. Indeed, we did not modify the herbage uptake by animals between the

simulations of the normal and drought conditions. Thus, the applied biomass removal under normal conditions was applied also under the unlimited water supply scenario. This removal would have been larger (either through a larger stocking rate, longer grazing periods, or application of a second cut in mowing paddocks) in the absence of drought. The proportion of removed biomass is thus likely too low, keeping the vegetation in a mature phase where senescence predominates on growth and green tissues vanish. Conversely, under drought conditions grazing or cutting renewed the vegetation to a vegetative stage leading to higher green tissue than under the unlimited water supply scenario. An alternative explanation is that drought events may trigger over-compensation of grassland growth (Zhou et al., 2022), but such effects are not likely to last for long periods as found in our simulation results.

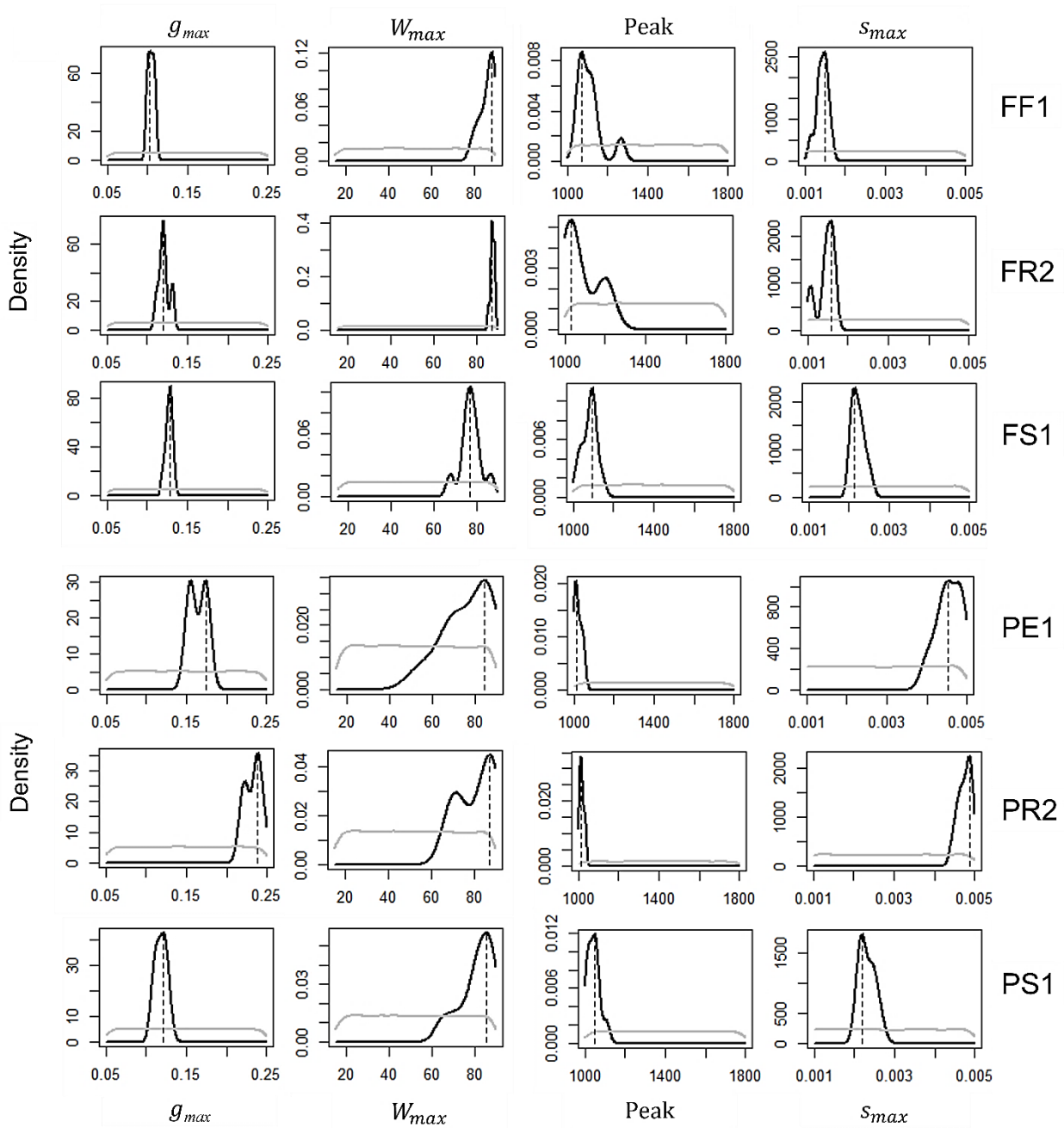
The result of this study supports the benefit of using a parsimonious process-based model that assimilates Sentinel 2 reflectance data for the assessment of managed grassland resistance and resilience to drought. The model is promising but may require additional developments to simulate temporal changes in the parameters related to the vegetation properties. For instance, considering the diversity of ecological syndromes exhibited by the plant species may help in explaining different resistance and resilience capacities between successive drought events and between different paddocks subjected to changes in management practices (Fry et al., 2021; Manea et al., 2016; Pouget et al., 2021; Stampfli and Zeiter, 2004). In addition, we considered the soil as a simple stock of water. The performance of the model may be further improved by accounting for the dynamics of the soil nutrient availability, which is recognized to be impacted by water deficits (Dujardin et al., 2012; Knapp et al., 2008). Indeed, during drought, the availability of nutrients, such as nitrogen, to plants is limited but nitrogen becomes excessively available right after droughts (Dujardin et al., 2012; Hofer et al., 2017; Lucci, 2019; Knapp et al., 2008). This further entails the inclusion of the practice of fertilization as a path for nutrient inputs. Ultimately, we raise the dilemma of trade-offs and priorities in the developments to better understand grassland response to drought and the challenges of increased model complexity. Models should remain reasonable for large-scale applications as permitted by satellite optical images.

Appendices

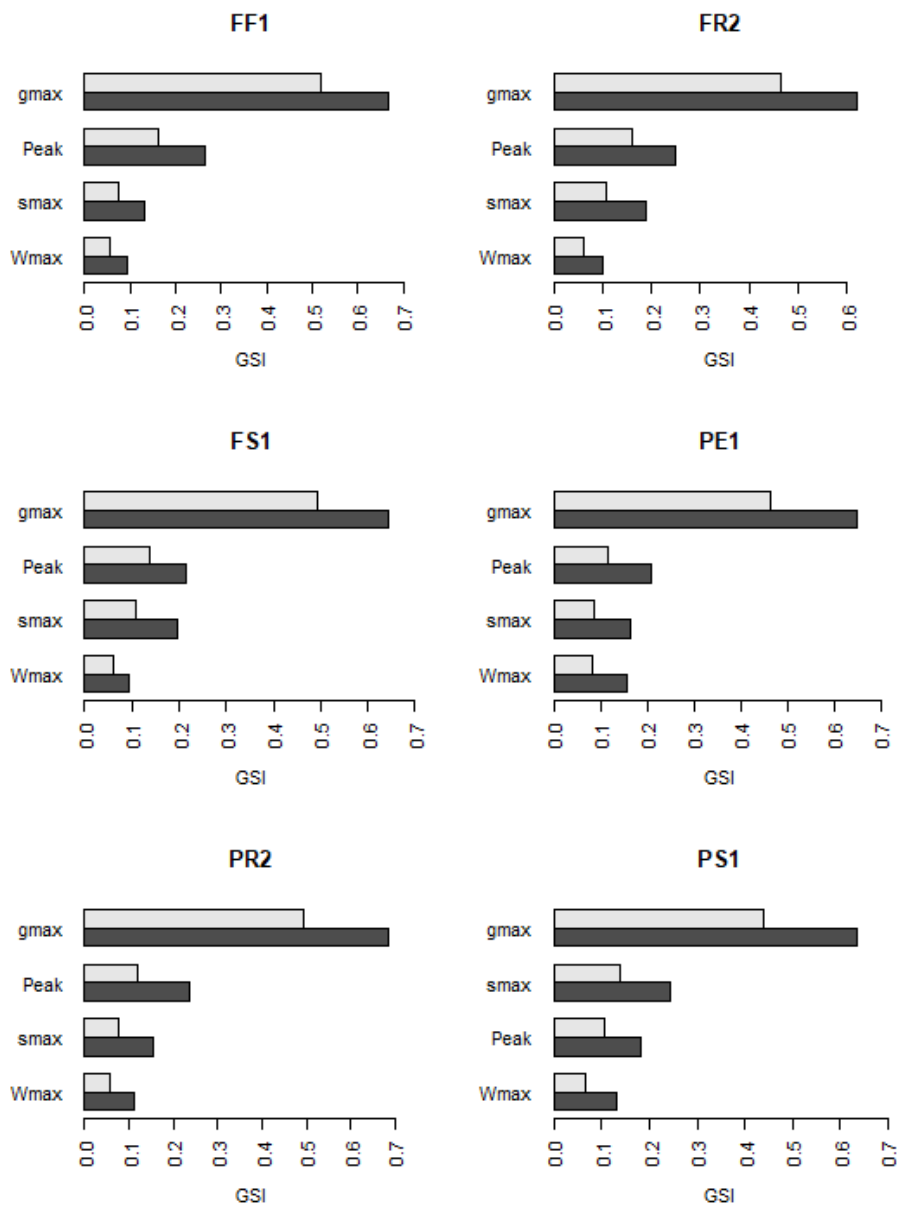
Appendix 3– A. Empirical relationship reference for the derivation of the Peak parameter. The figure was adapted from Duru et al., 2007. The Peak of flowering and Leaf life span are measured in terms of degree days (°C.d).



Appendix 3– B. Posterior distribution of the model parameters during the calibration phase. The derivation process originated from a uniform distribution (grey line). Multiple simulations of different parameter combinations were conducted for each paddock. The means of the best 30 parameter combinations were used as the calibrated parameter values. We conducted a visual inspection to determine if the best parameter estimates were within the expected parameter ranges. Both W_{max} and Peak were similar across all paddocks due to homogenous environmental and vegetation composition. The g_{max} and s_{max} were expected to be influenced by management activities.

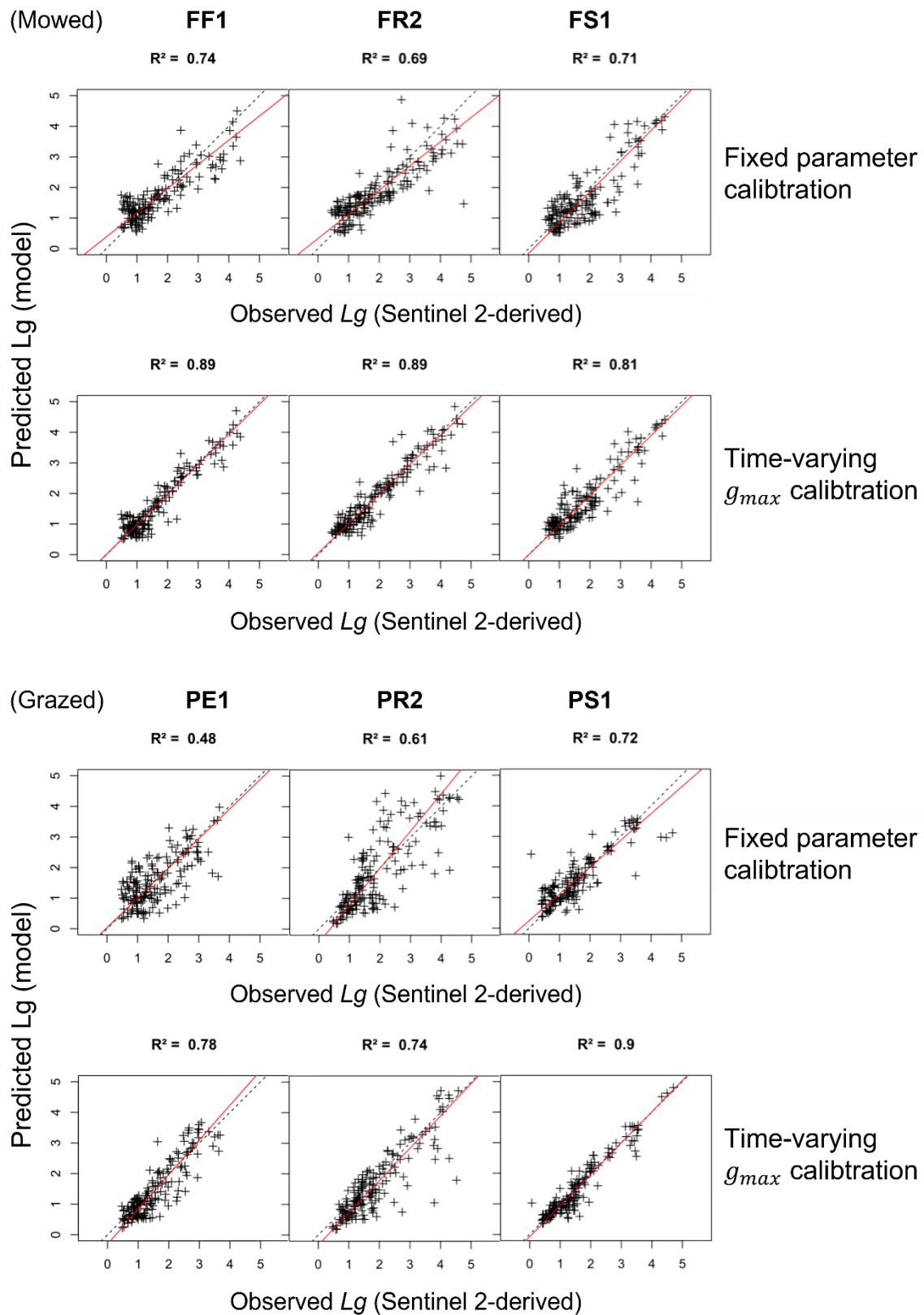


Appendix 3– C. Bar plots of the PCA generalised sensitivity indices of the LAI model. The light bars represent the main sensitivity of the indices and the dark bars the total sensitivity (including interactions with other parameters). The different panels represent different paddocks with different management regimes.

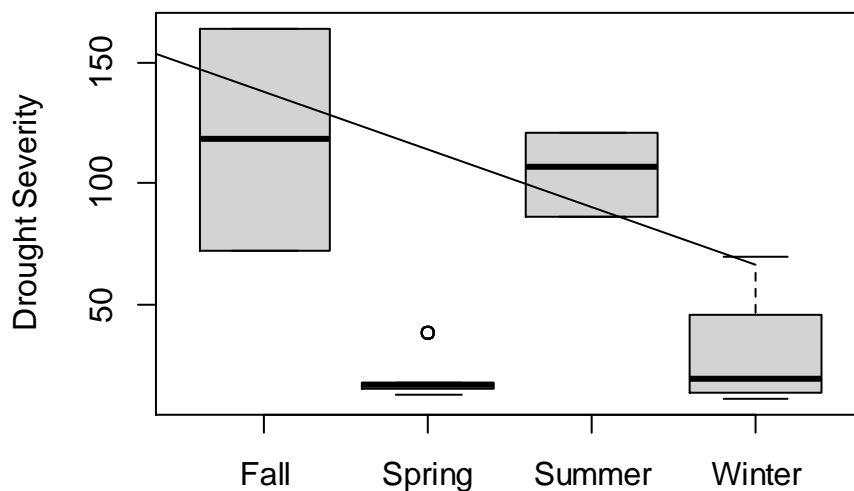


The model was run for combinations of parameter values set according to a full factorial design with 5 levels for each of the 4 parameters of the model. The levels ranged between values reported in the table3 - 3 of the main text. Then, the variability of the model outputs was decomposed in d canonical dynamics representing basic trajectories. Finally, ANOVA-based sensitivity indices were computed for each basic trajectory. These were summarized with the global sensitivity index that averages the sensitivity indices of the first two components weighted by their contribution to the total inertia.

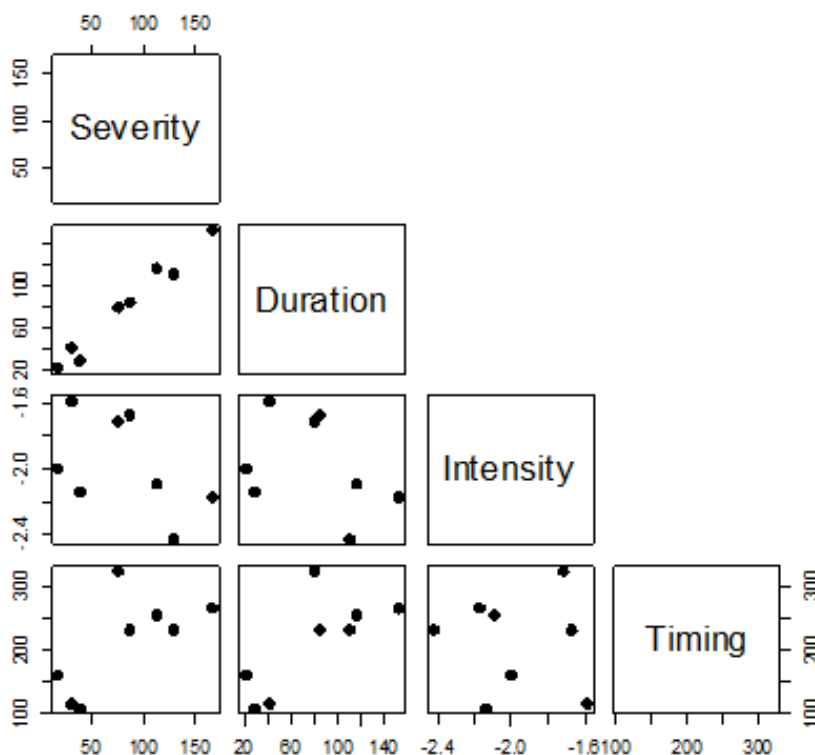
Appendix 3– D. Model validation per paddock based on the relationship between the model-predicted L_g and Sentinel 2-derived observed L_g .



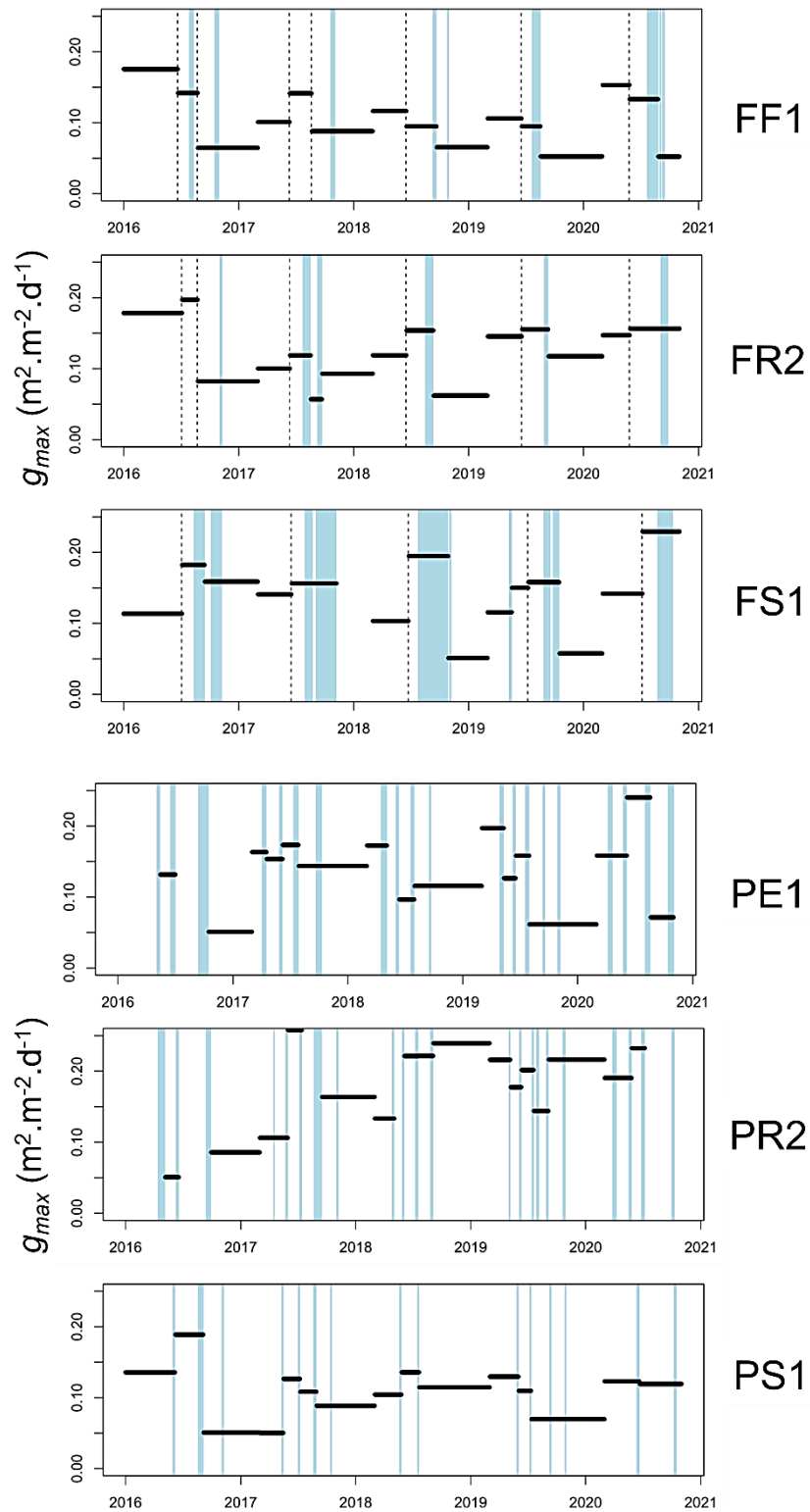
Appendix 3– E. Analysis of drought event timing or occurrence. Drought timing reflects the seasonality of drought events within a year which is quantified as the number of days. The seasons in the region were winter (December to February), spring (March to May), summer (June to August), and fall (September to November).



Appendix 3– F. Analysis of drought events based on all the available drought observations. Drought event severity depends mostly on drought duration. Drought timing reflects the seasonality of drought events within a year which is quantified as the number of days.



Appendix 3– G. Trajectories of the time-varying g_{max} calibrations (black solid horizontal lines) for all paddocks. The vertical broken lines are mowing event dates, while the blue polygons are the grazing event durations.



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GENERAL SYNTHESIS

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I. Summary

The main objective of this Ph.D. thesis was to take advantage of the potential of satellite image time series to improve knowledge of the response of managed grasslands to drought in real-life conditions and with large spatial and temporal coverages. A better understanding of the response of grasslands to drought promotes avenues to find solutions (agricultural practices, soil and climatic conditions, and plant functional diversity and community structure) to mitigate their negative effects and ensure the sustainability of ecosystem services.

To do so, I first reviewed and classified existing methodological assessment approaches of grassland response to drought that used remote sensing data and techniques. Then, based on this review, I selected the most appropriate approach to quantify the variability of grassland sensitivity to drought at the regional scale. This second chapter moved beyond the current knowledge by further identifying the drivers of said variability from a group of pedoclimatic factors, vegetation diversity, and management practices. The third chapter better decomposed the resistance and resilience capacities of managed grassland facing natural droughts using a parsimonious grassland growth model that assimilates satellite data.

Finally, this thesis focused on the overlapping elements of the remote sensing of vegetation properties, the ecology of agriculturally managed grasslands, and the climatology of drought severity.

J. Principal results

In Chapter 1, this thesis highlighted two main results from the review of current studies assessing grassland response to drought using remote sensing. First, the assessment approaches were classified into five groups, namely: (i) vegetation index threshold, (ii) year comparison, (iii) time series analysis, (iv) statistical inference, and (v) mechanistic modelling. The use of vegetation indices is a common component of all approaches, but each approach exhibits a varying number of inputs and complexity of analyses. The vegetation index threshold compares the response of grassland sites to the same drought event. As the most basic approach, it encounters difficulties in attributing drought impact from other disturbances. The year comparison requires at least two years with contrasting conditions (e.g., wet/normal, and dry, drought presence or absence). It quantifies drought impact as the difference between the vegetation index of the years of interest. However, this approach faces uncertainties in determining the true baseline or reference condition and drought severity level concerning the deferred years during comparison. The time series analysis addresses the uncertainties with the baseline and

drought severity levels. The time series analysis accounts for the inherent dynamic of grasslands and drought, and it analyses grassland response to drought based on the paired anomalies of long-term satellite reflectance and drought severity trajectories. Accordingly, its limitation lies in the required robustness and completeness of observations. Statistical inference is the most used approach that determines grassland response to drought from the statistical relationship of vegetation indices and drought severity. It requires multiple observations to establish a strong correlation. Despite the determined grassland response, it fails to properly differentiate between grassland resistance and resilience to drought. The mechanistic modelling approach allows the simulation of gap-free dynamics of grassland properties. With the assimilation of remote sensing data, comprehensive assessments of grassland resistance and resilience to drought can be done, especially in the absence of field data. Unfortunately, the informative output of models necessitates multiple types of data related to complex processes and requires constant parameter recalibration when implemented in other sites with different conditions. Despite the advantages and limitations of these assessment approaches, their application greatly depends on the research objectives and available data.

The thesis results filled the gap in the review of grassland response to drought assessment using remote sensing and showed consistency among existing reviews on the use of remote sensing for ecosystem studies. Similar approaches are used to estimate grassland biomass or classify land cover from satellite images, and to link satellite observations and field measurements. The use of vegetation index for grassland property estimates or grassland type and other ecosystem classification involves multiple thresholds and classification algorithms (Ali et al., 2016; Reinermann et al., 2020; Wang et al., 2022). Time series remote sensing data, despite the presence of gaps, provide better estimates of biomass (Ali et al., 2016; Reinermann et al., 2020; Wang et al., 2022) than single date estimates. Regression models, which are under the statistical inference approach, provide linkages between *in situ* measurements and satellite reflectance information (Ali et al., 2016; Wang et al., 2022). The simulation models correspond to mechanistic modelling with the use of remote sensing data to predict grassland growth parameters together with climate information (Ali et al., 2016; Reinermann et al., 2020). Despite these similarities among approaches, the review recognizes the difference between remote sensing use for grassland monitoring and grassland response to drought assessment. Then it focused on the description of the grassland response to drought assessment methods. Furthermore, this thesis closely provided and demonstrated the advantages and disadvantages of available assessment approaches for a given objective.

Second, the review identified that conducted studies on grassland response to drought using remote sensing were concentrated in the Mongolia Plateau in Central Asia and Great Plains in North America. Despite the coverage of studies on temperate grasslands, the potential of remote sensing for assessing

grassland response to drought has not been applied to all biogeographic regions of the world with few studies in the temperate regions of Western Europe. In a review of forest and grassland ecosystem health assessments using remote sensing, Soubry et al. (2021) found that assessment studies were mostly located in North America, Central Asia, and Western Europe. They identified disturbance regimes for forests and grasslands and found that the top five ecological stressors were climate change, grazing, fire regime, insect infestation, and invasive species and weeds (Soubry et al., 2021). However, among the climate change stressors, drought was reflected only in the forest and grassland of North America (Hoover et al., 2014; Olthof and King, 2000; Soubry et al., 2021). Reinermann et al. (2020), whose focus was on the use of remote sensing for grassland monitoring, also showed a small number of studies in the Western European region. In terms of manipulated rainfall experiments conducted on grasslands, Matos et al. (2020) found the concentration of study sites within North America and Western Europe. Ultimately, this thesis provided additional comprehension of the response of temperate managed grasslands located in parts of Western Europe. Doing so contributes to the better acknowledgment of the variability of grassland response to drought in space and time (Cardoso et al., 2011; Hortal et al., 2015; Ribeiro et al. 2016).

In Chapter 2, the regional assessment revealed that temperate managed grasslands have a large variability of sensitivity to drought within the mountainous Massif central region. This stresses the need to address the Hutchinson shortfall, which relates to a lack of knowledge of the variability of grassland response to drought, and the potential of remote sensing for said use. Field experiments have provided evidence on the variability of grassland response to drought (Cherwin and Knapp, 2012; Heisler-White et al. 2009; Knapp, Carroll, et al., 2015), but are limited by the unique implementation of drought-induced treatments, monitored variables, and by the spatial and temporal scales of the studies (Fraser et al., 2013). Field experiments implemented guidelines on the standardization of methodologies to address some of these concerns (Knapp et al., 2012). However, monitoring and observation of multiple grassland sites entail additional coordination (Knapp, Hoover, et al., 2015; Knapp et al., 2017). Chapter 2 also demonstrated that the use of remote sensing simplified the need for guidelines with standardized measures of grassland properties and drought severities over large spatial and temporal scales despite the inherent but manageable limitations of the Landsat satellite sensor being used for this purpose. The Landsat limitations are related to the temporal resolution, availability of cloud- and snow-free images, and scan-line corrector failure (Loveland et al., 2008).

Chapter 2 further identified the drivers of such variability among pedoclimatic factors, vegetation diversity, and management practices. Within expectations, the soil water holding capacity demonstrated its mitigating influence on grassland sensitivity to drought. Zhao et al. (2008)

demonstrated the importance of soil available water for plants using pot experiments. The water stressed soil condition yielded low values across parameters, such as leaf relative water, and chlorophyll contents (Zhao et al., 2008). Forte et al. (2023) performed a mesocosm experiment using grassland monoliths under different drought treatments. Soil moisture supports vegetation resprouting best during early drought conditions under larger water availability for growth (Forte et al., 2023). This chapter also found that high vegetation functional diversity decreased sensitivity to drought. This result confirms several experimental studies (Gherardi and Sala, 2015; Loreau et al., 2021; Schnabel et al., 2021; Yachi and Loreau, 1999) that revealed that high functional diversity provides a mitigating influence on grassland response to climatic variabilities, such as drought. Accordingly, the regional remote sensing study was able to detect complementary results to drought experiments.

On the opposite side, grazing increased sensitivity to drought, and the early use of grasslands also promoted higher sensitivity. However, Chapter 2 highlighted the inability of the statistical inference approach to differentiate between ecosystem resistance and resilience. For example, Bütof et al. (2012) and Deléglise et al. (2015) conducted field experiments that showed the high resilience or recovery of grazed grasslands compared to mowed ones.

Overall, the identified drivers of grassland response to drought (regional scale) demonstrated the complementarity between remote sensing studies and field experiment results. Chapter 2 revealed possible complex interactions between these drivers, which the correlations did not disentangle. The grazing and mowing practices, the influence of phenological developments of vegetation, and the occurrence of drought all coincide during the summer of the growing season. Nevertheless, these confounding factors may initiate new drought experiments. Caution should be drawn to the Chapter 2 result regarding the mitigating effect of nitrogen fertilization on grassland sensitivity to drought. N fertilization promotes the growth of selected tall grasses (Fiala et al., 2011; Xiong et al., 2018), and may increase the functional diversity and modify community weighted means of growth syndromes and specific leaf area, respectively (Niu et al., 2014). However, excessive N fertilization is ill-advised in grasslands during drought to avoid the risk of nitrate leaching (Klaus et al., 2020). Furthermore, N fertilization may further decrease species richness, which could ultimately lead to reduced grassland functional diversity (Kübert et al., 2019). Other management practices, such as grazing and mowing, also facilitate vegetation diversity, thus indicating cascading effects toward grassland sensitivity to drought.

As a new aspect in grassland sensitivity to drought studies, we revealed the importance of drought timescales. The strong mitigating effect of soil water holding capacity to sensitivity was highly prominent during drought timescales of 30 days or less. The mitigating effects of vegetation diversities and community structure were found at varying timescales. The influence of community weighted

mean (CWM) of seed mass was detected from 60 days or less. While the effect of CWM of specific leaf area (SLA) and functional dispersion of growth syndromes were observed at drought timescales of 60 days or more. All management practices influenced the sensitivity of grasslands to drought at all timescales.

Drought experiments are generally conducted with a short time scale within homogenous environmental conditions to maximize treatment effects (Yuan et al., 2017). Observational studies allow the inclusion of time scales in the assessment of response to drought (Yuan et al., 2017). Accordingly, remote sensing permits the consideration of time scales as well.

The regional assessment found a noisy relationship between vegetation index anomalies and drought severity indices. This suggests the role of confounding factors, such as the co-occurrence of grazing or mowing and drought, or the influence of other types of disturbances like vole infestation, or the occurrence of plant diseases. During the analysis, the regional assessment assumed constant values of species composition, leaf traits and thus functional diversity, and management practices. Whereas there are expected uncertainties regarding their values across time.

Chapter 3 further explored the influence of management practices on the grassland response to drought with the use of a process-based modelling approach assimilated with Sentinel 2 remote sensing data. It disentangled drought impact from other processes and moved beyond by assessing the resistance and resilience of managed grasslands to drought.

To do so, a simple model, with few parameters to calibrate and few input variables, was required. Such a model, together with satellite data, has already been used to simulate the dynamics of vegetation cover and soil water content in semi-arid tropical grasslands in Australia (Choler et al., 2010). However, it did not incorporate the influence of management or phenological processes which are of great importance in our system under study.

As highlighted in Chapter 1 and demonstrated in Chapter 2, the statistical inference approach was unable to decompose grassland responses into resistance and resilience due to the inherent characteristics of the approach and the absence of chronological trajectory information. The presence of data gaps and low temporal resolutions of satellite observations also contributed to the low accuracy in the determination of resistance and resilience. Thus, the interpretation of the results in Chapter 2 was limited to the overall grassland sensitivity and was unable to account for the different components of drought responses. This is of great importance because nutrient fertilization stimulates grassland resistance and resilience differently (Bharath et al., 2020).

This thesis succeeded in developing a simple process-based model of grassland green leaf area index (LAI) trajectories assimilated with Sentinel 2 time series observations. Climatic variables and

herbage use by grassland paddock management were the inputs of the model, and the maximal potential growth, the maximal amount of soil available water, phenology, and senescence rates were the four main model parameters. The local assessment used this simple model to simulate true climatic conditions (including drought periods) and non-drought conditions. Then it used a log response ratio to obtain both resistance and resilience of mowed and grazed paddocks. Chapter 3 found that both resistance and resilience showed a decreasing trend after a given threshold of drought severity of 80, which corresponds to a drought length longer than 40 days, with a constant modified SPEI of -2.0, or 54 days, with constant modified SPEI of -1.5. There was no significant difference between mowed and grazed paddocks for both the resistance and resilience capacities, but resilience was slightly higher for grazed paddocks than mowed ones. This result contrasts with Chapter 2 where we found that grazing promoted higher sensitivity to drought than mowing and findings from previous field experiments (e.g., Deléglise et al., 2015). Indeed, repeated grazing is expected to impede the storage of carbohydrates in plants and thus decrease the resilience of vegetation after drought (Zwicke et al., 2015; Volaire et al., 2020). Beyond the different approaches for assessing grassland response to drought between field/pot experiments, linear model (Chapter 2), and the simulation protocol (Chapter 3), the unexpected result may arise from the role of patchy grazing that is recognized to increase the spatial heterogeneity of vegetation (Adler et al., 2001; Bloor et al., 2020; Lei et al., 2016). Such spatial heterogeneity can result in higher functional diversity at the pixel/paddock scale (Bloor and Pottier, 2014) and ultimately improve grassland resilience to drought (Barkaoui et al., 2016; Folke et al., 2004; Standish et al., 2014).

Grazing results in a longer accumulation of seeds in the soil due to trampling and distributed open patches from uneven grassland vegetation cover (Jacquemyn et al., 2011; Müller et al., 2014), and consumed seeds by animals may germinate within manure (Gilhaus et al., 2017).

Some studies reported a negative effect of grazing on the soil seed bank (Dutoit and Alard 1995; Loydi et al., 2012, Sternberg et al., 2003). The impact of grazing on seed bank density is unclear and needs further investigations, especially comparisons with different mowing regimes. In conclusion, different processes may lead to greater resilience either under grazing or mowing. Future researches should be set up to disentangle the possible actions of grazing on ecophysiological processes and community assembly with opposite consequences on grassland resilience to drought.

K. Limitations of the thesis

This thesis used satellite image time series for the assessment of grassland sensitivity and response to drought. Unfortunately, satellite-sensor products that offer a long historical collection of observations, such as MODIS and Landsat, lack high spatial, temporal, and spectral resolutions all at

once (Appendix A). In the regional assessment, despite the daily revisits of MODIS, it has a low spatial resolution between 250 m to 500 m for seven basic bands related to vegetation properties. Then the high spatial (at most 10 m) and temporal (five days) resolutions of Sentinel 2 were available only at a short temporal range that started on 23 June 2015. Landsat image collection, which covers the year 1985 to 2019 and has a higher spatial resolution of 30 m, was considered in the regional grassland sensitivity to drought assessment despite the lower temporal resolution of 16 days. The difference in resolutions also limited the ability of the thesis to properly compare the used satellite image time series in Chapters 2 (Landsat) and 3 (Sentinel 2).

The relationship between the vegetation index anomalies and drought indices was noisy. Satellite-sensor data may be filtered and pre-processed to account for the occurrence of other disturbances linked to ground data. Recent studies have shown that mowing events can be detected for temperate managed grasslands using Sentinel 2 (Andreatta et al., 2022b), combinations of Sentinel 2 and Landsat 8 (Schwieder et al., 2022), and even combinations of optical and microwave satellite data (Lobert et al., 2021). Unfortunately, the detection of grazing rotations with remote sensing is more challenging due to the selective removal of biomass by animals (De Vroey et al., 2022) which results in the heterogeneity of grassland reflectance signals (Lobert et al., 2021). Furthermore, intensive grazing rotations commonly reflect mowing-like reflectance signals (De Vroey et al., 2021). Detailed management data are lacking for large grassland areas and over long periods. Even records of the influence of multiple disturbances with possible interactions (pests, diseases, and fires) are seldom available. This shortfall strongly limits the use of modelling approaches at very large scales. Methods exist for the determination of these specific disturbances, such as pest or plant disease infections (Terentev et al., 2022; Zhang et al., 2019); and fire (Dwyer et al., 2000; Rogers et al., 2020; Wang et al., 2004).

The simplicity of the grassland growth model of Chapter 3 was at the cost of a poor description of the processes influencing grassland dynamics. The model mainly focuses on the influence of soil available water for plants, phenological growth based on climatic variables, and herbage uptake practices. Thus, the model failed to account for soil nutrient cycles, and for the fine-scale dynamics of community composition which influences vegetation regrowth. At best, this model indirectly considered temporal changes of grassland basic properties with the time-varying parameter calibration approach.

The look-up table (LUT) is characterized as a fast, simple, and robust inversion method of radiative transfer models (Darvishzadeh et al., 2008; Weiss et al., 2000). However, the 30,000 random parameter simulations still posed computation challenges with multiple observations and pixels per paddock. Then if higher inversion accuracy is needed, the size of LUT simulations should be increased to 50,000

or more; however, this entails additional computation power (Weiss et al., 2000). Due to this computational concern, only the results from six paddocks, representing the two grassland management treatments, were presented. The lack of significant difference between the grazed and mowed paddocks may be due to the low number of observations.

L. Perspectives

This thesis has provided research avenues that can further expand the understanding of grassland response to drought using remote sensing. From a global point of view, the remote sensing-based assessment of drought impacts on grassland should be conducted to cover other grassland types from all regions of the world. Then the determination of the influence of various combinations of pedoclimatic factors, level of diversity, and management practices will lead to the comparison of results. Then the drivers of grassland response to drought may further be explored with new additional factors. The 29 grassland and local properties considered in this thesis, specifically in Chapter 2, were limited to the data availability and commonly considered vegetation-related diversity metrics and traits. Other traits more related to drought and factors external to the grasslands are to be considered. Finally, the methodological developments for the simple process-based model may take two directions of improvement.

Both the regional grassland sensitivity to drought assessment and process-based modelling assimilated with remote sensing data were driven by data availability. The use of linear models, in the regional assessment, was due to the lack of detailed management data, which hindered the implementation of the process-based model on the regional scale. In addition, the Landsat data, due to the 16-day temporal resolution, may not provide a good fit for the model in such a long time period. Satellite images with higher temporal resolutions may provide solutions, but their use will be dependent on the scale of the study (e.g., MODIS). Except for the detailed management data, the local scale process-based model lacks the characterization of the individual paddocks (i.e., soil and vegetation conditions) preventing the identification of significant drivers to grassland resistance and resilience. Overall, the regional assessment supported the identification of drivers to be included in the local scale process-based model. These drivers were the management practices and water availability in the soil for plants.

For the analysis of the drivers of grassland sensitivity to drought, the influence of management practices is one big challenge due to the diversity of implementation schemes and differences in monitored properties. For example, in Deléglise et al. (2015) the experimental blocks were either grazed six times or mowed three times per growing season. In Büttof et al. (2012), the frequency of pasture was unindicated, despite the three times per season use of meadows, fertilization is applied. In

the regional assessment of this thesis, the prominent management practice was considered per grassland parcels. In the local-scale assessment, grazing and mowing were done once or twice per growing season. Then grazing is implemented in the mowed paddocks based on the availability of vegetation biomass. These studies also monitored different properties such as forage production in Deléglise et al. (2015), the biomass growth rate in Bütof et al. (2012), and leaf area index (LAI) and vegetation index sensitivity in this thesis. Consequently, additional studies focusing on the influence of management practices on grassland response to drought are needed to clearly determine the influences of grazing and mowing.

The interactions between drivers should also be studied. The quantification of the cascading effects of drivers can ascertain the overall influence of factors on grassland response to drought. However, both these avenues will require substantial data for fitting more complex statistical models. Other plant traits more related to the response to drought should be prioritized. For example, root traits, such as root surface area and root length, directly influence the amount of water available to the plant.

Grasslands are open systems. Drivers that influence the response to drought are not limited to grasslands and include adjacent systems or features. The dry and warm topographic microclimate improves the stability and vegetation composition of calcareous grasslands in Germany (Mazalla et al., 2022). Ecosystems such as forests and grasslands generate microclimates that mitigate macroclimate warming (Bernath-Plaisted et al., 2023; Davis et al., 2018; De Frenne et al., 2013). Then the edges of ecosystems or ecotones also provide mitigating microclimate conditions (D'Odorico et al., 2013; Süle et al., 2018). Similarly, the proximity to water ponds increases grassland resistance to drought (Chen et al., 2022). Interestingly, consideration of the surrounding systems can enhance the understanding of grassland response to drought.

New developments with remote sensing technologies related to satellite sensors and algorithms (e.g., Cao et al., 2021; Chiarito et al., 2021; Morais et al., 2021) are expected to provide improvements in the quality and accuracy of vegetation monitoring. Currently, existing remote sensing products and techniques, such as SAR images (Abdel-Hamid et al., 2020), fusion of optical image sources (Gao et al., 2006; H. Liu et al., 2021), and merging of SAR and optical data (Potočník Buhvald et al., 2022; Garioud et al., 2020; Lobert et al., 2021) have been used for grassland monitoring and mapping. Image correction techniques help improve the accuracy of grassland monitoring (Ren et al., 2023). However, these are still unrealized for the assessment of grassland response to drought.

The increasing rate of advancement and number of satellites launched into space was a trend that started as early as the 1980s (Kramer and Cracknell, 2008). New satellite sensors, specifically, the nano- and microsatellites, continue to show advancements for environmental and ecosystem monitoring (Ustin and Middleton, 2021). Potential assessments of grassland response to drought with

a focus on the new and seldomly used satellite sensor products can first validate the technological developments, and produce new results with improved spatial, temporal, and spectral resolutions.

The simple process-based model of Chapter 3 requires additional improvements to represent the dynamics of the potential growth of grasslands (Reyes et al., 2017; Thirel et al., 2015). We can include additional eco-physiological processes to account for the nutrient availability, cycling, and use, which are connected with the water in the plant and soil (Henneron et al., 2019), or include grassland community species diversity dynamics or plant functional groups (Piseddu et al., 2022) to reflect the specific influence of plant strategies or traits on the ecosystem functioning related to growth under drought. Related to the time-varying growth parameter, the changes in the amount of used and stored carbohydrate reserves can be included to accurately simulate the plant regrowth after defoliation or change in seasons (Volaire, 1995; Boschma et al., 2003; Dube and Gwarazimba, 2000). Unfortunately, accounting for the soil-plant interactions and species-specific contributions to growth poses the risk of very complex models that should ideally be avoided to establish model identifiability and simplify the calibration process.

On the other hand, ecological processes have already been accounted for in complex models. This thesis provides value by once again demonstrating the use of satellite data in process-based models. Methods of satellite data assimilation can be either as calibration, forcing, or updating (Dorigo et al., 2007). Remote sensing can serve as an alternative source of inputs for existing models.

M. Recommendations for future studies

The generic term “response” has been used in the majority of the grassland response to drought studies. Fortunately, the selected assessment approaches help in determining how “response” is defined. Van Meerbeek et al. (2021) have positioned resistance, resilience, and recovery as properties of ecological stability. The vegetation index threshold reveals grassland resistance to drought. Year comparison, with some uncertainty, shows either resistance or resilience. The time series analysis, together with the mechanistic modelling, both allow detailed quantification of ecological stability properties. Then the statistical inference is mainly limited to the quantitative response or qualitative sensitivity. I recommend the avoidance of the generic use of “response”, especially if the selected approach allows the identification of resistance, resilience, and recovery. This will result in the increased comparability of studies of drought impact across different grassland types.

The spatial and temporal scales of studies and resolutions of data influence the results of the grassland response to drought assessment. Maintaining similar grassland reflectance and drought severity scales and resolutions can help avoid possible noise from mismatches. For instance, a weekly or higher temporal scale of grassland reflectance would provide more observations when paired with

drought severity indices modified into a daily time unit. Such grassland observations may be possible under cloud-free conditions or if highly correlated microwave and optical image observations are available. Ultimately, the spatial and temporal scales are crucial in the analysis and interpretation of results in remote sensing and ecological studies (Andreatta et al., 2022a; Gamon et al., 2020; Levin, 1992; Pescador et al., 2021).

In the assessment of grassland resistance, and resilience or recovery to drought using the statistical inference and mechanistic modelling approaches, multiple data sources provide improvements in the interpretation of results. However, this entails challenges in terms of data acquisition and standardization. I recommend the maximization of existing models and data sources in the quantification of drought severity. Similar to Chapter 2, programs and projects should be built on the existing datasets of previous research activities on the same site. Field collection methods should be replicable and standardized to allow the association with long-term satellite reflectance data of grasslands. But we discourage the use of satellite-based assessment of drought using vegetation indices. This generally indicates drought impact on vegetation, rather than actual drought severity.

Finally, this thesis successfully presented the potential of the mechanistic modelling approach for the assessment of grassland resistance and resilience to drought. I recommend the collection of long-term and detailed grassland parcel and environmental data or at least the grassland management data. Then we promote the consideration of parsimony or simplicity of the process-based models to avoid the difficulty of acquiring multiple data associated with the inputs and parameters of complex models but still provide near-accurate simulations. The assessment of grassland response components to drought using process-based models should be as simple as possible to allow focus on the investigations of drivers.

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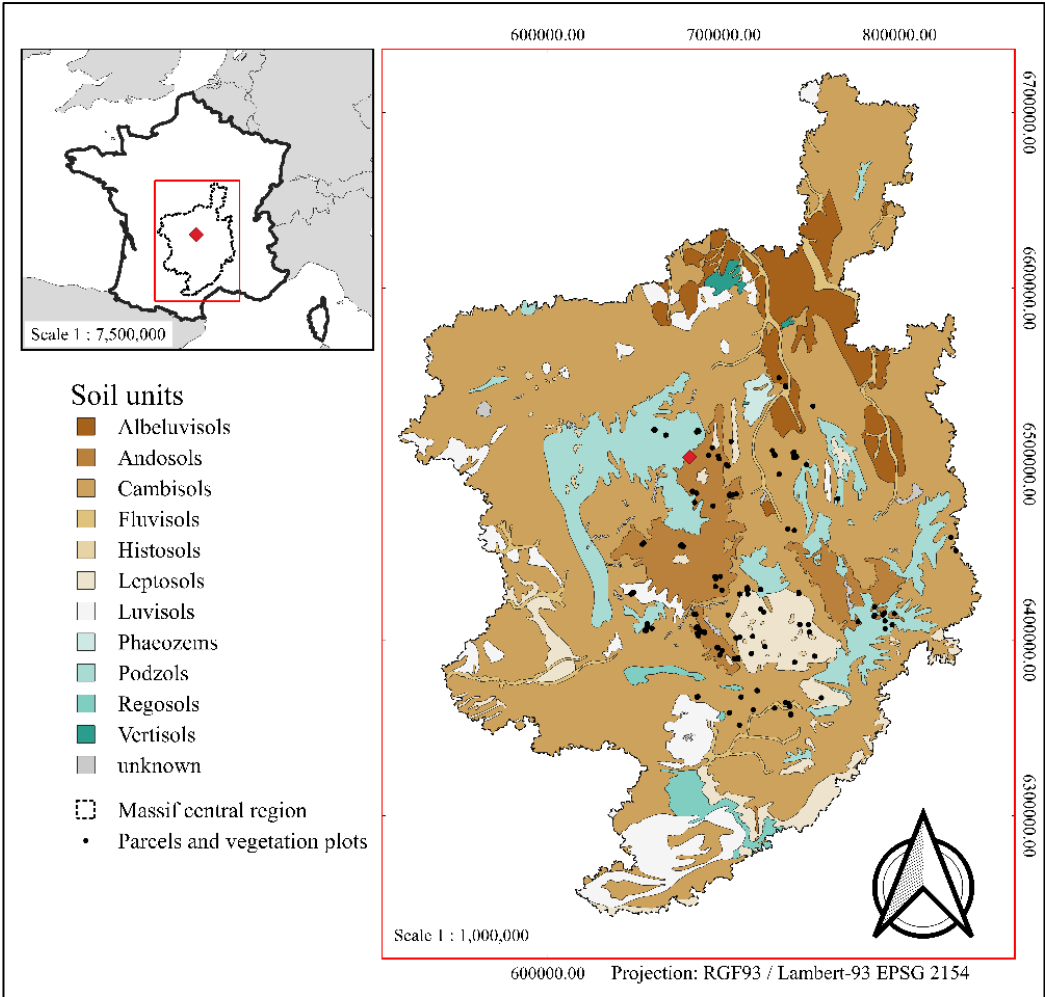
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GENERAL APPENDICES

Appendix A. Summary of optical satellite-sensor resolutions.

Satellite	Sensor	Duration	Spatial (m)	Temporal (days)	Spectral range (μm)	Spectral bands (count)	Radio-metric (bit)
METOP-A/B	Global Ozone Monitoring Experiment-2 (GOME-2)	2006 to present	80000 \times 40000	1.5	0.24 to 0.79	15	16
NOAA 6 to 19 of NOAA - POES / NOAA-20	Advanced Very High-Resolution Radiometer (AVHRR)	1979 to 2019	1000	1	0.58 to 12.5	4 to 6	16
Terra and Aqua	Visible Infrared Imaging Radiometer Suite (VIIRS) Moderate Resolution Imaging Spectroradiometer (MODIS)	2017 to present	375; 750	1	0.41 to 12.0	22	12
Landsat 1 to 5	Multispectral Scanner System (MSS)	2000 to present	250; 500; 1000	1 to 2; 16	0.41 to 14.23	36	12
Landsat 4 to 5	Thematic Mapper (TM)	1972 to 1999	60	16	0.5 to 1.1	4	6
Landsat 7	Enhanced Thematic Mapper (ETM) +	1982 to 2013	30; 120	16	0.45 to 12.5	7	8
Landsat 8 and 9	Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	1999 to 2022 (science mission)	15; 30; 60	16	0.45 to 12.5	8	9
Satellite pour l'Observation de la Terre (SPOT) 1 to 5	High Resolution Visible (HRV); High Resolution in the Visible and Infrared (HRVIR); High Resolution Geometry (HRG)	2013 to present	15; 30; 100	16; 8	0.43 to 12.51	11	12
SPOT 4 and 5	VEGETATION	1986 to 2015	2.5; 10; 20	26	0.48 to 1.75	5	8
SPOT 6 and 7	New Astrosat Optical Modular Instrument (NAOMI);	1998 – 2014	1 000	26	0.44 to 1.65	4	8
Sentinel 2A and 2B	Multi-Spectral Imager (MSI)	2012 and 2014 (launched dates)	1.5; 6	26	0.45 to 0.89	5	12
Venus	VEN μ S SuperSpectral Camera (VSSC)	2015 and 2017 to present	10; 20; 60	5	0.44 to 2.19	13	12
IKONOS	Multispectral and panchromatic sensor	2017 to 2020	5	2	0.42 to 0.91	12	10
QuickBird	Multispectral and panchromatic sensor	1999 – 2015	0.82; 3.28	3	0.40 to 0.90	5	16
WorldView-1/2/3/4	Multispectral and panchromatic sensor	2001–2015	2.62; 0.65	1 to 3.5	0.45 to 0.90	5	16
RapidEye	RapidEye Earth-imaging System	2007 – present	0.31; 1.24	1	0.45 to 0.90	1.7	11
Planet	SuperDove or PSB.SD	2008 – 2015	5	1	0.44 to 0.85	5	8
		2016 to 2022	3	1	0.43 to 0.88	3	8

Appendix B. Distribution of soil units in the Massif central region (ESDAC).



Appendix C. Summary of the reflectance bands of Landsat 8, Sentinel 2, and VENuS. The central wavelengths are the mean of the minimum and maximum band values.

Band Description	Landsat 8 bands	Central Wavelength (nm)	Sentinel 2 bands	Central Wavelength (nm)	VENuS bands	Central Wavelength (nm)
(Atmospheric correction) *					1	415
Coastal	1	443	1	443	2	440
Blue	2	482	2	490	3	490
Green	3	562	3	560	4	555
(Land)*					5	620
(DEM)*					6	620
Red	4	655	4	665	7	667
Red edge			5	705	8	702
Red edge			6	740	9	742
Red edge			7	783	10	782
Near-infrared (NIR)			8	842		
Narrow NIR	5	865	8A	865	11	865
Water Vapor			9	945	12	910
Shortwave infrared (SWIR) Cirrus			10	1,375		
SWIR1	6	1,610	11	1,61		
SWIR2	7	2,200	12	2,190		
Panchromatic	8	590				
Cirrus	9	1,375				
Thermal infrared (TIRS) 1	10	10,800				
TIRS 2	11	12,000				

* VENuS band description (<https://venus.cnes.fr/en/VENUS/index.html>)

Appendix D. Satellite reflectance indices used in the study. Input bands were the blue (B), green (G), red (R), near-infrared (NIR), and shortwave infrared (SWIR) 1 and 2.

Index	Formula	Purpose / Description	References
NDVI	$(\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$	Commonly used for vegetation biomass (green)	Rouse et al., 1974
ARVI	$(\text{NIR} - [(2 * \text{R}) - \text{B}]) / (\text{NIR} + [(2 * \text{R}) - \text{B}])$	Less sensitive to atmospheric effects compared to NDVI	Kaufman and Tanré, 1992
DVI	$\text{NIR} - \text{R}$	Differentiates vegetation and soil.	Richardson and Wiegand, 1977
EVI	$2.5 * (\text{NIR} - \text{R}) / (\text{NIR} + 6 * \text{R} - 7.5 * \text{B} + 1)$	For canopy conditions in high biomass areas	Huete et al., 2002
EVI2	$2.5 * (\text{NIR} - \text{R}) / (\text{NIR} + (2.4 * \text{R}) + 1)$	EVI without the blue band	Jiang et al., 2008
GCI	$(\text{NIR} / \text{G}) - 1$	For chlorophyll estimation	Gitelson et al., 2003
GEMI	$n * (1 - 0.25 * n) - [(\text{R} - 0.125) / (1 - \text{R})]$ where, $n = [2 * (\text{NIR}^2 - \text{R}^2) + (1.5 * \text{NIR}) + (0.5 * \text{R})] / (\text{NIR} + \text{R} + 0.5)$	For vegetation cover; non-linear index	Pinty and Verstraete, 1992
GNDVI	$(\text{NIR} - \text{G}) / (\text{NIR} + \text{G})$	For chlorophyll estimation; NDVI uses the Green instead of Red band	Gitelson et al., 1996
GVM1	$([\text{NIR} + 0.1] - [\text{SWIR}2 + 0.02]) / ([\text{NIR} + 0.1] + [\text{SWIR}2 + 0.02])$	For vegetation water content	Ceccato et al. (2002)
IPVI	$\text{NIR} / (\text{NIR} + \text{R})$	For vegetation biomass	Crippen, 1990
MSR	$([\text{NIR} / \text{R}] - 1) / \text{sqrt}([\text{NIR} / \text{R}] + 1)$	For biophysical parameters	Chen, 1996
MTVI2	$(1.5 * [1.2 * (\text{NIR} - \text{G})] - [2.5 * (\text{R} - \text{G})]) / \text{sqrt}([(2 * \text{NIR}) + 1]^2 - [6 * \text{NIR} - (5 * \text{sqrt}(\text{R})) - 0.5])$	For green leaf area index (LAI) estimation	Haboudane et al., 2004
NDSVI	$(\text{SWIR}1 - \text{R}) / (\text{SWIR}1 + \text{R})$	For senescence detection	Qi et al., 2002
NDWI	$(\text{NIR} - \text{SWIR}1) / (\text{NIR} + \text{SWIR}1)$	For vegetation liquid water content; similar formula to Land Surface Water Index (LSWI)	Gao, 1996; Xiao et al., 2004
NLI	$(\text{NIR}^2 - \text{R}) / (\text{NIR}^2 + \text{R})$	For vegetation cover; accounts for leaf angle distribution	Goel and Quin, 1994
NMDI	$(\text{NIR} - [\text{SWIR}1 - \text{SWIR}2]) / (\text{NIR} + [\text{SWIR}1 - \text{SWIR}2])$	For soil and vegetation moisture	Wang and Qu, 2007
NRI	$(\text{G} - \text{R}) / (\text{G} + \text{R})$	For plant nitrogen status	Filella et al., 1995
OSAVI	$(\text{NIR} - \text{R}) / (\text{NIR} + \text{R} + 0.16)$	For vegetation health; minimizes soil effect; standardized vegetation condition of 0.16	Rondeaux et al., 1996
SAVI	$(1 + \text{L}) * ([\text{NIR} - \text{R}] / [\text{NIR} + \text{R} + \text{L}])$ Vegetation: Low (L = 1) Intermediate (L = 0.5) High (L = 0.25)	For vegetation health; minimizes soil effect	Huete, 1988
SIPI	$(\text{NIR} - \text{B}) / (\text{NIR} + \text{B})$	For vegetation phenology (bulk carotenoids to chlorophyll ratio)	Penuelas et al., 2011
SLAVI	$\text{NIR} / (\text{R} + \text{SWIR}2)$	For specific leaf area	Lymburner et al., 2000
SRVI or SR	NIR / R	For leaf area index	Jordan, 1969
TVI	$\text{sqrt}(\text{NDVI} + 0.5)$	For green leaf area index (LAI) estimation	McDaniel and Haas, 1982
VARI	$(\text{G} - \text{R}) / (\text{G} + \text{R} - \text{B})$	Less sensitive to atmospheric effects; based on ARVI	Gitelson et al., 2002

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SCIENTIFIC PRODUCTIONS

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2. Scientific communications

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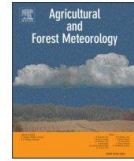
Luna D., Pottier J. and Picon-Cochard C. (2022, May 18). Variability and drivers of grassland sensitivity to drought using satellite reflectance indices [Poster presentation]. 25th Edition of Journées Scientifiques de l'Ecole Doctorale Sciences de la Vie, Santé, Agronomie, Environnement. Clermont-Ferrand, France.

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Variability and drivers of grassland sensitivity to drought at different timescales using satellite image time series

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ABSTRACT

Drought is expected to increase in frequency and severity with climate change, leading to more intense impacts on grasslands and their associated ecosystem services. Complementary to ground experiments, remote sensing technologies allow for the study of drought impacts with large spatio-temporal coverage in real-life-conditions. We aimed to quantify the variability of grassland sensitivity to drought using a long-term satellite image time series of 394 temperate permanent grassland plots to identify factors influencing these sensitivities. Accordingly, we assessed the slope of the linear relationship between satellite-based vegetation status, using the standardized anomalies of the vegetation indices (VIs), and drought severity, using a modified version of the Standardized Precipitation Evapotranspiration Index (SPEI), from 1985 to 2019. The process was repeated for 24 VIs and five SPEI timescales. We then conducted a linear model selection procedure, using the grassland sensitivity derived from the most responsive VIs (i.e., VIs for which anomalies indicated a tighter linear relationship with the modified SPEI), to identify which grassland properties influenced sensitivity to drought. A total of 29 properties, grouped into pedoclimate, agricultural management, and vegetation diversity factors, were derived from ground measurements. Overall, we demonstrated that the influence of predictors on grassland sensitivity to drought varied across the drought integration timescales. Our results highlighted the significant mitigating effect of soil water holding capacity on sensitivity to drought for short timescales of fewer than 30 days. The date of first herbage use by farmers was positively related to grassland sensitivity to drought across all timescales. We also demonstrated that higher vegetation diversity significantly reduced sensitivity to drought. However, for the long timescales of drought integration, such influence was mainly redundant with management (i.e., shared partition of variance) suggesting complex cascading effects between agricultural practices and plant community structure that still need to be addressed comprehensively in future studies.

1. Introduction

Meteorological droughts – in other words, deficits in the climatic water balance – of varying severity, frequency, and duration affect several components of agroecosystems, with serious consequences for

agricultural production and environmental health (Howden et al., 2007). Similar to other agroecosystems, managed grasslands are influenced by drought impacts. The increasing frequency and severity of drought threaten the multiple ecosystem services – provision, regulation, and cultural – provided by grasslands and their associated

Abbreviations: ARVI, atmospherically resistant vegetation index; C:N, carbon to nitrogen ratio; CWM, community weighted mean; DIVGRASS, plant functional DIversity of GRASSlands; DVI, difference vegetation index; EVI, enhanced vegetation index; EVI2, enhanced vegetation index 2; Fdis, functional dispersion; GCI, green chlorophyll index; GEMI, global environment monitoring index; GNDVI, green normalized difference vegetation index; GVMI, global vegetation moisture index; IPVI, infrared percentage vegetation index; K₂O, potassium oxide; MgO, magnesium oxide; MSR, modified simple ratio; MTVI2, modified triangular vegetation index 2; NDSVI, normalized difference senescence vegetation index; NDVI, normalized difference vegetation index; NDWI, normalized difference water index; NIR, near infrared; NLI, non-linear index; NMDI, normalized multi-band drought index; NRI, nitrogen reflectance index; OSAVI, optimized soil-adjusted vegetation index; P₂O₅, phosphorus pentoxide; RS, remote sensing; SAFRAN, *Système d'Analyse Fournissant des Renseignements Adaptés à la Nivologie*; SAVI, soil-adjusted vegetation index; SIPI, structure insensitive pigment index; SLA, specific leaf area; SLAVI, specific leaf area vegetation index; SOC, soil organic carbon; SON, soil organic nitrogen; SPEI, standardized precipitation evapotranspiration index; SRVI, simple ratio vegetation index; SWHC, soil water holding capacity; SWIR, shortwave infrared; TVI, transformational vegetation index; TWI, terrain wetness index; VARI, visible atmospherically resistant index; VI, vegetation index.

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biodiversity (Bengtsson et al., 2019; Chang et al., 2021; Hofer et al., 2016; Zwicke et al., 2013). Grasslands contribute significantly to milk and meat production (O'Mara, 2012) and provide an estimated one billion jobs around the world (Buisson et al., 2022). In addition to provisioning services, grasslands securely store an estimated 30.6% of terrestrial carbon below ground in the roots and soil (Bai and Cotrufo, 2022; Lei et al., 2016) and host a large number of species, some of which are endangered (Dengler et al., 2014). Unfortunately, extreme drought events are well recognized to be detrimental to grassland biodiversity and ecosystem function (Newbold et al., 2016; Strömberg and Staver, 2022). One of the most evident consequences is the reduction of net ecosystem productivity, which reduces agricultural production but also converts grasslands from sinks to sources of carbon (Ciais et al., 2005; Lei et al., 2016; Nagy et al., 2007; Zhang et al., 2020).

Knowledge of grassland sensitivity to drought and its determinants has emerged from field experiments and, more recently, from Earth surface observations. Field observations and semi-controlled experiments have provided, thus far, the most comprehensive insights regarding grassland properties that either promote or suppress vegetation sensitivity to drought. The most obvious properties, or drivers, are related to pedoclimatic conditions. Higher sensitivity to drought has been found in grasslands that are topographically exposed to solar radiation (Yang et al., 2020), situated at low elevations (Catorci et al., 2021; Gharun et al., 2020), and found on soils with low water retention capacity (Buttler et al., 2019). Additionally, grassland management practices, which refer to the modalities of fertilizer application and herbage usage by mowing and/or grazing, have been tested partially and sometimes have revealed mixed effects. High fertilizer addition can either increase sensitivity to drought (Bharath et al., 2020; Klaus et al., 2016; Rose et al., 2012) or have no effect (Vogel et al., 2012; Weisser et al., 2017). More frequent mowing events have been related to stronger negative effects of drought (Vogel et al., 2012; Weisser et al., 2017; Zwicke et al., 2013), and grazing has been associated with greater sensitivity to drought than mowing (Deléglise et al., 2015). Finally, experimental studies have further highlighted the mixed influences of grassland diversity. Higher taxonomic or functional diversity has often been associated with lower sensitivity to drought (Grange et al., 2021; Griffin-Nolan et al., 2019; Isbell et al., 2015; Kreyling et al., 2017), but some studies have indicated an opposite effect of species richness (Vogel et al., 2012; Weisser et al., 2017) or the absence of effect (de Boeck et al., 2018). According to these findings from drought experiments conducted in managed grasslands, the properties influencing vegetation sensitivity to water deficit can be categorized into pedoclimatic, management, and biodiversity drivers.

Despite their incontestable scientific value, the results provided by semi-controlled experiments conducted at the field level reveal some limitations. These experiments are, in essence, restricted in their design (e.g., limited combinations of rainfall regimes, levels of diversity, type of soils, etc.) and geographic coverage. These limitations hinder the analysis of complex combinations of potential drivers that prevail in real-life conditions (Fraser et al., 2013; Matos et al., 2020) and prevent the generalization of the results to all biogeographic contexts on Earth. In addition, those experiments usually report limited temporal coverage of grassland responses to drought over one or few successive growing seasons (Hoover and Rogers, 2016). Although coordinated and long-term observations and experiments (Fraser et al., 2013; Knapp et al., 2017a, 2017b; Lemoine et al., 2016) push those limitations, spatially and temporally wider analyses of existent grasslands are needed.

The rapid development of Earth observation techniques tremendously increases both spatial and temporal coverage of agroecosystem monitoring (Ali et al., 2016; Anderson, 2018; Arun Kumar et al., 2021; Reinermann et al., 2020). Therefore, recent studies have assessed the response of natural ecosystems and agricultural lands to drought severity using satellite images at a wide range of spatial scales (Jiao et al., 2019; Maurer et al., 2020; Vicente-Serrano, 2007;

Vicente-Serrano et al., 2013). Such assessment is based either on the quantification of the relationship between the local satellite reflectance and climatic variables (Cabello et al., 2012; Graw et al., 2017; Nanzad et al., 2019), or it is based on the satellite product anomalies and the measured standardized drought indices (e.g., Li et al. 2015, 2022, Ye et al. 2020). Consequently, these relationships depict the sensitivity of vegetated surfaces to drought events (Vicente-Serrano et al., 2013). Afterward, remotely sensed sensitivity can be related to geographic variations of a set of environmental parameters, considered to be the hypothetical drivers of vegetation response to drought.

Remote sensing (RS) analyses of drought effects on vegetated surfaces are based on various methodological choices. Regarding drought estimates, studies frequently used the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI). From here, the standardized precipitation indices can be used to determine drought severity at different timescales (Vicente-Serrano et al., 2010; Nanzad et al., 2019), but seldom considered in studies (Almeida-Nauñay et al., 2022; An et al., 2020; Dong et al., 2019; Zhao et al., 2018). Research that considered multiple drought timescales has identified grassland and cultivated vegetation response to drought to be best correlated at a timescale of one to three months (e.g., Almeida-Nauñay et al. 2022, An et al. 2020, Zhao et al. 2018). However, these studies used monthly meteorological data. Finer climate data resolution, such as weekly or daily, is needed to reveal more accurate impacts of meteorological variations on vegetation property changes (Salehnia et al., 2018; Wang et al., 2015). Regarding RS-based vegetation condition estimates, studies generally used Normalized Difference Vegetation Index (NDVI) or the Enhanced Vegetation Index (EVI), or their derivatives, such as the Vegetation Condition Index (VCI), and the Vegetation Health Index (VHI; Graw et al., 2017; Kogan et al., 2004; Picoli et al., 2019; Vicente-Serrano, 2007). Aside from these greenness-based satellite proxies, indices related to the hydric status of vegetation, such as the Normalized Difference Water Index (NDWI) or Land Surface Water Index (LSWI), have emerged in other studies (Bajgain et al., 2015; Picoli et al., 2019). However, vegetation indices (VI), such as the NDVI, are used to represent multiple vegetation properties and do not always perform well in the assessment of drought when implemented in other ecoregions (Bajgain et al., 2015; Ebrahimi et al., 2010; Maurer et al., 2020). These discrepancies in methodological choices between studies limit the generalization of the published results and their comparison.

Thus far, the RS studies have attempted to identify the drivers of vegetation sensitivity to drought through a focus on specific categories of drivers, namely, the abiotic environment, land management, and vegetation properties, usually in isolation. Some of these categories have been understudied in grasslands. The investigated drivers are in topographic factors for forests and shrublands (Cartwright et al., 2020), and soil properties, such as the soil water holding capacity for different land covers (Ji and Peters 2003; Thoma et al., 2019). Some studies further considered the influence of land use (Burrell et al., 2020; Munson et al., 2016; Tollerud et al., 2020) and, in the case of grasslands, the type of agricultural management (Burrell et al., 2020; Catorci et al., 2021; Graw et al., 2017; Wagle et al., 2019). A final group of studies has highlighted the importance of vegetation cover (De Keersmaecker et al., 2015) and vegetation diversity (De Keersmaecker et al., 2016; van Rooijen et al., 2015) through the lens of taxonomic diversity rather than functional diversity. These studies have contributed to a better understanding of why some types of vegetation are more sensitive to drought than others, although the influence of abiotic factors in grassland deserves more attention. However, an important gap of knowledge remains in the assessment of the relative influences of these different drivers – classified as pedoclimatic, agricultural management, and biodiversity factors – at the same time.

In this study, we pursued two main objectives. First, we aimed to quantify the sensitivity of managed grassland to drought at various timescales using satellite-based VI anomalies that were best related to

irregularities of climatic water balance (i.e., SPEI). This was conducted over a 34-year period for a vast geographic region predominantly covered by typical Western European grasslands managed for cattle and sheep breeding. Second, we aimed to assess the relative influence of pedoclimate, agricultural management practices, and vegetation diversity factors on grassland sensitivity to drought. To do so, RS-based assessments of sensitivity to drought were analysed against 29 grassland descriptors measured at the ground level for the 394 vegetation plots of the study area.

2. Material and methods

2.1. Study area

The Massif central is a mountainous region ranging from 300 to 1885 metres above sea level in France. It exhibits four climatic zones: mountainous and semi-continental in the major center areas, with influences of oceanic climate in both the northern and western parts, and of Mediterranean climate near the southeastern part (Joly et al., 2010). The mean annual cumulative precipitation, between 1985 and 2019, was 1067 millimetres (mm) with a standard deviation of 348 mm, while the mean annual temperature was 9.3 °C with a standard deviation of 1.96 °C. The 85,000 square kilometres (km²) region is covered mostly by managed perennial grasslands representing 60% of agricultural areas, which comprise one-third of the French permanent grasslands.

Our analyses included a total of 143 grassland parcels. These parcels were homogenous areas of management with heterogeneous vegetation, topography, and soil characteristics. An average of three vegetation plots were distributed within each grassland parcel (minimum of one and maximum of 10 plots). The subsequent analyses, therefore, were based on the 394 vegetation plots distributed among the 143 parcels (Fig. 1). These plots have an average area of 25 square metres (m²) and range from 2 to 100 m². The sampling design aimed to represent the main types of grassland vegetation within the Massif central region (Galliot et al., 2020; Hulin et al., 2012, 2019; Le Hénaff et al., 2021).

2.2. Data

We collected satellite images and meteorological data from 1985 to 2019 for each of the 394 vegetation plots to quantify the temporal changes in vegetation reflectance and drought severity, respectively. We further characterized the pedoclimate, agricultural management practices, and vegetation diversity of these plots from ground observations collected by several projects implemented in the region during the period of interest.

2.2.1. Drought estimates over the 1985–2019 period

We built the time series of the local climatic water balance, computed as the difference between precipitation and potential evapotranspiration (P-PET), during the 1985–2019 period. To do so, we used

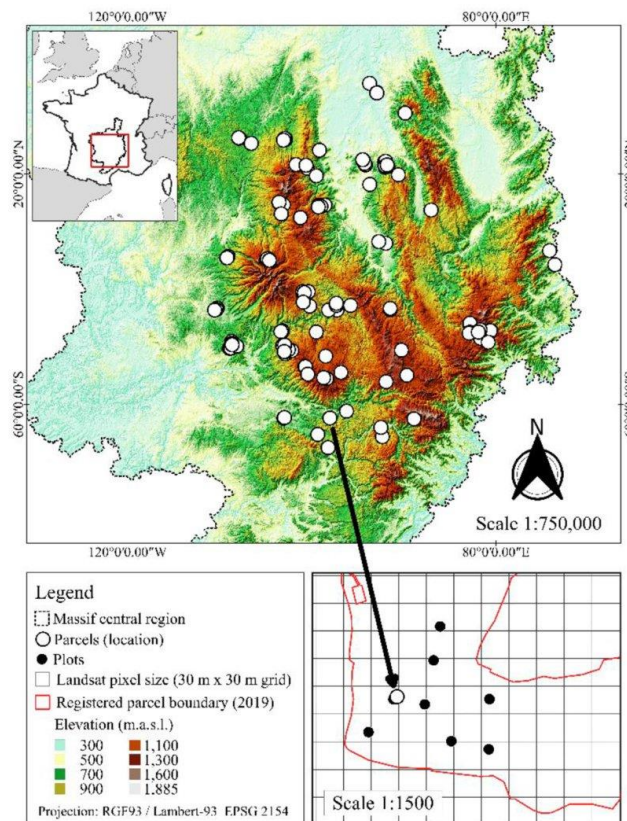


Fig. 1. Distribution of the grassland parcels and vegetation plots in the Massif central region (France). The main map depicts the topographic elevation and relief from a 25 m x 25 m digital elevation model of the Copernicus Land Monitoring Service (<http://land.copernicus.eu/pan-european/satellite-derived-products/eu-dem/eu-dem-v1.1/view>). The lower right inset map presents the vegetation plots found with a parcel, together with the Landsat 30 m x 30 m pixel grid.

the meteorological records from the *Système d'Analyse Fournissant des Renseignements Adaptés à la Nivologie* (SAFRAN) data for France (Durand et al., 1993). SAFRAN provides daily information on a set of meteorological parameters in NetCDF or as raster with a spatial resolution of 8 km x 8 km. We checked the local uncertainty of the SAFRAN estimates with spatially accurate daily records from a set of 140 local meteorological stations within the Massif central region (Météo-France, 2021). Our comparisons revealed tight linear relationships between the two data sources, validating the use of SAFRAN for assessing local variations of the climatic water balance in the study area (Appendix A).

Modified standardized precipitation evapotranspiration index (SPEI). We then quantified the drought severity with a modified version of SPEI. The original version of this index is based on the long-term time series of the climatic water balance (D), which is the difference between the monthly precipitation (P) and potential evapotranspiration (PET) measurements integrated over a given timescale of one, three, six, nine, 12 and 24 months (Beguería et al., 2014; Pei et al., 2020; Vicente-Serrano et al., 2010; Zargar et al., 2011). For example, a seasonal or three-month drought timescale is the integration of D_i at a given month and the two preceding months.

$$D_i = P_i - PET_i \tag{1}$$

where $i = \text{month}$

To compare the surplus and deficit of the water balance between different sites with different climates or dates, the aggregated D_i values are standardized. To do so, the D time series is fitted into a log-logistic distribution using a three-parameter probability distribution function. The probability distribution of D is standardized to obtain the SPEI using the approximation of Abramowitz and Stegun (1965). The statistical distribution seeks to define the normal expectation. Negative SPEI values indicate a deficit of the water balance with respect to normal conditions, while positive values indicate a surplus of precipitation. Since the SPEI is multi-scalar, we could analyse the effect of different types of droughts (Vicente-Serrano et al., 2010) and discriminate between short and frequent water deficits (shortest timescales) and long and infrequent water deficits (longest timescales).

To address our objectives, we modified the classic SPEI in two ways. First, changes in grassland growth and conditions due to drought and precipitation occur at daily temporal scales (Salehnia et al., 2018; Wang et al., 2015). Consequently, the impacts of short-duration droughts (i.e., fewer than 30 days) will not be properly estimated by the monthly

classic SPEI, especially when such brief drought events are distributed between two consecutive months. Accordingly, we used daily climate data and integrated for a given day the difference between P and PET over the 15, 30, 60, 90, or 120 preceding days. Second, the small number of D observations can lead to a weak goodness-of-fit in the probability distribution step. In climate studies, the World Meteorological Organization (WMO) recommended a 30-year period of climatic data when establishing climatic normal (Marchi et al., 2020; Rigal et al., 2019). However, the climatic water balance across the years rarely exhibits a good and smooth distribution. Thus, instances with the classic SPEI may result in abrupt changes between months or large differences with two adjacent months. For the modification, encouragement was found from Russo et al. (2014) by defining a new set of data, A_d , in the following:

$$A_d = \bigcup_{y=1985}^{2019} \bigcup_{i=d-15}^{d+15} D_{y,i} \tag{2}$$

with d , a given day, and $D_{y,i}$, the water balance of day i in year y . This new set of data A (Eq. (2)) exhibits an increase in the number of observations, which helps improve the goodness-of-fit of the log-logistic distribution used for the standardization procedure of the SPEI.

We demonstrate in Fig. 2 the differences between the classic and modified SPEI using the 2003 and 2018 drought years in Europe (Buras et al., 2020). Both SPEIs were expressed in a one-month or 30-day timescale, and both were based on a 34-year climatic water balance time series within our study site. In relation to the concerns expressed in the previous section, we first revealed a more detailed trajectory of drought severity along the dates of the modified SPEI. By shifting from the use of monthly to daily climatic water balance data, the modified SPEI captured the minor drying and wetting events. Consequently, better transitions between the months were prominent in the modified SPEI as compared to the classic SPEI.

2.2.2. Standardized anomalies of vegetation reflectance over the 1985–2019 period

Similar to the estimation of drought severity with a modified version of the SPEI, we computed the standardized anomalies of local vegetation reflectance indices. We first extracted the reflectance bands of Landsat 4, 5, 7, and 8 over the period of 1985–2019 for each of the 394 vegetation plots from Google Earth Engine (Gorelick et al., 2017) using the *reticulate* package in R (Ushey et al., 2022). Landsat images offer a sufficiently fine spatial resolution (30 m x 30 m) to account for vegetation heterogeneity – in other words, they discriminate between different

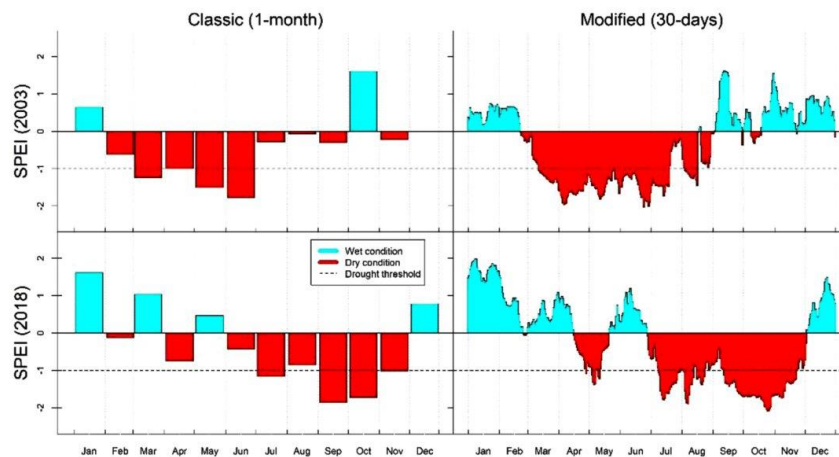


Fig. 2. Comparison of the classic (left) and modified (right) SPEI using the 2003 (top) and 2018 (bottom) drought years in Europe.

vegetation plots within the same parcel, as depicted in Fig. 1), and temporal resolution (16 days) to monitor vegetation reflectance changes over the course of a growing season. These extractions resulted in a mean number of 519 cloud- and snow-free images per vegetation plot.

We then computed the standardized reflectance anomalies of all 24 VIs (Appendix B) related to vegetation properties, such as greenness, cover, moisture-content, and senescence (Bajgain et al., 2015; Davidson et al., 2006; Wu, 2014). Here, we adapted the same standardization procedure of our modified SPEI to quantify the deviation of VIs of a given clear day – in other words, free of clouds or snow cover – to the statistical distribution of VIs of the same day plus the 15 days before and after over the period of 1985–2019. This standardization allowed the spatio-temporal comparisons among plots.

2.2.3. Local properties of the grasslands

The local descriptions of the 394 vegetation plots were inherited from several past projects that collected information on management activities, botanical composition, soil properties, and topographic conditions between 2008 and 2019 (Galliot et al., 2020; Hulin et al., 2019).

Pedoclimate. At the parcel level, the soil properties were assessed with a total of 11 physical and chemical parameters. We considered direct soil measures such as the pH; carbon to nitrogen ratio; concentration of phosphorus, potassium, and magnesium; soil organic carbon; and soil organic nitrogen. We further derived variables that are well-recognized to influence the response of vegetation to meteorological drought. First, we computed the soil water holding capacity (SWHC) from the measured percentage of clay, percentage of sand, and bulk density using a pedotransfer function developed and validated for French soils (Román Dobarco et al., 2019). Second, we derived the aspect (expressed as 0 to 180° from north to south, respectively), elevation (in metres above sea level), and the Terrain Wetness Index (TWI; Beven and Kirkby, 1979; Böhner and Selige, 2006) of the vegetation plots from the 25 m x 25 m spatial resolution digital elevation model from the Copernicus Land Monitoring Service (2016).

Agricultural management. Management information was collected in two phases; the first was in 2008–2009, then in 2016–2017. This information included the amount of nitrogen (N) fertilization, specific dates of use, and type of use. We assumed from field experience and some farmer interviews that these agricultural practices had seen minimal changes over the past 30 years, especially the use of herbage, and, therefore, may be representative of grassland management for the entire period of 1985–2019. We then summarized these data to obtain: (i) the total amount of nitrogen fertilization from the applied organic and inorganic nitrogen, expressed in kg ha^{-1} ; (ii) the average number of uses per year based on the number of grazing rotations and harvesting dates; (iii) the prominent type of use, computed as the difference between the total number of grazing and mowing events for a two-year period, with positive values indicating the predominance of grazing, negative values the predominance of mowing, and zero equal numbers of grazing and mowing events; and (iv) the date of first use expressed in cumulative growing degree days. This was computed as the sum of the growing degree days of the date of first grazing or mowing event recorded for two years of monitoring and then averaged. Expressing the date of first use in thermal time instead of Julian days allowed the comparison between vegetation plots distributed along a large elevation gradient (Perrotte et al., 2019), and minimize the effect of between-year variability of meteorological conditions. Indeed, the farmers manage their parcels according to the grass growth which may lead to variation in calendar dates of management events between years but not in cumulative growing degree days, or at least to a lesser extent.

Vegetation diversity. Botanical surveys were conducted at the level of vegetation plots, in which all species were identified, and their local

abundances were estimated visually. From these *relevés* (surveys), we first derived taxonomic diversity indices: species richness, the Shannon diversity index, and Simpson's diversity index. Then, we used a trait database compiled for 1300 plant species of open habitats of the Massif central (Baseflor in Julve, 1998; DIVGRASS in Carboni et al., 2016; Choler et al., 2014), together with the plot botanical records, to assess local functional indices. We considered plant traits associated with growth syndromes (specific leaf area [SLA] and plant height), phenology (first flowering and length of flowering periods in months), and reproductive ability (seed mass). We computed the community weighted mean (CWM) of each trait, which is recognized to be associated with ecosystem functions (Garnier et al., 2004; Grime, 1998) and grassland response to drought (Pérez-Ramos et al., 2012). We further assessed the functional diversity, which has been linked to the ecosystem stability (Hallett et al., 2017), of each vegetation plot. We used the functional dispersion index (Nunes et al., 2017) of each trait, plus a two-dimensional functional space composed of plant height and SLA to summarize plant growth syndromes.

2.3. Statistical analyses

The simplified workflow indicating the various analytical stages needed to quantify grassland sensitivity to drought and to identify its drivers is presented in Fig. 3. It includes variable inputs and the variable selection procedure in the candidate statistical models.

2.3.1. Computing remotely sensed grassland sensitivity to drought

Some studies have used statistical inference methods to relate grassland response with climatic variables (De Keersmaecker et al., 2016; Nanzad et al., 2019; Thoma et al., 2019) or drought severity (Jiao et al., 2019, 2021; Li et al., 2015, 2022; Maurer et al., 2020). Similar to these studies, we assessed the grassland sensitivity to drought as the slope of the linear relationship between the standardized VI anomalies and the modified SPEI (Li et al., 2022). As depicted in Fig. 4, in the case of vegetation insensitive to drought, we expect this slope to be not significantly different from zero and positive in the case of sensitive vegetation to drought. This was done for each of the 394 vegetation plots using time series data in the period 1985–2019 (Appendix C). The slopes per plot were estimated with a mean number of 519 paired values of the standardized VI anomalies and the modified SPEI falling within the growing season from March to November.

The process described above was repeated for the 24 VIs across the five drought timescales, specifically, for 15, 30, 60, 90, and 120 days. We then assessed how the various VIs and drought timescales affected the estimated sensitivities to drought. To do so, we performed a two-way ANOVA with VIs and timescales as factors. The variance of the residuals, therefore, indicates the fluctuation among plots amid the variation due to methodological choices.

The slope of the linear relationship between the standardized VI anomaly and the modified SPEI, used as an estimate of grassland sensitivity to drought, was assigned as the dependent variable in the subsequent analyses that sought to identify the drivers of grassland response to drought.

2.3.2. Statistical modeling of grassland sensitivity to drought

We conducted a linear model selection procedure to quantify the influence of pedoclimatic characteristics, agricultural management, and vegetation diversity on the sensitivity to drought of the 394 vegetation plots. We assigned the grassland sensitivity to drought – in other words, the slope of the linear relationship between the standardized VI anomaly and the modified SPEI – as the response variable and the pedoclimate, management, and diversity factors as the explanatory variables (Fig. 3). We compiled a total of 29 candidate variables (Table 1), all of which were pre-selected based on their biological meaning and possible effect on grassland response to drought, as described in the local properties section (2.2.3). To avoid possible multicollinearity, we first computed

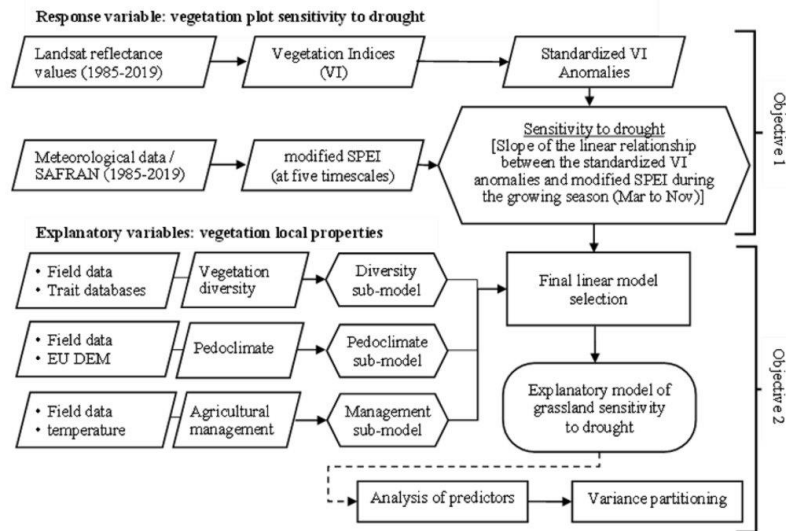


Fig. 3. Simplified workflow for assessing grassland sensitivity and its drivers. Grassland sensitivity to drought, from Objective 1, was used as the response variable for Objective 2. The selected diversity, pedoclimate, and management factors from the respective sub-models served as the explanatory variables.

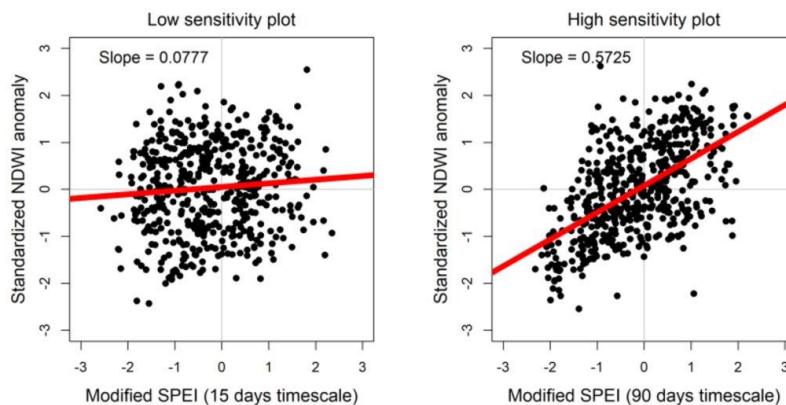


Fig. 4. Low and high grassland sensitivities to drought for two selected timescales of different sample plots. (The threshold for low sensitivity or insensitivity is 0.1.).

pairs correlation between the 29 variables. For pairs with a Pearson correlation greater than 0.5, which is more conservative than the recommended 0.7 threshold (Graham, 2003), we removed the variable with the less tangible biological meaning. Then, we conducted a two-stage selection procedure to seek the most explanatory model of vegetation plot sensitivity to drought. The first stage entailed selecting sub-models for each of the three categories of explanatory variables, where vegetation plot sensitivities were also used as the response variable. In doing so, we optimized the inclusion of the best predictors in the final model with similar weight between each category. The second stage consisted of selecting the final linear model with all categories of the previously selected predictors. For both stages, we performed backward and forward stepwise selection based on the Akaike Information Criterion (AIC), which aims to maximize the goodness-of-fit of the final model and minimize its complexity (Venables and Ripley, 2002). Such a procedure may lead to competing models, with similar complexity and close explanatory power but a different combination of

predictors. These models have differences in AIC of less than 4 (Burnham and Anderson, 2004). Among these models, we selected the ones with the greatest power of prediction to detect all significant drivers. To compare the effect size of various predictors, we computed the beta coefficients from the selected models. Finally, we partitioned the variance explained by pedoclimate, management, and vegetation diversity factors by partial regressions of the final model. The partitions explained by the explanatory categories were assessed with the unbiased adjusted R^2 (Peres-Neto et al., 2006).

Note that these analyses were repeated for the most responsive VI-derived sensitivities and at five different timescales of the modified SPEI. Since these analyses were conducted in the linear regression framework, we visually checked for homogeneity of variances and normality of the residuals (Appendix D).

Lastly, all analyses were performed within the R environment (R Core Team, 2021).

Table 1
List of the 29 grassland local properties used to predict grassland sensitivity to drought of the vegetation plots distributed in the Massif central region, France.

Type	Variable	Unit	Definition	Level of measurement
Pedoclimate	SWHC	cm ³ cm ⁻³	Total water amount that the soil can store for plant use, computed using a pedotransfer function	Parcel*
	C:N	–	Ratio of carbon and nitrogen contents in the soil	Parcel*
	K ₂ O	% of fine dry soil	Soil potassium content available for plants	Parcel*
	MgO	% of fine dry soil	Soil magnesium content available for plants	Parcel*
	P ₂ O ₅	% of fine dry soil	Soil phosphorus content available for plants	Parcel*
	pH	–	Acidity or alkalinity of the soil	Parcel*
	SON	%	Nitrogen content available in the soil organic matter	Parcel**
	SOC	%	Carbon content available in the soil organic matter	Parcel*
	TWI	–	Topographic wetness index, this was extracted using the SAGA TWI algorithm in QGIS	Plot**
		North- or south- facing slopes (or aspect)	degree	Azimuth direction of land surface exposure
Agricultural management	Altitude	m.a.s.l.	Vertical distance from the Earth's surface to a point of interest	Plot**
	Date of first use	degree	Actual date of first defoliation or harvest; variable expressed in cumulative growing degree days	Parcel***
	Type of use	count	Number of uses as either more grazing (+), more mowing (-), or equal number (zero)	Parcel****
Vegetation diversity	Mean number of uses	count	Mean of the total number of mowing and grazing dates	Parcel****
	Nitrogen fertilization	g.ha ⁻¹	Total organic and inorganic nitrogen applied in the field	Parcel****
	CWM length of flowering	month	Community weighted mean of flowering period duration	Plot****
	CWM first flowering	month	Community weighted mean of start of flowering period	Plot****
	CWM seed mass	mg	Community weighted mean of seed mass	Plot****
	CWM plant height	m	Community weighted mean of plant height	Plot****
	CWM SLA	m ² .kg ⁻¹	Community weighted mean of specific leaf area	Plot****
	Fdis length of flowering	–	Functional dispersion of flowering period duration	Plot****
	Fdis first flowering	–	Functional dispersion of start of flowering duration	Plot****
	Fdis seed mass	–	Functional dispersion of seed mass	Plot****
	Fdis plant height	–	Functional dispersion of plant height	Plot****
	Fdis SLA	–	Functional dispersion of specific leaf area	Plot****
	Fdis growth	–	Functional dispersion of growth syndromes	Plot****
	Species richness	–	Number of individual species in a community	Plot****
	Simpson's diversity index	–	Taxonomic measure relative to abundance within a community	Plot****
		Shannon diversity index	–	Taxonomic measure of diversity within a community

Data sources are either from.

* field measurements

** European Union Digital Elevation Model

*** farmer interview

**** botanic relevés and trait database

3. Results

3.1. Variations of grassland sensitivity to drought

The estimated grassland sensitivity to drought differed according to multiple sources of variation, which could be decomposed between (i) the influence of the VI being used to assess vegetation reflectance anomalies, (ii) the timescale of computation of the modified SPEI, and (iii) the variability between vegetation plots, in other words, geographic variability. A two-way ANOVA revealed a significant effect of the VI being used (F [24, 49,224] = 2643, *p* < 0.001) with a sum of squares of 589.46 and a significant effect of the timescale (F [1, 49,224] = 4358, *p* < 0.001) with a sum of square of 40.5. The sum of squares of the residuals, corresponding to the geographic variation between vegetation plots, was 454.4. From this analysis we can conclude that the VI being used was the most important source of variation of the estimated sensitivities to drought in our study, closely followed by geographic variability, while the timescale was a far less important source of variation.

Among the 24 VIs used to quantify grassland sensitivity to drought, the Normalized Difference Water Index (NDWI) and the Global Vegetation Moisture Index (GVMI) exhibited the highest slopes and goodness-of-fit between the standardized VI anomalies and the modified SPEI (Fig. 5). This indicates that both VIs were the best to reveal vegetation response to variation in the climatic water balance. The slope values between the NDWI and the GVMI were highly correlated (*r* = 0.98) and

ranged between -0.1 and 0.58. However, values between -0.1 and 0.1 were not significantly different from 0. Therefore, slopes below or equal to 0.1 are interpreted as insensitivity to drought. Slope values above 0.1 indicate that negative values of the modified SPEI – in other words, climatic water balance lower than the normal expectation – are associated with negative NDWI or GVMI anomalies – in other words, the NDWI or the GVMI lower than the normal expectation. Therefore, positive slopes above 0.1 are interpreted as a negative response (i.e., sensitivity) of vegetation to drought (Fig. 4). Despite the high responsiveness of the anomalies of these two moisture-based indices with the modified SPEI, their maximum R² values were 0.35.

The vegetation sensitivity to drought, as estimated with the NDWI or the GVMI, varied somewhat between the timescales of calculation of the modified SPEI (Fig. 6). The mean sensitivity increased from 15 to 60 days, and then slightly decreased for 90 and 120 days. Then, the geographic variation of sensitivity to drought (i.e., between vegetation plots) was similar between all timescales with a standard deviation ranging from +/- 0.07 to 0.093.

3.2. Drivers of grassland sensitivity to drought

The best models depicting the effect of the pedoclimatic factors, management, and vegetation diversity on grassland sensitivity to drought estimated either with the NDWI or the GVMI were very close (Appendix E). The obtained R² for the NDWI and the GVMI ranged from

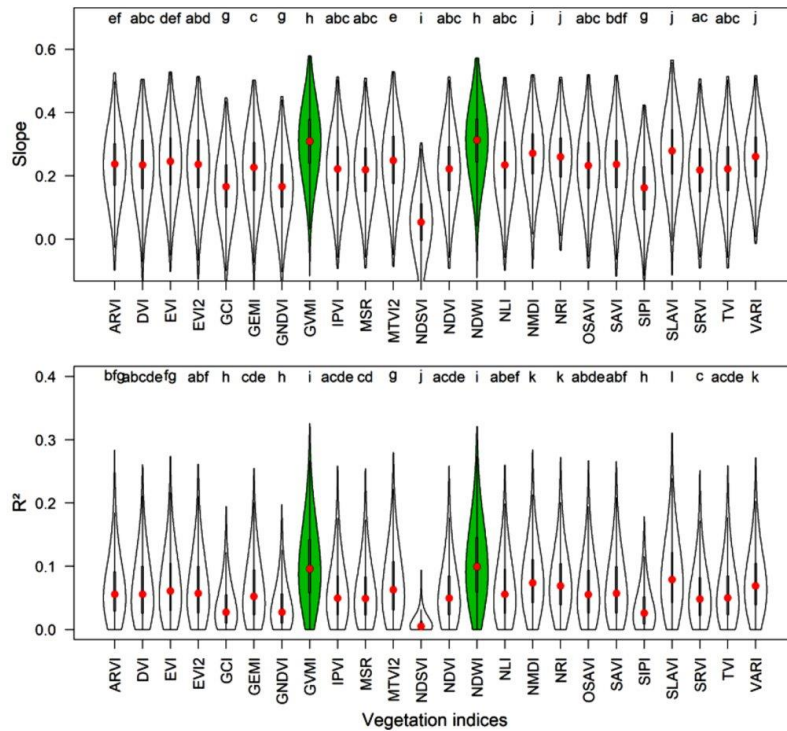


Fig. 5. Comparison of grassland sensitivity to drought estimated from a number of satellite-based VIs. The variability represented by the violin plots includes the fluctuation among the 394 vegetation plots and the five drought timescales. The descriptions of the VIs are available in Appendix B. Grouping labels at the top of the graphs are Tukey test results.

0.35 to 0.62 and 0.37 to 0.59, respectively, depending on the timescale of calculation of the modified SPEI. For both indices, the highest R^2 values were obtained from the short timescales of 30 and 15 days, while R^2 values below 0.5 were obtained for the timescale > 60 days.

Hereinafter, we present the averaged model beta coefficients and averaged variance partitions between the two selected indices in Figs. 7 and 8, respectively. Overall, we found different sets of selected explanatory variables and explanatory powers depending on the timescale of calculation of the modified SPEI.

We distinguished among three groups of predictors based on the beta coefficients across the five timescales. The first group included four variables with similar effects, whatever the timescale considered. The date of first use by farmers had a strong (beta coefficient >0.35) positive effect on grassland sensitivity to drought, with delayed use in the growing season associated with high sensitivity to drought. The type of use – dominance of mowing or grazing – had a moderate and positive effect ($0.10 < \text{beta coefficient} < 0.35$), except for the 15 days timescale. This must be interpreted as a greater sensitivity to drought in grazed than in mown grasslands. The nitrogen fertilization had a moderate but negative or mitigating effect ($-0.35 < \text{beta coefficient} < -0.10$) on sensitivity except for the 120 days timescale. It also exhibited a slightly more negative beta coefficient for the 15 days timescale.

The second group included predictors with a clearly stronger effect at short timescales of 15 and 30 days. The most important in terms of effect size was the SWHC, which exhibited the strongest mitigating effect on grassland sensitivity to drought (-0.58 and -0.56). South-facing slopes, a radiation exposure parameter, had a moderate positive effect (0.26 and 0.19), while the CWM seed mass had a moderate but negative effect (-0.17 and -0.14) for the short timescales. Finally, the soil content of

MgO had a moderate positive effect (0.25) for the shortest timescale of 15 days and a weak effect (below 0.1) for other timescales.

The third group involved five predictors with higher effects for long timescales. However, these predictors had an overall weak (beta coefficient <|0.10|) to moderate effect on grassland sensitivity. Four of them were descriptors of vegetation diversity. In order of importance, the functional dispersion of growth syndromes (Fdis (growth)), had an increasing but moderate negative effect ($-0.35 < \text{beta coefficient} < -0.10$) on sensitivity as the timescale increased. The CWM SLA had constant weak and negative effects from the 60 to 120 days timescales. The CWM plant height also had a weak negative effect (-0.09) but only for the 120 days timescale, and the Shannon diversity index had a weak positive effect (0.08) for the 90 and 120 days timescales. The fifth predictor of this group was the TWI with a weak (-0.07) and moderate (-0.14) negative effect on grassland sensitivity for 60 and 120 days timescales, respectively. Finally, the soil pH revealed an opposite weak effect for long timescales.

The highlighted variations in effect size with timescale of the calculation of the SPEI translated into changes in the partitions of variance explained by the pedoclimate, management, and diversity of vegetation plots (Fig. 8; Appendix F). The pure partition of the pedoclimate was the most important for the short timescales of 15 and 30 days with 32.59% and 38.02%, respectively. These led to the higher explanatory power of the final models with 57.57% and 68.69% of the variation of sensitivity to drought explained at the 15 and 30 days timescales, respectively, compared with the 36.06%, 22.21%, and 38.22% explained total variances at the timescales of 60, 90, and 120 days. Other pure partitions did not change noticeably across the five timescales. The pure management effect explained approximately 15%

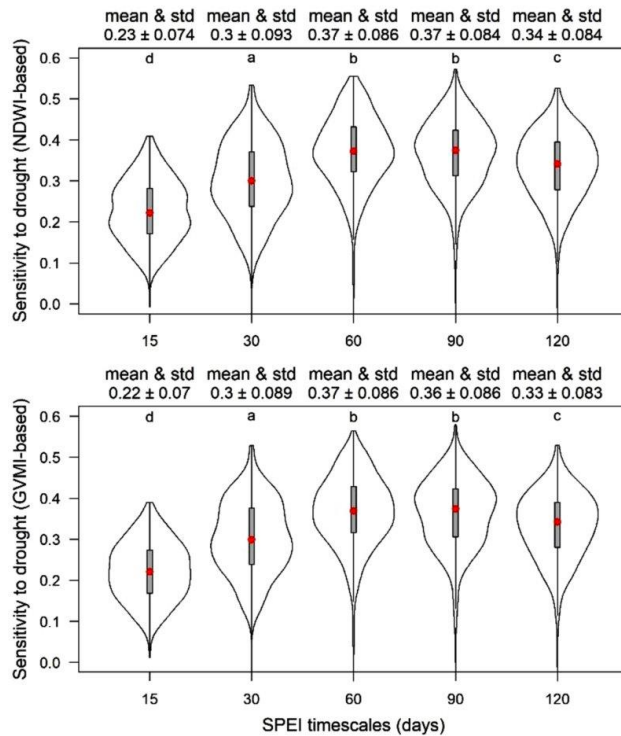


Fig. 6. Variability of grassland sensitivity to drought, as estimated from the linear relationship between the standardized reflectance anomaly, using the NDWI (top) and the GVMI (bottom), and standardized meteorological water balance index (modified SPEI), compared among the different drought timescales. Variability was measured with the standard deviation (std) among the vegetation plots ($n = 394$) per timescale computation. Grouping labels at the top of the graphs are Tukey test results.

of the total variance for all timescales. Then the partitions associated with diversity effects summed between 10% and 20% over the timescales but were largely shared with the management effect.

4. Discussion

Using long-term satellite image time series and meteorological data, we demonstrated the significant variability of grassland sensitivity to drought over a vast geographic region dominated by open habitats maintained for cattle and sheep grazing. We further quantified the influence of a set of factors related to the pedoclimatic, agricultural management, and vegetation diversity on the assessed vegetation responses. We found that their relative effect and explanatory power varied with the duration and frequency of drought events.

4.1. Quantifying geographic variations of grassland sensitivity to drought

We improved the current satellite-based methods of quantification of vegetation response to drought in two ways. First, we demonstrated, based on the comparison of 24 VIs, that indices accounting for SWIR bands (shortwave infrared bands between 1.57 and 1.65 nanometres (nm) for SWIR1 and between 2.11 and 2.29 nm for SWIR2) outperformed other indices for detecting the effects of meteorological drought on vegetated surfaces. Indeed, indices such as the NDWI and the GVMI were specifically developed for remote sensing of vegetation water content (Ceccato et al., 2002; Gao 1996) and have an immediate response to moisture changes, while greenness indices – specifically, NDVI – exhibit lagged effects (Liu et al., 2017; Tong et al., 2017) and are not directly related to the hydric status of vegetation, especially during moderate drought intensity (Bajgain et al., 2015; Chandrasekar et al., 2010; Gu et al., 2007). Although many studies have proved the

usefulness of greenness indices such as NDVI (Catorci et al., 2021; De Keersmaecker et al., 2016; Ji and Peters, 2003; Nanzad et al., 2019) or EVI (Cabello et al., 2012; Cartwright et al., 2020; Munson et al., 2016; Zhou et al., 2019), these were outperformed by moisture-based indices in this study. Second, we highlighted the importance of the timescale of calculation of standardized drought severity indices such as the SPEI. The estimated sensitivities differed significantly between timescales ranging from 15 to 120 days. Generally, previous studies have considered only one timescale (Horion et al., 2019; Hossain and Li, 2021; Lu et al., 2021; Ma et al., 2016; Maurer et al., 2020). Other studies that scrutinized multiple timescales considered much coarser ones, than we did, with monthly meteorological data (Almeida-Naunay et al., 2022; Li et al., 2015; Liu et al., 2017; Xu et al., 2021).

Despite recent developments, satellite-based assessments of vegetation response to drought may still suffer from a few limitations. First, the relationships between VI anomalies and the modified SPEI were noisy overall. Indeed, anomalies of grassland reflectance may arise from multiple natural phenomena, including pest attacks (e.g., voles increasing bare soil), vegetation diseases, or compositional changes in the vegetation. Anomalies of the climatic water balance index (SPEI) were computed from the SAFRAN data with fine daily temporal resolution but coarse spatial resolution (8 km x 8 km grid). Despite the high correlation with field meteorological stations (Appendix A), our estimates of the modified SPEI still may not fully capture the fine-scale climatic variations, especially in mountainous regions. Second, our procedure for calculating the long-term normal reflectance of each day and each vegetation plot tolerates the 30-day variation of grazing and mowing events between years. We assumed that management practices were closely similar from 1985 to 2019, however, we cannot guarantee that sporadic changes in management over time have not occurred. Further developments may address this issue in two ways: (i) detection

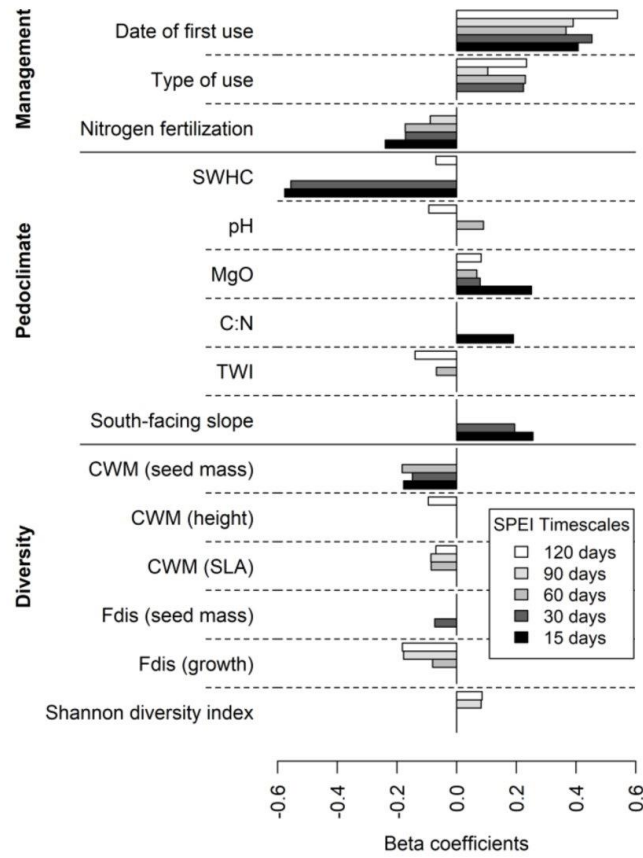


Fig. 7. Beta coefficients of model predictors of grassland sensitivity to drought averaged between the NDWI- and GVMi-based models at different timescales. Negative beta coefficients reduce sensitivity to drought, while positive values increase sensitivity.

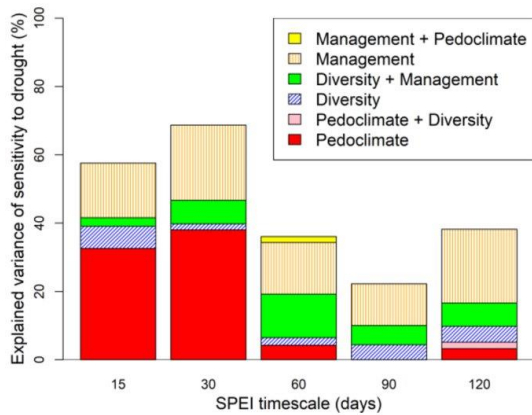


Fig. 8. Variance partitioning of the model predictors of grassland sensitivity to drought. The average NDWI- and GVMi-based model values at different timescales were used. Model predictors were grouped into pedoclimate, management, and diversity categories.

of management events with fine temporal resolution satellite products (e.g., Sentinel 1 and 2; Griffiths et al., 2020; Kolecka et al., 2018; Lobert et al., 2021), despite the fact that the temporal extents of Sentinel images are currently too short – in other words, eight years for Sentinel 1 and seven years for Sentinel 2 – to estimate the normal vegetation reflectance along the growing season, or (ii) precise recording of the daily sequence of practices along the growing season with the help of farmers. Regarding other sources of disturbance, new RS techniques should be developed to better discriminate the spectral signature of drought from other natural or anthropogenic disturbances and stresses (McDowell et al., 2015). Despite these methodological limitations, we argue that our procedure provided at least an unbiased, although noisy, estimate of grassland sensitivity to drought. This allowed us to provide better understanding of its main drivers.

4.2. The strong pedoclimatic influence prevails at short timescales

We revealed the buffering effects of the soil water holding capacity (SWHC; Buttler et al., 2019; Thoma et al., 2019) and topographic exposure to solar radiation (Gharun et al., 2020; Jiao et al., 2021; Yang et al., 2020) on vegetation sensitivity to climatic water balance deficit, as demonstrated by previous studies. Obviously, these were highly expected. However, our findings further indicated that these strong buffering effects hold true only for short and frequent droughts, then completely vanish from the 60 days timescale (Bodner et al., 2015; Finn

et al., 2018). Interestingly, for longer timescales, our results revealed the emerging but moderate role of the TWI. This indicates that large-scale hydrological processes related to land surface topography may relay local pedoclimatic buffers when the water deficit becomes too long, which may have implications for the management of agricultural drains. Indeed, such land preparation either hampers or promotes horizontal movements of water in soils. Depending on the topographic context, the removal of an existing drain or the installation of new ones may thus help mitigate the impact of drought on grasslands.

The influence of soil chemical properties also prevailed for the short timescale. High values of MgO and C:N ratio increased sensitivity to drought, especially for the 15-day timescale, but the MgO influence was still significant for longer timescales. Magnesium limitation is recognized to impede several ecophysiological processes that enhance drought tolerance (Shao et al., 2021; Tränkner and Jaghdani, 2019; Waraich et al., 2011). In this respect our results are contradictory. A first alternative explanation is that the selection of soil magnesium (Mg) concentration in our model does not reflect an effect of this chemical component on vegetation sensitivity to drought but is a consequence of repeated droughts in some of the vegetation plots. Indeed, it has been demonstrated that, under water deficit conditions, Mg accumulates in the soil because of a reduced plant uptake (Sardans et al., 2008). A second alternative explanation is the influence of an unknown factor correlated with soil Mg concentration. The soil C:N ratio response is directly modified by N fertilization (Soussana and Lemaire, 2014), and it is expected to mirror fertilization response to drought sensitivity, but in the opposite way because N is the denominator.

4.3. On the importance of herbage use

The date of first use by farmers was the primary management factor explaining grassland sensitivity to drought for whatever timescale of SPEI considered. This was expressed in thermal time (cumulative growing degree days). Doing so, the date of first use better reflects grassland phenology than calendar dates and allows comparisons among plots located at different altitudes while it minimizes the influence of between-year variation of meteorological conditions. Our results indicated that late agricultural uses during the growing season were associated with higher sensitivity to drought. The effect of the date of first use on grassland sensitivity to drought has not been tested in isolation thus far; instead, it is often mixed with cutting frequency (Zwick et al., 2013). We may still interpret our result in light of the timing of herbage use and the occurrence of droughts during the growing season. The timing of drought occurrence has already been highlighted to play a key role in drought impacts on grasslands (Denton et al., 2017; Edwards and Chapman, 2011; Hahn et al., 2021). Although droughts do not have identical occurrences between years, they often occur in late spring and summer in the Massif central. Thus, late uses are more likely to coincide with strong water deficits. However, it is well recognized that defoliation combined with water stress depletes carbohydrate reserves on which plant regrowth and stress tolerance depend (Kahmen et al., 2005; Volaire et al., 1994) and lessens the maintenance of above-ground productivity (Ma et al., 2020). Additionally, the influence of the date of use of farmers may also arise indirectly from its effect on plant community structure, as we discuss in the next section.

We further found strong evidence of greater sensitivity of vegetation to drought in preferentially grazed paddocks than in preferentially mown ones. It should be noted that usually mown grasslands may be grazed early in spring or during the autumn regrowth. Our results confirm previous findings from grassland experiments (Deléglise et al., 2015). The role of repeated defoliation by grazers along the course of the growing season, compared to sudden cuts, tends to maintain grassland vegetation in the vegetative phase (Bloor et al., 2020; Lei et al., 2016). As a result, plants allocate fixed carbon to leaf regrowth at the expense of carbohydrate storage and root growth necessary to ensure soil water and nutrient uptake, which can reduce their tolerance to drought (Amiard

et al., 2003; Frank, 2007; Xu et al., 2013). Nevertheless, further research is needed to determine whether grazing pressure has additive or combined effects on the drought response of grasslands (Ruppert et al., 2015).

4.4. The joint influence of vegetation diversity and agricultural management

Overall, vegetation diversity explained a substantial part of the variance of grassland sensitivity to drought. Several descriptors had weak to moderate individual effects, but once they were summed together, they had substantial effects, especially for longer timescales. Such effects were largely shared with agricultural management. In this respect, we interpret the role of vegetation diversity on grassland sensitivity to drought together with the effect of N fertilization and the date of first use.

Our results suggest a complex cascade of effects involving the influence of N fertilization on vegetation diversity and the influence of vegetation diversity on drought tolerance. We found that the Shannon diversity index increased grassland sensitivity to drought, whereas functional diversity and N fertilization had the opposite effect. Regarding taxonomic diversity and N fertilization, our findings seem to contradict those of several grassland experiments (Kübert et al., 2019; Bharath et al., 2020; Meng et al., 2021). However, N fertilization is also recognized to reduce taxonomic diversity (Humbert et al., 2016; Louault et al., 2017; Niu et al., 2014; Socher et al., 2013) but, at the same time, increase functional diversity of growth syndromes and the CWM SLA (Louault et al., 2017; Niu et al., 2014). Nevertheless, greater functional diversity of growth syndromes may result in greater asynchrony of species responses to drought, which has been related to better grassland resilience (Loreau and de Mazancourt, 2013; Muraina et al., 2021). The role of functional diversity has even been suggested to be more important than the potential effect of taxonomic diversity on grassland stability (Valencia et al., 2020). Therefore, the positive effect of the Shannon diversity index that emerged from our results may be interpreted as a spurious effect. We must warn that this conclusion should be taken with caution for management recommendations. Indeed, the effect of N fertilization in other contexts or at much higher levels of application may reduce species richness to a greater extent and result in a reduction of grassland functional diversity and, ultimately, an increase in grassland sensitivity to drought.

Beyond the direct influence of the date of first use on sensitivity to drought, as discussed in the preceding section, the greater sensitivity of late-use grasslands may also be mediated by changes in vegetation. However, our results do not allow to infer the underlying causal relationships. Delays in mowing or grazing have been demonstrated to increase taxonomic diversity when postponed from early to late spring or summer (Humbert et al., 2012). However, taxonomic diversity had only a weak effect in our study and, thus far, the consequences of delaying mowing or grazing on functional diversity remains unknown. Otherwise, delayed mowing or grazing may favor species with late phenology and reduce light use efficiency (Gaujour et al., 2012), which may result in a lower CWM SLA. This is consistent with our finding that lower drought sensitivity was associated with high SLA. However, SLA reduction usually works as a phenotypic adjustment to water stress (Wellstein et al., 2017), which contradicts our results.

Finally, we found that plant communities with heavier seeds were associated with lesser sensitivity to drought. This has already been reported in semi-arid grasslands (Martínez-López et al., 2020) dominated by annual species. Indeed, in stressful conditions, the post-drought establishment and survival of seedlings are more successful for large seeds that contain more reserves. Regeneration in permanent grasslands is mostly clonal and, in normal conditions, depends more on buds than seeds (Benson and Hartnett, 2006). However, in a long-term drought experiment conducted in mountainous grasslands dominated by perennials, Stampfli and Zeiter (2004) found that post-drought vegetation

dynamics were driven largely by recruitment from seeds. We were unable to clearly discriminate how the CWM seed mass was influenced by agricultural practices. Our result highlights the need to conduct new studies on drought mitigation through agricultural management, with an explicit focus on how different practices influence the composition and diversity of the regeneration syndromes of grassland species.

5. Conclusions

Our study revealed high variability of satellite-based vegetation sensitivity to drought, at different timescales, across a wide geographic region dominated by permanent grasslands maintained for cattle and sheep breeding, using moisture-based reflectance indices retrieved from Landsat images. Through the indices, vegetation was most responsive to drought for the 60 and 90 days timescales. We demonstrated that variations of satellite-based sensitivity to drought within and between grassland parcels can be explained by pedoclimatic, agricultural management, and vegetation diversity factors. We underlined that the soil water holding capacity (SWHC) worked logically as a strong buffer for meteorological droughts but only for the shortest time scales of fewer than 30 days. Additionally, agricultural management had also a strong influence, either independent or largely shared with vegetation diversity. This suggests complex indirect effects involving changes in functional composition and diversity of the grassland plant communities. Accordingly, such complexity may be disentangled by future experimental studies focusing on the ecological consequences of the timing of herbage use, tests of interactions between several management practices and analyses of multivariate causal relationships. Finally, better RS-based assessment of vegetation sensitivity to drought is required to discriminate between drought events and other types of disturbances, whether natural or agricultural.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The primary data used in this study can be requested from the AEOLE consortium at sidam@aura.chambagri.fr.

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Appendices



Appendix A. Precipitation, potential evapotranspiration, and mean temperature correlation between the SAFRAN and field meteorological stations within the Massif central region

Climatic variables	R ²	Slope	Intercept
Precipitation (P)	0.80	0.84	0.25 mm
Potential evapotranspiration (PET)	0.88	0.90	0.24 mm
Mean temperature	0.96	0.90	-1.33 °C

Appendix B. Satellite reflectance indices used in the study. Input bands were the blue (B), green (G), red (R), near infrared (NIR), and shortwave infrared (SWIR) 1 and 2

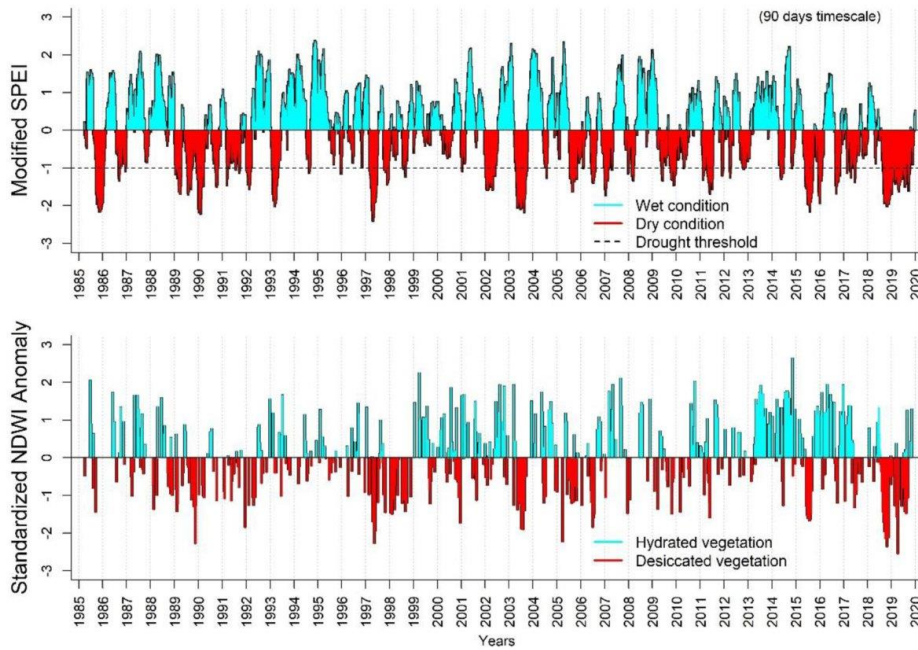
Index	Formula	Purpose / Description	Refs.
NDVI	$(NIR - R) / (NIR + R)$	Commonly used for vegetation biomass (green)	Rouse et al. (1974)
ARVI	$(NIR - [(2 * R) - B]) / (NIR + [(2 * R) - B])$	Less sensitive to atmospheric effects compared to NDVI	Kaufman and Tanré (1992)
DVI	$NIR - R$	Differentiates vegetation and soil.	Richardson and Wiegand (1977)
EVI	$2.5 * [(NIR - R) / (NIR + 6 * R - 7.5 * B + 1)]$	For canopy condition in high biomass areas	Huete et al. (2002)
EVI2	$2.5 * [(NIR - R) / (NIR + (2.4 * R) + 1)]$	EVI without the blue band	Jiang et al. (2008)
GCI	$(NIR / G) - 1$	For chlorophyll estimation	Gitelson et al. (2003)
GEMI	$n * (1 - 0.25 * n) - [(R - 0.125) / (1 - R)]$ where, $n = [2 * (NIR^2 - R^2) + (1.5 * NIR) + (0.5 * R)] / (NIR + R + 0.5)$	For vegetation cover; non-linear index	Pinty and Verstraete (1992)

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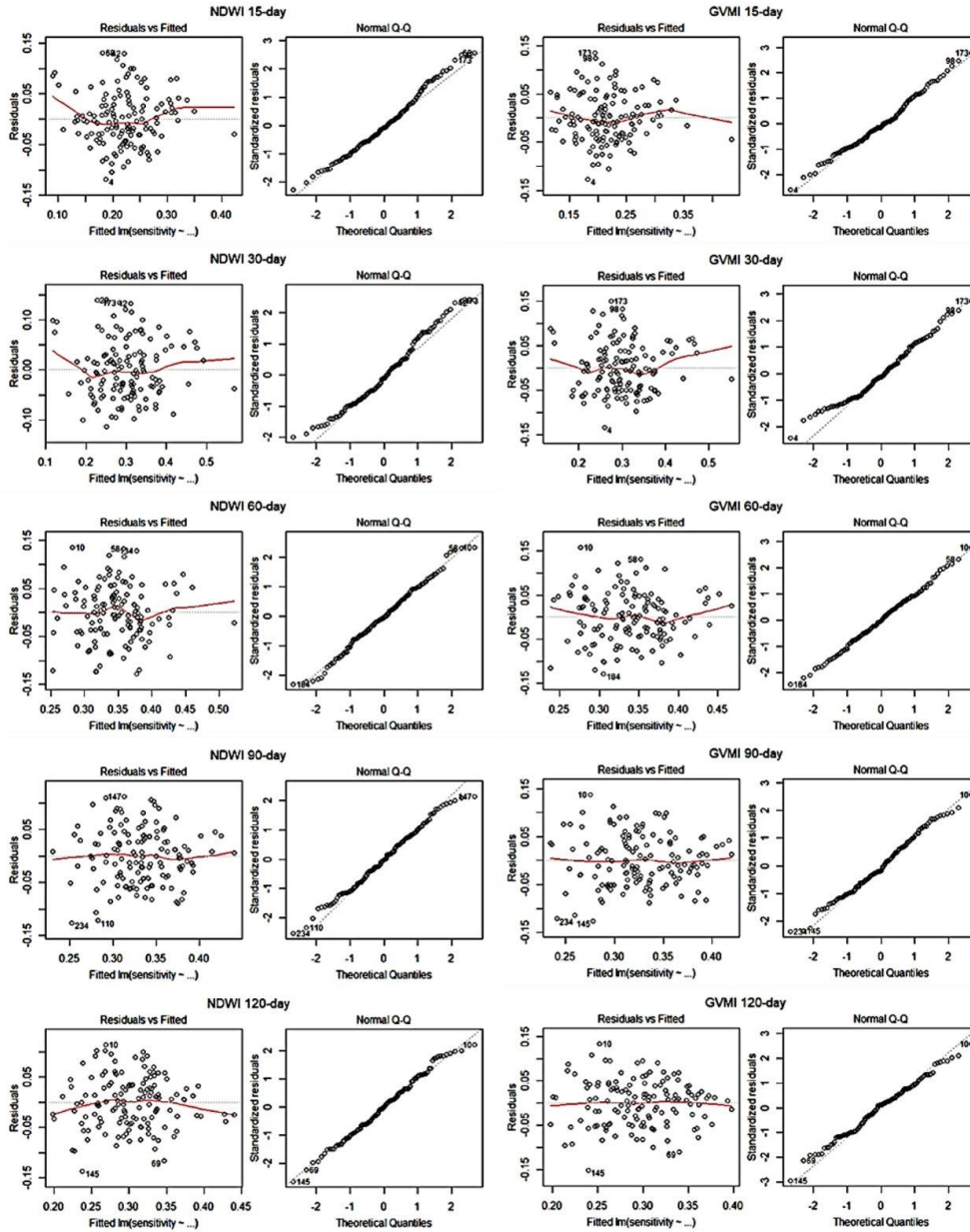
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Index	Formula	Purpose / Description	Refs.
GNDVI	$(NIR - G) / (NIR + G)$	For chlorophyll estimation; NDVI using the Green instead of Red band	Gitelson et al. (1996)
GVMI	$([NIR + 0.1] - [SWIR2 + 0.02]) / ([NIR + 0.1] + [SWIR2 + 0.02])$	For vegetation water content	Ceccato et al. (2002)
IPVI	$NIR / (NIR + R)$	For vegetation biomass	Crippen (1990)
MSR	$(NIR / R) - 1 / \sqrt{((NIR / R) + 1)}$	For biophysical parameters	Chen (1996)
MTVI2	$(1.5 * [1.2 * (NIR - G)] - [2.5 * (R - G)]) / \sqrt{((2 * NIR) + 1)^2 - [6 * NIR - (5 * \sqrt{R}) - 0.5]}$	For green leaf area index (LAI) estimation	Haboudane et al. (2004)
NDSVI	$(SWIR1 - R) / (SWIR1 + R)$	For senescence detection	Qi et al. (2002)
NDWI	$(NIR - SWIR1) / (NIR + SWIR1)$	For vegetation liquid water content; similar formula with Land Surface Water Index (LSWI)	Gao (1996), Xiao et al. (2004)
NLI	$(NIR^2 - R) / (NIR^2 + R)$	For vegetation cover; accounts for leaf angle distribution	Goel and Quin (1994)
NMDI	$(NIR - [SWIR1 - SWIR2]) / (NIR + [SWIR1 - SWIR2])$	For soil and vegetation moisture	Wang and Qu (2007)
NRI	$(G - R) / (G + R)$	For plant nitrogen status	Filella et al. (1995)
OSAVI	$(NIR - R) / (NIR + R + 0.16)$	For vegetation health; minimizes soil effect; standardized vegetation condition of 0.16	Rondeaux et al. (1996)
SAVI	$(1 + L) * ((NIR - R) / [NIR + R + L])$ Vegetation: Low ($L = 1$) Intermediate ($L = 0.5$) High ($L = 0.25$)	For vegetation health; minimizes soil effect	Huete (1988)
SIPI	$(NIR - B) / (NIR + B)$	For vegetation phenology (bulk carotenoids to chlorophyll ratio)	Penuelas et al. (2011)
SLAVI	$NIR / (R + SWIR2)$	For specific leaf area	Lymburner et al. (2000)
SRVI or SR	NIR / R	For leaf area index	Jordan (1969)
TVI	$\sqrt{NDVI + 0.5}$	For green leaf area index (LAI) estimation	McDaniel and Haas (1982)
VARI	$(G - R) / (G + R - B)$	Less sensitive to atmospheric effects; based on ARVI	Gitelson et al. (2002)

Appendix C. Time series of drought (top) and vegetation (bottom) conditions from 1985 to 2019 of one sample plot



Appendix D. Plots for the visual tests of the homogeneity of variances and normality of residuals of the final NDWI- and GVMi-based models



Appendix E. NDWI- and GVMi-based model summaries and beta coefficients

Modified SPEI 15 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.4391	5.546	0	0.3758	5.344	0	
Type of use	0.0989	1.05	0.2956	–	–	–	
Nitrogen fertilization	–0.1905	–2.517	0.0131	–0.2872	–3.953	0.0001	
Mean number of uses	0.1063	1.372	0.1725	0.1226	1.538	0.1267	
SWHC	–0.4728	–6.714	0	–0.6793	–7.757	0	
MgO	0.1673	2.188	0.0305	0.3356	4.189	0.0001	
C:N	–	–	–	0.3815	3.859	0.0002	
TWI	–0.0576	–0.84	0.4025	–0.0885	–1.291	0.1993	
South-facing slope	0.2393	3.562	0.0005	0.2729	3.936	0.0001	
CWM (seed mass)	–0.1614	–1.964	0.0518	–0.1932	–2.422	0.0169	
CWM (height)	–0.1173	–1.404	0.1629	–0.1123	–1.367	0.1741	
CWM (SLA)	–	–	–	0.0736	0.934	0.3523	
Fdis (growth)	–0.0782	–1.003	0.3177	–0.1011	–1.296	0.1974	
Shannon diversity index	–0.1253	–1.522	0.1306	–0.0934	–1.126	0.2625	
	R ² :	0.519		R ² :	0.5235		
	Adjusted R ² :	0.4724		Adjusted R ² :	0.4731		
Modified SPEI 30 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.4628	6.446	0	0.4442	5.803	0	
Type of use	0.221	2.648	0.0091	0.2269	2.434	0.0164	
Nitrogen fertilization	–0.1645	–2.285	0.024	–0.177	–2.388	0.0185	
Mean number of uses	0.1109	1.618	0.1083	0.0774	1.072	0.286	
SWHC	–0.5526	–8.839	0	–0.5577	–8.532	0	
pH	0.0562	0.839	0.4032	0.0729	1.031	0.3044	
MgO	0.1144	1.625	0.1067	0.1579	2.174	0.0316	
South-facing slope	0.2006	3.373	0.001	0.188	3.058	0.0027	
CWM (seed mass)	–0.1538	–2.322	0.0219	–0.1426	–2.079	0.0397	
CWM (SLA)	–	–	–	–0.0841	–1.184	0.2387	
Fdis (seed)	–0.1466	–2.49	0.0141	–	–	–	
Fdis (growth)	–0.0893	–1.341	0.1825	–0.0613	–0.906	0.3669	
Shannon diversity index	–0.0488	–0.684	0.4953	–0.0867	–1.168	0.245	
	R ² :	0.62		R ² :	0.5955		
	Adjusted R ² :	0.5833		Adjusted R ² :	0.5563		
Modified SPEI 60 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.3587	3.971	0.0001	0.3748	4.202	0.0001	
Type of use	0.1982	1.773	0.0786	0.2625	2.362	0.0197	
Nitrogen fertilization	–0.1708	–1.894	0.0605	–0.1732	–1.903	0.0593	
pH	0.1435	1.642	0.1031	0.1798	2.141	0.0342	
MgO	0.1363	1.667	0.0979	0.1086	1.301	0.1957	
C:N	–	–	–	–0.1223	–1.422	0.1575	
TWI	–	–	–	–0.1348	–1.821	0.071	
CWM (seed mass)	–0.2145	–2.469	0.0149	–0.1494	–1.834	0.069	
CWM (SLA)	–0.0817	–0.901	0.3694	–0.1698	–1.868	0.0641	
Fdis lengthflow	0.0711	0.79	0.4312	–	–	–	
Fdis (growth)	–0.1606	–1.819	0.0714	–0.0823	–1.005	0.3169	
Shannon diversity index	0.1009	1.128	0.2615	0.0499	0.55	0.5836	
	R ² :	0.3709		R ² :	0.4039		
	Adjusted R ² :	0.321		Adjusted R ² :	0.3514		
Modified SPEI 90 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.394	4.374	0	0.3875	4.311	0	
Type of use	0.1533	1.355	0.178	0.2089	1.927	0.0562	
Nitrogen fertilization	–0.1206	–1.407	0.1618	–0.1759	–1.94	0.0546	
Mean number of uses	–0.0922	–1.016	0.3118	–0.0876	–0.957	0.3405	
pH	–	–	–	0.0768	0.884	0.3786	
MgO	0.1078	1.263	0.2089	0.1064	1.244	0.2159	
TWI	–	–	–	–0.119	–1.549	0.124	
CWM (seed mass)	–0.0992	–1.058	0.2922	–	–	–	
CWM (height)	–0.1471	–1.547	0.1243	–0.1107	–1.304	0.1946	
CWM (SLA)	–0.1027	–1.204	0.2307	–0.1722	–2.004	0.0472	
Fdis (growth)	–0.2052	–2.353	0.0202	–0.1495	–1.736	0.0851	
Shannon diversity index	0.1652	1.809	0.0729	0.1166	1.25	0.2137	
	R ² :	0.3531		R ² :	0.3755		
	Adjusted R ² :	0.3018		Adjusted R ² :	0.3206		
Modified SPEI 120 days		NDWI			GVMI		
Predictors	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)	
Date of first use	0.5767	6.859	0	0.5008	5.793	0	
Type of use	0.2317	2.272	0.0248	0.2372	2.274	0.0247	

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Modified SPEI 120 days Predictors	NDWI			GVMI		
	Beta coefficient	t value	Pr(> t)	Beta coefficient	t value	Pr(> t)
Nitrogen fertilization	–	–	–	–0.1021	–1.168	0.2449
Mean number of uses	–0.0714	–0.807	0.4213	–0.0796	–0.904	0.3676
SWHC	–0.138	–1.807	0.0731	–	–	–
pH	–0.1856	–2.302	0.023	–0.115	–1.376	0.1712
MgO	0.1643	1.975	0.0505	0.123	1.495	0.1374
TWI	–0.1372	–1.815	0.072	–0.1413	–1.908	0.0587
CWM (seed mass)	–0.0859	–0.966	0.3362	–	–	–
CWM (height)	–0.19	–1.943	0.0543	–0.1135	–1.314	0.1913
CWM (firstflow)	0.0899	1.031	0.3046	–	–	–
Fdis (seed)	–0.0783	–1.058	0.2919	–0.0416	–0.551	0.5828
Fdis (growth)	–0.2099	–2.582	0.011	–0.1531	–1.844	0.0676
Shannon diversity index	0.1714	1.989	0.049	0.113	1.245	0.2154
	R ² :	0.4541		R ² :	0.4285	
	Adjusted R ² :	0.3965		Adjusted R ² :	0.3732	

Appendix F. Variance partitioning of NDWI- and GVMI-based models across timescales

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Assessment of grassland sensitivity to drought in the Massif central region using remote sensing

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Abstract

Drought is a natural phenomenon that is expected to increase in frequency and duration with climate change, leading to more intense disturbance of ecosystems like grasslands. Moreover, the sensitivity of grasslands to drought is expected to differentiate across wide spatial extents. To assess and explain these sensitivity variations, knowledge of several grasslands and local parameters must be considered. Our study focused on 143 permanent grasslands in the Massif Central Region of Metropolitan France. With the use of satellite remote sensing, we quantified the relationship between vegetation index anomalies and a modified version of the Standardized Precipitation-Evapotranspiration Index (mSPEI) to acquire grassland sensitivity values. The anomalies are estimates of the historic long-term fluctuations of grassland vegetation reflectance to climatic water balance from 1985 to 2019. A model selection procedure was implemented to determine whether the derived sensitivities can be attributed to explanatory variables such as vegetation diversity, pedoclimatic conditions, or management practices. Then a variance partitioning of the included explanatory variables was performed. Our results highlight the key influence of available soil available water capacity and time of first use on grassland sensitivity to drought of the selected parcels in the region, but also of plant functional diversity.

Keywords: drought, mSPEI, grassland response, sensitivity, remote sensing, vegetation index

Introduction

The Intergovernmental Panel for Climate Change has projected an overall increasing trend in the global temperature due to climate change, together with more frequent and longer extreme climatic events (IPCC, 2021). Among these events, droughts have large-scale impacts on ecosystems like grasslands. However, the grassland responses or sensitivities to drought are expected to vary across wide spatial extents depending on the grassland's local properties. A better understanding of grassland drought sensitivity, over large extents outside of controlled experiments, may help promote agricultural practices supporting grassland stability. To do so, remote-sensing technologies offer new opportunities for fine-resolution monitoring of grasslands (Reinermann et al., 2020). This study aims to assess the variability of grassland drought sensitivity over the Massif central using remotely sensed vegetation dynamics and highlight key drivers of sensitivity, including pedoclimate, biodiversity, and agricultural management.

Materials and methods

We analysed the drought sensitivity of 394 plots from 143 permanent grassland parcels distributed over the Massif central (AOP field surveys, 2008-2019) using satellite-based remote sensing. To do so, we first mapped the severity of drought events from 1985 to 2019, with a modified version of the Standardized Precipitation-Evapotranspiration Index (mSPEI; Beguería, et al. 2010) computed from the daily climatic data provided by the *Système d'Analyse Fournissant des Renseignements Atmosphériques à la Neige* (SAFRAN) meteorological data of France. Then, we derived standardized vegetation index (VI) anomalies over the same period. These anomalies are values of the departure of

VI from their long-term daily mean. The VI time series were calculated from Landsat images from 1985 to 2019. Finally, we quantified grassland drought sensitivity, during the growing season (March to November), as the regression slope between the standardized VI anomalies and mSPEI (Ji and Peters, 2003). From 25 computed VIs and based on a Principal Component Analysis (PCA), we selected the Normalized Multi-band Drought Index (NMDI), which was developed for monitoring soil and vegetation moisture (Wang and Qu 2007). To better understand the drivers of grassland drought sensitivity, we implemented a statistical model selection procedure with drought sensitivity as the response variable. The explanatory variables, derived from the field surveys and the Copernicus Land Monitoring services' high-resolution digital elevation model, pertain to three categories: 1) management practices, 2) vegetation diversity, denoted by the taxonomic and functional indices plus the community weighted mean of traits related to growth, phenology, and reproduction, and 3) pedoclimatic conditions, depicted by soil physical and chemical properties (including soil available water capacity or AWC), terrain wetness index and aspect. Lastly, we performed a variance partitioning of the model explanatory variables to quantify their relative influences.

Results and Discussion

In our study, we found a large variability of satellite-sensed drought sensitivities of the Massif central grasslands (Figure 1) with a 35.62% coefficient of variation. The model selection procedure led to a final sensitivity model with seven explanatory variables and an R-squared of 0.52 (Table 1). According to the variance partitioning (Figure 2), pedoclimatic factors explained the largest part (35%) of variation. From these factors, AWC had a strong negative effect on drought sensitivity. Expectedly, higher soil water retention capacity mitigates meteorological drought. In contrast, a south-facing slope promoted sensitivity most likely due to higher solar radiation exposure (local underestimation of mSPEI) compared to north-facing slopes. Management factors explained 23% of the total variation. From the model, delayed first uses resulted in higher drought sensitivity. Such factor has been understudied so far, hindering a clear understanding of its effect on grassland drought sensitivity. Grasslands that were preferentially grazed (type of use) showed higher drought sensitivity in contrast to rather mowed grasslands. This is consistent with the field experiment by Deléglise, et al. (2015), where drought conditions in grazing

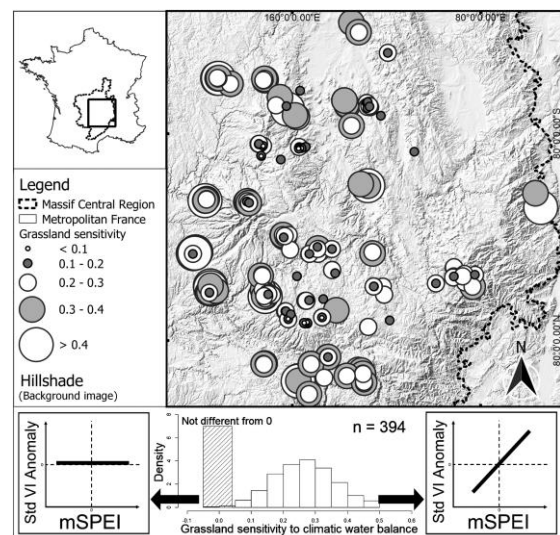


Figure 1. Spatial (top) and statistical (bottom) distributions of drought sensitivities in the Massif central. Sensitivities are the slope of the linear relationship of the standardized (std) VI anomaly and mSPEI.

Table 1. Final sensitivity model (R-squared is 0.5242) and variance partitioning results.

Category	Explanatory variable	Beta coefficient	t value	Pr(> t)
Pedoclimate	AWC (topsoil)	-0.5396292	-8.603	2.27e-14
	South-facing slope (aspect)	0.2355297	3.656	0.000372
Management	Time of first use (as GDD)	0.5163540	7.081	8.23e-11
	Type of use (grazing or mowing)	0.2936155	3.812	0.000213
	Mean number of uses	0.1295399	1.853	0.066173
Diversity	Fdis: plant growth form	-0.1600510	-2.379	0.018819
	CWM: plant height	-0.1416316	-1.978	0.050051

plots led to lower annual biomass than in mowing plots. The mean number of uses per year also increased sensitivity. When grasslands are frequently used throughout the growing season, stored carbohydrates, which are necessary for plant regrowth, may become limited during drought events (Fulkerson and Donaghy, 2001). Our model also underlined the role of diversity (9%), which is mostly shared with the pedoclimatic and management factors. We found that more diverse plant growth strategies promoted lesser drought sensitivity, as already shown in experimental studies (Weisser, et al. 2017). In addition, grassland plots with taller plants, or higher CWM height, exhibited lower drought sensitivity, as confirmed by Nunes, et al. (2017).

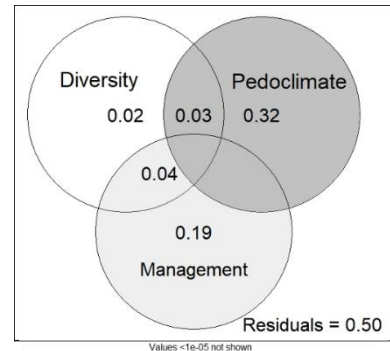


Figure 2. Variance partitioning of the main variable categories (R package: vegan).

Conclusion

Using remote sensing, we assessed drought sensitivities of a wide range of grasslands across the Massif central region. These sensitivities were highly variable, but the majority of these variabilities could be explained by pedoclimatic, diversity, and management factors. AWC had the largest influence. We also underlined the role of diversity shared with pedoclimatic and management on grassland drought sensitivity, which is in line with previous grassland-drought field experiments. We here further assessed the relative importance of these drivers in real agricultural systems.

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Variability and drivers of grassland sensitivity to drought using satellite spectral indices

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Context

Drought is expected to increase in severity and frequency with climate change. This will lead to varying impacts on grasslands within regions and across timescales. Our study aims to (i) quantify the variability of grassland sensitivity to drought, and (ii) identify factors influencing these sensitivities.

Methods

We assessed the sensitivity to drought of 394 permanent grassland plots within the Massif Central (Figure 1). In our workflow (Figure 2), grassland sensitivity was determined as the relationship between the standardized anomalies of the satellite-based vegetation indices (VI) and modified Standardized Precipitation – Evapotranspiration Index (SPEI; Vicente-Serrano, et al. 2010). Then we performed a model selection procedure comprising of the sensitivity to drought of the most responsive standardized VI anomaly, together with the pedoclimate, agricultural management, and vegetation diversity factors. We repeated the model selection across seven timescales. Lastly, variance partitioning of all selected models were conducted to determine the influence per factors types.



Figure 1. Grassland plots within the Massif Central region.

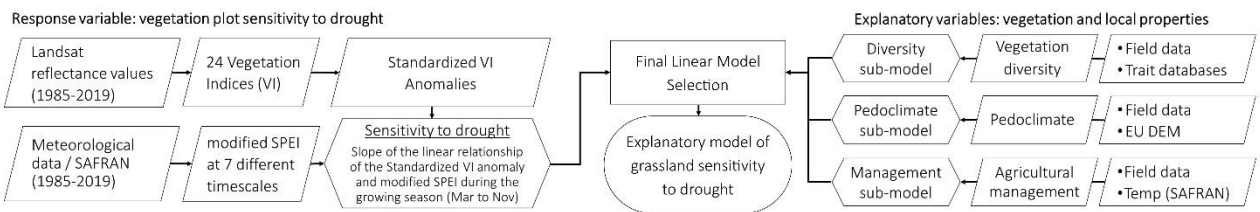


Figure 2. General workflow.

Results

i. Variability of grassland sensitivity to drought

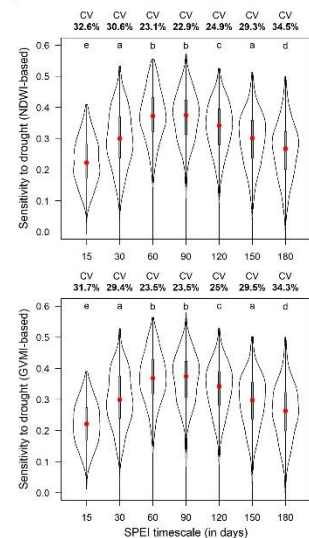


Figure 3. Sensitivity to drought at different timescales based on NDWI and GVMi. Groupings labels at the top of the graphs are Tukey test results.

ii. Drivers of grassland sensitivity to drought *

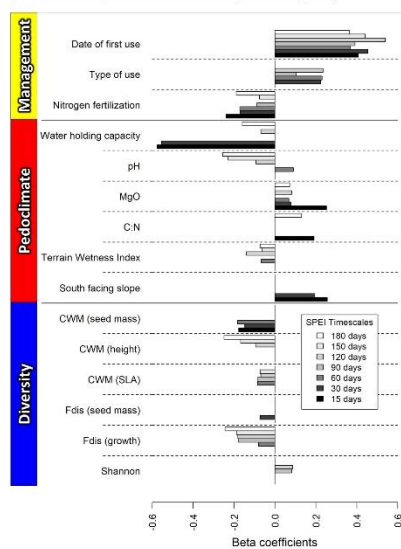


Figure 4. Beta coefficients of model predictors at different timescales. (value > 0 = increases sensitivity; values < 0 = decreases sensitivity)

*Inputs were averaged values of NDWI- and GVMi-based models

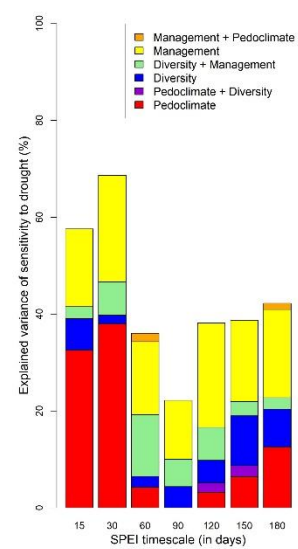


Figure 5. Variance partitioning summary of predictor types.

Conclusions

- Variability of grassland sensitivity to drought is high and ranged from 23 - 34% across all timescales .
- Soil water holding capacity (SWHC) has the highest drought mitigating effect at short timescales (15– and 30-days). Wherein, a high SWHC decreases grassland sensitivity to drought.
- Functional diversity of growth syndromes has an increasing mitigating effect as timescale increases.
- Date of first use by farmers has high positive effect across all timescales. Delayed date of first use increases sensitivity.
- Diversity and management share influence across all timescales, which calls for comprehensive study.
- Drought timescales should be considered when studying drivers of grassland sensitivity to drought.

Reference:

Vicente-Serrano, S. Beguería, S. and López-Moreno, J.I., (2010). A Multiscale Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. Journal of Climate. 23: 1696-1718. 10.1175/2009/CL12909.1.





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Investigating drivers of grassland sensitivity to drought in the Massif Central Region using Remote Sensing

Aims

Drought has a large-scale impact, but grassland sensitivity may not be the same across wide spatial extents. Using (satellite) remote sensing, this study aims to:

- 1- determine variability of permanent grassland sensitivity to drought in the Massif Central Region, and
- 2- scrutinize potential drivers of these sensitivity.



A network of parcels used either for grazing of cows, heifers, sheep, mowing for hay and silage, or both.

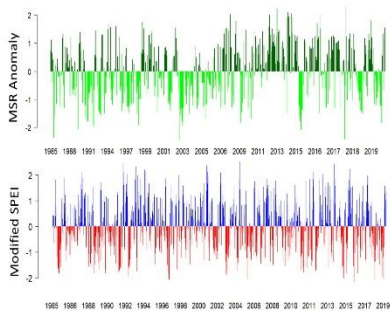
Methods

For assessing the sensitivity of grasslands we investigated the relationship between vegetation reflectance anomalies (Modified Simple Ratio or MSR) and the modified Standardized Precipitation – Evapotranspiration Index (mSPEI).

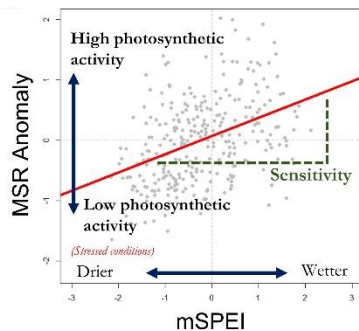
- MSR indicates photosynthetic activity of vegetation cover similar to the Normalized Difference Vegetation Index (NDVI) except that it does not saturate with high vegetation productivity on the ground.
- mSPEI is a standardized drought intensity index based on the balance between evapotranspiration and precipitation. It is a modified version of the classical SPEI (Beguería, et al. 2010) with finer temporal resolution.

For assessing the drivers of vegetation sensitivity to drought, we conducted a model selection procedure including explanatory variables related to vegetation diversity (Shannon, functional richness, functional dispersion, functional dispersion), management (herbage exploitation intensity, N fertilisation), pedoclimate (4 textural variables, organic matter stock and altitude). We further performed a variance partitioning of the selected model.

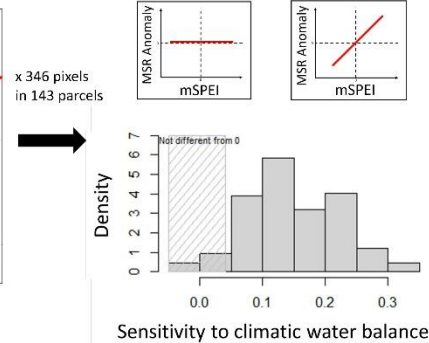
The variability of vegetation sensitivity to climatic water balance



Time-series data of MSR anomaly (observed MSR - long-term MSR mean across the years) and mSPEI. Covering the period from 1985 to 2019, data sources were Landsat 4, 5, 7, and 8, and Système d'Analyse Fournissant des Renseignements Atmosphériques à la Neige (SAFRAN).



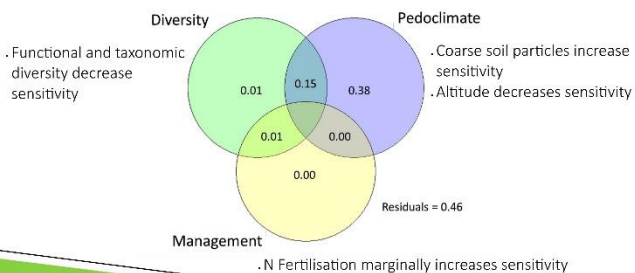
Sensitivity to drought based from the relationship of the MSR anomaly and mSPEI (Thoma, et al. 2018). / Scatterplot was based on one parcel.



Density

Drivers of vegetation sensitivity

Selected model: sensitivity ~ Shannon + Fric + FEve + FDis + NFerti+ SF + LG + A + altitude



Conclusion

- MSR anomalies are sensitive to climatic water balance.
- This sensitivity is highly variable over the Massif Central Region.
- Consistent with expectation, soil particle sizes influence grassland sensitivity.
- Functional diversity together with soil also a non-negligible part of sensitivity
- Management has a weak effect, but this should be nuanced by the inaccurate description of agricultural practices.

Perspective

- Other parameters (e.g., landscape configuration) may improve the analyses of sensitivity.
- A better understanding of management influence requires better descriptions of the fertilization and herbage exploitation.

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Beguería, Santiago, et al. (2010). The Standardized Precipitation - Evapotranspiration Index (SPEI): a multiscalar drought index. 10.1002/2014.0022898.
Thoma, David, et al. (2018). Landscape pivot points and responses to water balance in national parks of the southwest U.S. Journal of Applied Ecology. 56. 10.1111/1365-2664.13250.

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Longitude 3.144245°



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