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Par Ulysse GAUDARÉ

**L'expansion de l'agriculture biologique permettrait-elle
d'atténuer les émissions de gaz à effet de serre d'origine
agricole ? Une approche systémique à l'échelle mondiale**

**Systemic evaluation of the potential of organic farming to mitigate
agricultural greenhouse gas emissions at the global scale.**

Sous la direction de : Thomas Nesme
(co-directeur : Sylvain Pellerin)

Au sein de l'UMR ISPA (Interaction Sol Plante Atmosphère) associant l'INRAE et
Bordeaux Sciences Agro. Financée par l'ADEME et le méta-programme Métabio.

Soutenue le 19 Janvier 2022, devant le jury composé de

Mme CHENU, Claire	Professeure	AgroParisTech (FR)	Rapportrice
M. HALBERG, Niels	Professeur	Aarhus University (DN)	Rapporteur
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Mme DETANG-DESSANDRE, Cécile	Directrice de recherche	INRAE (FR)	Présidente
M. SMITH, Laurence	Professeur associé	Reading University (UK)	Examineur
M. PIERART, Antoine	Docteur	ADEME (FR)	Invité

“I think it's much more interesting to live not knowing than to have answers which might be wrong. I have approximate answers and possible beliefs and different degrees of uncertainty about different things, but I am not absolutely sure of anything and there are many things I don't know anything about, such as whether it means anything to ask why we're here. I don't have to know an answer. I don't feel frightened not knowing things, by being lost in a mysterious universe without any purpose, which is the way it really is as far as I can tell.”

Richard Feynman

Résumé

L'agriculture et les autres usages des terres sont responsables de 23% des émissions anthropiques mondiales de gaz à effet de serre (GES). Pour atteindre les objectifs fixés par l'Accord de Paris, il est nécessaire de réduire les émissions de GES dans tous les secteurs y compris l'agriculture. L'Agriculture Biologique (AB) apparaît comme un modèle agricole prometteur du fait (i) du non recours aux engrais azotés de synthèse – et de la réduction des émissions de N₂O associées – et (ii) de pratiques favorisant le stockage de carbone (C) dans les sols – et donc le retrait de CO₂ atmosphérique. Cependant l'AB est souvent critiquée pour ses rendements plus faibles, engendrant potentiellement des changements d'usage des terres si ce mode de production se développait. Plusieurs études ont estimé que la généralisation de l'AB serait de nature à atténuer les émissions de GES d'origine agricole (de -3 à -40%), mais celles-ci n'ont pas tenu compte des rétroactions systémiques potentielles que le développement de ce mode de production pourrait générer. Ces rétroactions sont principalement le fait d'une plus forte compétition pour les ressources fertilisantes organiques avec une potentielle cascade d'effets menant à (i) une réduction de la disponibilité en azote pour les cultures engendrant une réduction des rendements, (ii) une réduction des entrées de C et des stocks de C dans les sols agricoles et (iii) des changements d'usage des terres liés à un besoin accru de surfaces agricoles. Si l'effet de ces rétroactions sur la production alimentaire mondiale a été étudié dans une récente étude, leurs effets sur les émissions de GES n'ont encore jamais été explorés à l'échelle mondiale. L'objectif de cette dissertation est d'évaluer l'effet d'une généralisation de l'AB – ainsi que des rétroactions systémiques qu'elle engendre – sur les émissions de GES d'origine agricole. Pour répondre à cet objectif, nous avons couplé le modèle GOANIM – modèle simulant la disponibilité en azote et ses conséquences sur la productivité des cultures dans des scénarios de généralisation de l'AB – à trois autres modèles : le modèle N₂O-CH₄ adapté des directives du GIEC pour estimer les émissions de N₂O et CH₄ des activités agricoles, un modèle simulant la dynamique du C dans les sols agricoles (RothC) pour estimer les changements de stocks de carbone organique des sols et un modèle visant à estimer un changement de besoin en terres agricoles en fonction des rendements agricoles et des régimes alimentaires (GlobAgri-AgT) pour estimer le changement d'usage des terres. Les résultats obtenus montrent qu'une généralisation de l'AB verrait les émissions de GES d'origine agricole augmenter de 56% comparées aux émissions actuelles. Cette augmentation nette s'explique par (i) une baisse de 60% des émissions annuelles de N₂O et CH₄ (-3.1 Gt CO₂eq.an⁻¹), (ii) une augmentation des émissions de CO₂ liée au déstockage du carbone des sols agricoles (+2.3 Gt CO₂eq.an⁻¹) et (iii) des émissions de CO₂ induites par des changements d'usage des terres (+3.7 Gt CO₂eq.an⁻¹). De plus, nous avons trouvé une réponse non-linéaire des émissions mondiales de GES en fonction de la part des surfaces agricoles mondiales occupées par l'AB. Ainsi, dans un scénario où l'AB ne couvre que 20% des surfaces agricoles mondiales, les émissions de GES mondiales pourraient être réduites de 70%. Ce résultat suggère l'existence d'un développement optimal de l'AB minimisant les émissions de GES d'origine agricole. Par ailleurs, nos résultats permettent d'identifier des pratiques en AB (comme la généralisation des cultures intermédiaires) qui permettraient d'améliorer les effets de l'AB sur les émissions de GES. L'approche utilisée dans cette dissertation est une base méthodologique qui permettra l'analyse d'autres scénarios incluant une plus grande diversité de pratiques, apportant un éclairage sur les pistes ouvertes aux producteurs et décideurs publics pour réduire les émissions de GES d'origine agricole.

Mots clés: Agriculture Biologique, Agriculture Conventiennelle, Agronomie Globale, Gas à effet de serre, Cycle de l'Azote, Production animales, Usage des terres, Systèmes alimentaire Globales, Modélisation

Abstract

Agriculture and other land uses are responsible of 23% of global anthropogenic greenhouse gas (GHG) emissions. In order to reach the goal set by the Paris Agreement, it is necessary to reduce GHG emissions in all sectors, including agriculture. Organic farming appears to be a promising farming system, due to (i) the non-use of synthetic nitrogen fertilizers – and the associated reduction of N₂O emissions – and (ii) practices that promote soil carbon sequestration – and therefore the removal of atmospheric CO₂. However, organic farming is often criticized for its lower yields, potentially leading to land-use changes if this mode of production was to expand. Several studies have estimated that the expansion of organic farming worldwide would mitigate GHG emissions from agriculture (from -3 to -40%), these studies have not taken into account the numerous systemic feedbacks that the development of this farming system could generate. These feedbacks are mainly due to a stronger competition for organic fertilizing resources with potential effects leading to (i) a reduction of nitrogen availability for crops resulting in yields reduction, (ii) a reduction of C inputs and C stocks in agricultural soils and (iii) land-use changes related to an increased need for agricultural land. While the effect of these feedbacks on global food production has been investigated in a recent study, their effects on GHG emissions have not yet been explored on a global scale. The objective of this dissertation is to assess the effect of a widespread adoption of organic farming – and the systemic feedbacks it generates – on GHG emissions in agriculture. To meet this objective, we combined the GOANIM model – a model that simulates nitrogen availability and its consequences on global crop productivity under scenarios of widespread adoption of organic farming – to three other models: the N₂O-CH₄ model adapted from the IPCC guidelines to estimate N₂O and CH₄ emissions from agricultural activities, a model simulating the C dynamics in agricultural soils (RothC) to estimate changes in soil organic carbon stocks, and a model that estimate changes in agricultural land requirements as a function of agricultural yields and diets (GlobAgri-AgT) to estimate land-use changes. Our results show that a global expansion of organic farming would see agricultural GHG emissions increase by 56% compared to current emissions. This net increase would be explained by (i) a 60% decrease in annual N₂O and CH₄ emissions (-3.1 Gt CO₂eq.yr⁻¹), (ii) an increase in CO₂ emissions related to carbon depletion from agricultural soils (+2.3 Gt CO₂eq.yr⁻¹) and (iii) GHG emissions induced by land-use changes (+3.7 Gt CO₂eq.yr⁻¹). Furthermore, we found a non-linear response of global GHG emissions as a function of the share of global agricultural lands occupied by organic farming. Thus, in a scenario where organic occupies only 20% of the world's agricultural area, global GHG emissions could be reduced by 70%. This result suggests the existence of an optimal development of organic farming minimizing agricultural GHG emissions. Furthermore, our results allow us to identify practices in organic farming (such as systemic use of cover crops) that would improve the effects of organic farming on GHG emissions. The approach used in this dissertation is a methodological basis that will allow the analysis of other scenarios including a greater diversity of practices, shedding light on the possibilities for producers and public decision makers to reduce GHG emissions in agriculture.

Keywords: Organic Farming, Conventional Farming, Global Agronomy, Greenhouse gas, Nitrogen Cycle, Livestock productions, Land uses, Global food system, Modelling

Résumé substantiel

Le XXI^e siècle sera marqué par les problèmes sociaux et environnementaux mondiaux induits par le développement passé et actuel des sociétés industrielles. Les activités humaines modifient le système terrestre, et plusieurs limites environnementales ont déjà été franchies (Rockström et al., 2009). Parmi celles-ci, le changement climatique mondial représente une menace directe pour les sociétés humaines (IPCC, 2021). L'augmentation des concentrations atmosphériques de gaz à effet de serre (GES) – due aux émissions produites par les activités humaines – est le principal facteur du changement climatique mondial observé (IPCC, 2021). Au cours de la période 1750-2019, les concentrations atmosphériques de CO₂, CH₄ et N₂O ont augmenté respectivement de 47, 156 et 23 %.

Dans ce contexte, l'agriculture est à la fois un contributeur important du changement climatique – par ses émissions de GES et ses effets d'altération de l'albédo – et une victime – car la production alimentaire mondiale est menacée par le changement climatique. L'agriculture est responsable de 23% des émissions anthropiques mondiales de GES (IPCC, 2021), avec trois gaz principaux : CO₂ (54% des émissions du secteur agricole, CH₄ (24%) et N₂O (18%). Pour maintenir l'augmentation de la température moyenne mondiale bien en-dessous de 2°C en 2050 – comme défini par l'accord de Paris en 2015 – une forte réduction des émissions de GES de ce secteur est attendue (IPCC, 2018).

L'agriculture biologique est souvent présentée comme une option pour réduire les émissions de GES du secteur agricole à l'échelle mondiale (Muller et al., 2017; Niggli et al., 2009). Les précédents travaux aillant estimé l'effet d'un passage mondial à l'agriculture biologique se sont jusqu'à présent basé sur des méta-analyses basées sur des expérimentations. Ces méta-analyses ont montré que l'agriculture biologique réduisait les émissions de N₂O à l'échelle de la parcelle (Skinner et al., 2014) et augmentait la séquestration du carbone dans le sol à cette même échelle (Gattinger et al., 2012). Toutefois, les rendements plus faibles (Ponisio et al., 2015; Seufert et al., 2012) mettent en péril ce potentiel effet bénéfique de l'agriculture biologique, car ils pourraient entraîner des changements d'usage des terres (déforestation, conversion de prairies en cultures) dans un monde entièrement géré de manière biologique et, par conséquent, engendrer des émissions de GES supplémentaires. En outre, ces méta-analyses caractérisent des situations où l'agriculture biologique occupe une faible part des terres agricoles – moins de 2 % de la surface agricole mondiale (IFOAM, 2020). De récentes études ont montré que l'expansion de l'agriculture biologique à grande échelle engendrerait des rétroactions systémiques modifiant profondément les systèmes de production alimentaire (Barbieri et al., 2021; Smith et al., 2018). Ces modifications se traduiraient par une baisse des rendements des cultures menées en agriculture biologiques et une baisse du nombre d'animaux d'élevage. Un tel effet de l'expansion de l'agriculture biologique sur les systèmes de production alimentaire pourrait avoir d'importants effets sur les émissions de GES dans un monde complètement cultivé en agriculture biologique.

Cette thèse a pour but de discuter du potentiel de l'expansion de l'agriculture biologique à l'échelle mondiale pour réduire les émissions nettes de GES du secteur agricole, en considérant les rétroactions systémiques possible liées à cette expansion de l'agriculture biologique. Ce travail est basé sur (i) une estimation de la production alimentaire mondiale dans des scénarios d'expansion mondiale de l'agriculture biologique – en considérant les rétroactions systémiques – et (ii) une estimation des émissions de GES dans ces scénarios. Les émissions mondiales dans les scénarios d'expansion de l'agriculture biologique seront comparées à un scénario de base représentant les émissions de GES actuelles du secteur agricole. Dans ce scénario de base, nous avons supposé un équilibre entre la

demande et la production alimentaires, se traduisant par l'absence de changement d'affectation des terres. L'agriculture biologique occupant actuellement moins de 2 % des terres agricoles mondiales (IFOAM, 2020), nous avons considéré que les émissions de GES agricoles actuelles constituaient une bonne approximation des émissions de l'agriculture conventionnelle de la planète. Ce travail est basé sur une approche de modélisation couplant un modèle de production alimentaire agricole mondial (GOANIM) – adapté à l'expansion de l'agriculture biologique – et des modèles estimant les émissions de GES de l'agriculture et liées aux changements d'affectation des terres.

GOANIM (Global Organic Agriculture Nitrogen Model) est un modèle biophysique et d'optimisation linéaire spatialement explicite (résolution de 5 minutes d'arc, soit des mailles d'environ 10x10km à l'équateur) qui simule le bilan d'azote des terres cultivées dans des scénarios d'expansion de l'agriculture biologique mondiale – en tenant compte des flux d'azote entre l'atmosphère, les sols des terres cultivées, les sols des prairies, le bétail et l'alimentation humaine (Barbieri et al., 2021). Le bilan azoté des terres cultivées et ses effets sur le rendement des cultures sont estimés pour une série de 61 espèces végétales. Comme il est difficile de transporter les engrais organiques sur de longues distances (Bartelt et Bland, 2007), le modèle GOANIM suppose que les engrais organiques azotés sont produits et appliqués à l'échelle de la maille où ils sont produits. Par conséquent, tous les flux d'azote et le budget d'azote des terres cultivées sont estimés à l'échelle de la maille. De même, afin de respecter la réglementation biologique visant à l'autosuffisance des exploitations d'élevage biologique (Lampkin et al., 2017), les aliments pour animaux sont supposés être produits dans la maille où le bétail est situé et, les populations de bétail dans chaque maille sont limitées par la disponibilité des aliments dans celle-ci. GOANIM vise à maximiser la production alimentaire dans chaque maille (à partir de produits d'origine végétale et animale). Pour ce faire, il maximise la population de chacune des 9 espèces animales considérées afin de (i) minimiser la compétition pour la nourriture entre les animaux et les humains et (ii) maximiser la disponibilité de l'azote dans les terres cultivées par l'application de fumier. Ce module d'optimisation alloue également le fumier aux différentes espèces de plantes cultivées afin de maximiser la quantité de calories produites par unité d'azote organique appliqué.

Dans GOANIM, les différences entre l'agriculture biologique et l'agriculture conventionnelle sur les rotations des cultures et les rendements des cultures ont été incluses dans une première version. Cependant, en raison du manque d'études fournissant des informations sur les différences mondiales entre la productivité et les stratégies d'alimentation du bétail biologique et conventionnel, ces différences n'avaient pas été incluses dans le modèle jusqu'à présent. Pourtant, les animaux d'élevage jouent un rôle clé dans les systèmes d'agriculture biologique en fournissant des éléments nutritifs aux terres cultivées (par la production de fumier) et des aliments à forte densité nutritionnelle pour la consommation humaine (Lampkin et al., 2017; Mottet et al., 2017). Dans le premier chapitre de cette thèse, nous comblons un manque d'informations en proposant une première comparaison globale mettant en évidence les différences entre l'agriculture biologique et l'agriculture conventionnelle en matière de productivité animale, de stratégie d'alimentation et d'efficacité de l'utilisation des aliments chez les bovins laitiers, les porcs et les volailles (poules pondeuses et poulets de chair). Nous avons constaté (i) une productivité animale inférieure de 12 % dans le cadre du traitement biologique, (ii) des différences significatives dans la stratégie d'alimentation, en particulier pour les bovins laitiers biologiques nourris avec une proportion plus faible de concentrés et d'aliments en concurrence avec l'alimentation humaine que dans les systèmes conventionnels, (iii) une efficacité globale de l'utilisation des aliments inférieure de 14 % dans le cadre du traitement biologique (-11 et -47 % pour les bovins laitiers biologiques et les poulets de chair, respectivement) compensée par (iv) une concurrence plus faible de 46 % entre l'alimentation humaine et animale chez les bovins laitiers

biologiques. Ces résultats fournissent des informations essentielles sur la durabilité de la gestion du bétail biologique. Ils sont également essentiels pour modéliser l'expansion de l'agriculture biologique à l'échelle mondiale tout en évitant de surestimer la production de l'agriculture biologique dans les scénarios de transposition à plus grande échelle.

Nous avons ensuite utilisé les estimations de ce chapitre I pour apporter plus de précision à la simulation de la production animale dans GOANIM - en modifiant la composition de la ration alimentaire du bétail et les niveaux de productivité. Outre ces précisions, nous avons également affiné la définition de la production animale du modèle GOANIM en (i) considérant les animaux non productifs dans l'estimation des besoins nutritionnels des animaux et leurs excréments d'azote, (ii) limitant la récolte de fourrage dans les prairies permanentes pour respecter un niveau de pâturage durable (Erb et al., 2016), (iii) en limitant la récolte de fourrage dans les prairies temporaires pour respecter un seuil techniquement réalisable d'extraction de la biomasse (Soussana and Lemaire, 2014) et (iv) en appliquant les nouvelles lignes directrices du GIEC sur la gestion du fumier et les pertes d'azote dans l'environnement (émissions de N_2O et N_2 , lixiviation de l'azote et volatilisation du NH_3). Cette nouvelle version de GOANIM estime une perte de 57 % des rendements agricoles (exprimés en $kcal.ha^{-1}$) ainsi qu'une réduction de 66% de la population animales (exprimée en unité gros bovins). Ces modifications, ont potentiellement un effet important sur les émissions de GES liées aux activités agricoles, sur les stocks de carbone organique du sol et sur les besoins en terres agricoles pour nourrir la planète.

L'augmentation des stocks de carbone organique du sol dans les terres agricoles étant essentielle pour atténuer le changement climatique et l'agriculture biologique est souvent considérée comme une option prometteuse pour y parvenir. Jusqu'à présent, les preuves de stocks de carbone organique du sol plus élevés, dans les fermes biologiques que dans les fermes conventionnelles, reflètent des situations où l'agriculture biologique occupe de petites fractions des terres agricoles mondiale, avec un accès à de grandes quantités de ressources de fertilisation organique - accès qui pourrait être réduit avec l'expansion de l'agriculture biologique (Seufert and Ramankutty, 2017). Dans le second chapitre de cette thèse, nous avons couplé la dernière version de GOANIM (V2) à un modèle estimant la dynamique du carbone organique des sols (RothC, (Coleman et al., 1997; Martin et al., 2007)). À l'aide de cette approche de modélisation, nous avons estimé les changements de stocks mondiaux de carbone organique des sols suite à une conversion complète des terres agricoles (prairies et cultures combinées) mondiales à l'agriculture biologique. Nous avons constaté que (i) les apports mondiaux de carbone aux sols (résidus de culture et effluents d'élevage combinés) seraient réduits de 39 % dans les terres cultivées mais resteraient inchangés dans les prairies, ce qui entraînerait (ii) une réduction de 6, 8 et 10 % des stocks mondiaux de carbone organique des sols agricoles (terres cultivées et prairies confondues) respectivement 20, 50 et 100 ans après cette transition. Ces résultats suggèrent que l'expansion de l'agriculture biologique pourrait réduire son propre potentiel d'atténuation du changement climatique par la séquestration du carbone dans les sols. Cependant, ce potentiel pourrait être maintenu lorsque des pratiques appropriées sont mises en œuvre pour atténuer les limitations en azote et augmenter les apports de carbone dans les sols – telles que l'implémentation de cultures intermédiaires dans les rotations de cultures.

Comme mentionné précédemment, les preuves d'émissions de GES réduites dans les fermes biologiques comparées aux fermes conventionnelles ne tenaient pas compte des changements systémiques profonds qui accompagneraient l'expansion de l'agriculture biologique - comme la concurrence accrue pour les engrais biologiques. À l'aide d'une approche de modélisation couplant la dernière version de GOANIM à trois autres modèles – (i) une adaptation des consignes du GIEC pour

estimer les émissions de N₂O et CH₄ (IPCC, 2019a), (ii) RothC pour estimer les émissions de CO₂ provenant des changements de stocks de carbone organique des sols et (iii) et GlobAgri-AgT pour estimer les émissions de GES liés aux changements d'usage des terres (Le Mouél et al., 2018) – nous avons estimé le bilan mondial des émissions de GES dans différents scénarios d'expansion de l'agriculture biologique. Ces scénarios tenaient compte de différentes parts des terres agricoles mondiales sous gestion biologique (20, 40, 60, 80 et 100 %) et en partaient de l'hypothèse d'un changement des régimes alimentaires afin que la demande alimentaire mondiale moyenne s'adapte à l'offre alimentaire mondiale moyenne. Nous avons constaté une augmentation de 56 % des émissions de GES d'origine agricole dans un monde entièrement géré de manière biologique par rapport aux émissions actuelles (considéré comme la référence). Cette augmentation des émissions de GES est principalement due aux changements d'utilisation des terres (+3,7 Gt CO₂eq.an⁻¹) et aux pertes de stocks de carbone organique des sols agricoles (+2,3 Gt CO₂eq.an⁻¹), partiellement compensées par une réduction de 60% des émissions de N₂O et de CH₄ (-3,1 Gt CO₂eq.an⁻¹). Nous avons également constaté qu'une conversion de 20 % des terres agricoles mondiales à l'agriculture biologique (associée à une adaptation des régimes alimentaires humains) réduirait les émissions de GES de 70 % par rapport au scénario de référence. Plus généralement, nous avons constaté une réponse non linéaire des émissions de GES à la part des terres agricoles mondiales occupées par l'agriculture biologique, ce qui suggère l'existence d'une part optimale d'agriculture biologique (estimée ici à 20 %) qui minimiserait les émissions de GES du secteur agricole. Dans nos scénarios, l'existence de cet optimum est co-dépendant d'une adaptation des régimes alimentaires. Cet optimum pourrait être modifié si des pratiques appropriées étaient mises en œuvre dans l'agriculture biologique pour améliorer (i) la séquestration du carbone dans le sol (comme les cultures intermédiaires), ou (ii) si des réductions dans les pertes et gaspillages alimentaires sont opérés.

Toutefois, ces résultats doivent être utilisés avec précaution car ils dépendent fortement des hypothèses - pour la plupart conservatrices - faites sur les pratiques agricoles mises en œuvre dans l'agriculture biologique ainsi que sur des hypothèses fortes sur les régimes alimentaires. Notons tout de même que cette thèse souligne que l'agriculture biologique pourrait s'étendre de façon importante. Une multiplication par 10 des surfaces agricoles occupées par l'agriculture biologique (actuellement, l'agriculture biologique occupe moins de 2% des surfaces agricoles mondiales) permettrait de réduire les émissions de GES, à condition que des changements systémiques profonds soient appliqués au système agroalimentaire. Premièrement, nos travaux suggèrent qu'une refonte profonde du secteur de la production animale est nécessaire avec l'expansion de l'agriculture biologique, notamment via le développement de systèmes de production mixtes (culture-élevage) à l'échelle de la ferme ou du territoire. Deuxièmement, nos travaux, ainsi que d'autres études, montrent que de profonds changements dans les modes de consommation alimentaire sont nécessaires parallèlement à cette expansion de l'agriculture biologique (Barbieri et al., 2021, 2021; Morais et al., 2021; Poux and Aubert, 2018). Les modes de consommation doivent s'orienter vers une consommation réduite de produits animaux ainsi que la réduction des pertes et gaspillages de produits alimentaires. Enfin, cette thèse montre qu'un monde entièrement géré de manière biologique entraînerait une augmentation des émissions de GES si les pratiques agricoles n'étaient pas fortement modifiées - notamment par la mise en œuvre de pratiques qui augmenteraient la disponibilité des nutriments dans les terres cultivées ou augmenteraient les stocks de carbone organique des sols. Toutes ces conditions doivent être considérées dans les politiques visant à augmenter la part de l'agriculture biologique à large échelle, comme le Green Deal européen qui vise à atteindre 25% d'agriculture biologique dans l'union européenne d'ici 2030.

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Global introduction – methodologies and goals



The 21st century will be scarred by social and environmental global issues induced by the past and current development of industrial societies. The Earth system is being altered by human activities, and several planetary boundaries have already been crossed (Rockström et al., 2009). Among them, global climate change represents a direct threat to human societies (IPCC, 2021). Increased greenhouse gas (GHG) atmospheric concentrations – due to emissions from human activities – is the main driver of the observed global climate change (IPCC, 2021). During the 1750-2019 period, CO₂, CH₄ and N₂O atmospheric concentrations have increased by 47, 156 and 23% respectively.

In this context of global climate change, agriculture is both a significant contributor – through GHG emissions and altered albedo effects – and a victim – as global food production is at risk with climate change (IPCC, 2021). Agriculture, is responsible of 23% of global anthropogenic GHG emissions (IPCC, 2021), with three main gases: CO₂, CH₄ and N₂O. To maintain the global mean temperature increase well below 2°C in 2050, sharp reduction in GHG emissions from this sector is expected (IPCC, 2018).

Organic farming is often presented as an option to reduce GHG emissions from the agricultural sector (Muller et al., 2017; Niggli et al., 2009). Meta-analyses of field experiments showed that organic farming reduces field scaled N₂O emissions (Skinner et al., 2014) and increases field scale soil carbon sequestration (Gattinger et al., 2012). However, lower yields (Ponisio et al., 2015; Seufert et al., 2012) put at risk this potential beneficial effect of organic farming as they might lead to land-use changes – and additional GHG emissions – in a fully organically managed world. Additionally, those meta-analyses characterise situations where organic farming occupies small share of agricultural lands – less than 2% of the agricultural area globally (IFOAM, 2020). Recent studies have provided evidence that organic farming expansion at large scale would deeply modify the food production systems (Barbieri et al., 2021; Smith et al., 2018) – with a drop of organic crop yields and livestock population. Such effect of organic farming expansion on the food production systems might affect the potential of organic farming expansion to reduce GHG emissions globally.

In this dissertation, we will discuss the potential of organic farming to reduce global GHG emissions from the agricultural sector, accounting for all systemic feedbacks due to organic farming expansion. This introductory chapter will first present the state of the art (i) on GHG emissions from the agricultural sector and (ii) in organic farming and, on (iii) the systemic feedbacks due to organic farming expansion. It will then present the main scientific objectives and hypothesis of this PhD. After discussing the methodological objectives and the different modelling options, this chapter will introduce the overall modelling approach used in this dissertation. Finally, a short outline will introduce the following chapters of this dissertation.

Greenhouse gas emissions from the agricultural sector

GHG emissions from the agricultural sector are made of three main gases: CO₂ (54% of total GHG emission from the agricultural sector expressed in CO₂ equivalent), CH₄ (24%) and N₂O (18%) (Tubiello et al., 2014). In this first section, we will present the biochemical processes resulting in emissions of those three gases and the related potential mitigation options.

CO₂ emissions from the agricultural sector

In the AFOLU sector, two main sources of CO₂ emissions are often considered: (i) CO₂ emissions from biophysical processes and (ii) CO₂ emissions due to on farm energy use – meaning CO₂ emissions from fossil fuel burning directly on farm, and CO₂ emitted in the production of the electricity used on farm. While those two sources of CO₂ emissions are affected by different processes, agricultural practices play a key role in reducing emissions in those sectors.

Emissions of CO₂ from biophysical processes are to be considered within the wider carbon cycle. In the global terrestrial carbon cycle, two main carbon pools are to be considered: (i) the terrestrial lands pool – composed of C stored in the organic plant biomass (560 Pg C), soil organic matter (2400 Pg C in the first 2 meters of soil) and soil inorganic matter (695 Pg C in the first meter of soil) – and (ii) the atmospheric pool composed of CO₂ (760 Pg C) (Lal, 2004a). Here we will focus on the organic components of the terrestrial lands pool (2960 Pg C) which is 3.9 times higher than the carbon stock in the atmospheric carbon pool. These two carbon pools are linked through two opposite carbon fluxes: (i) atmospheric CO₂ removal by plant photosynthesis and (ii) CO₂ emissions by plants, animals or soil respiration. Photosynthesis is a biochemical process that uses H₂O and CO₂ to produce O₂ and glucose – glucose is then used in the plant metabolism to produce other organic component of the plant biomass. Respiration, is a biochemical process that uses glucose to produce energy for organisms (plants, animals and micro-organisms). In aerobic conditions, respiration uses O₂ in the process and produces H₂O and CO₂. The net atmospheric CO₂ removal from plant – meaning the difference between atmospheric CO₂ removed by photosynthesis and CO₂ emitted by plant respiration – is called the NPP. When those two fluxes (atmospheric CO₂ removal and CO₂ emissions from organisms' respiration) are unbalanced they lead to net emissions or removal of atmospheric CO₂, and a reduction or increase in the carbon stock of the terrestrial lands pool. Here, we detail two main effects of agricultural activities on the organic carbon stock in terrestrial lands pool: (i) changes in soil organic carbon stocks in agricultural lands and (ii) changes in soil and plant biomass organic carbon stocks in lands converted to agricultural lands.

In agricultural lands, soil organic carbon stocks decrease or increase result in a balance (negative or positive, respectively) between soil carbon inputs – as plant residues or animal excretion (manure) – and CO₂ emissions from soil organic matter mineralisation (Lal, 2004b). The amount of soil carbon inputs in agricultural lands depends on the global NPP and the share of this NPP that returns to agricultural soils – either directly as plant residues or indirectly as manure. In agricultural lands, the NPP depends on pedo-climatic conditions, water and nutrient availability. Therefore, agricultural practices that improve nutrient availability (e.g., through fertilization) and water management have direct effects on agricultural lands NPP. In croplands, crops are cultivated in a limited period of time over the year, while in the remaining time soils can either be bare – resulting with the absence of NPP in that period of time – or covered by other plants. Improving crop rotations can increase the

cultivation period and therefore the overall NPP of croplands (Mcdaniel et al., 2017) – especially when high carbon fixing species are included in crop rotations (such as temporary pastures or cover crops (Poepflau and Don, 2015; Vertès and Mary, 2007)). Crop rotations can also be managed to improve nutrient availability in agricultural lands, by including N fixing plants such as legumes and avoiding loss of nutrient through leaching (Mazzoncini et al., 2011). Bare soils also increase soil organic carbon mineralisation rate (Coleman et al., 1997). Avoiding period with bare soil in croplands therefore helps to maintain high level of soil organic carbon stocks in agricultural lands.

Globally, the decrease in organic carbon stocks of the terrestrial lands are mostly caused by changes in land uses (Lal, 2004a). Converting land cover with high organic carbon stock (in both plant biomass and soils) – such as forest, wetlands or natural grasslands – towards land cover with lower organic carbon stock – such as croplands – results in CO₂ emissions to the atmosphere. These CO₂ emissions from land-use changes are due to either (i) immediate emissions if the plant biomass present in the initial land-use is burned or (ii) more slowly following organic matter decay over decades (Moutinho and Schwartzman, 2005). More generally, the amount of CO₂ emitted by a land-use change correspond to the difference in organic carbon stocks between the initial and the new land use.

CH₄ emissions from the agricultural sector

Methane (CH₄) is a product of organic matter decomposition in anoxic conditions. In the agricultural sector, such conditions of organic matter decomposition are found in (i) the livestock digestive system (enteric fermentation), (ii) in some systems of manure storage and (iii) in flooded rice lands.

Livestock digestive system – and especially those of ruminant livestock – create anoxic conditions for the degradation of organic matter, leading to CH₄ emissions from enteric fermentation. CH₄ emissions from enteric fermentation depend on the livestock species considered and the composition of its feed ration (IPCC, 2019b; Mottet et al., 2017). Forage-based feed rations are less digestible compared to concentrate-based feed ration, resulting in higher CH₄ emissions from enteric fermentation per animal (Beauchemin et al., 2008; IPCC, 2019b; Patra, 2012; Pellerin et al., 2015).

CH₄ emissions from organic matter decomposition during manure storage depends on (i) storage duration and manure pile (ii) temperature, (iii) humidity and (iv) aeration. High level of humidity or compact manure storage increase anoxic conditions leading to CH₄ emissions, while temperature influences the microbial activity. A better management of these conditions as well as reduced duration of manure storage can help reduce CH₄ emissions (Chadwick, 2005; Pardo et al., 2015; Pattey et al., 2005; Smith et al., 2008).

Compared to other crops, rice production has the specificity to be potentially flooded, creating anoxic conditions for soil and plant organic matter decomposition, thereby leading to CH₄ emissions. Therefore, reducing the flooded period can reduce CH₄ emissions by reducing the anoxic period for organic matter decomposition (Cai et al., 1997; IPCC, 2019b; Smith et al., 2008). Better management of organic amendments in rice lands, and especially better timing regarding flooded period can therefore reduce CH₄ emissions (Cai et al., 1997; Smith et al., 2008).

N₂O emissions from the agricultural sector

N₂O is a co-product of two chemical processes: nitrification and denitrification. Nitrification is the biological oxidation process of ammonia (NH₄⁺) into nitrite (NO₂⁻) and then of nitrite into nitrate (NO₃⁻). Denitrification is the biological reduction of nitrate into N₂. In the agricultural sector, we identify two sources of N₂O emissions. *First*, direct emissions due to nitrification and denitrification in agricultural soils or in manure storage facilities. *Second*, indirect emissions due to transfer of nitrogen (N) from agricultural lands to other ecosystems through leaching (as nitrate) and volatilisation (as ammonia) – in those other ecosystem N₂O emissions are also due to nitrification and denitrification.

Globally, soil nitrogen has three main origins: (i) atmospheric N deposition on lands, (ii) biological N fixation by N fixing-plants (such as leguminous crops) and (iii) synthetic N fertilizer application (van Groenigen et al., 2015). Soil nitrogen is included in a larger N cycle interconnecting N in crop biomass, in grass biomass and in livestock production systems through plant based livestock feed and livestock manure application on agricultural lands (Smil, 1999). There is direct N₂O emissions due to nitrification and denitrification processes at difference step of this N cycle.

First, N₂O emissions in agricultural soils depends on N inputs for fertilization either as (i) recycled crop residues, (ii) manure application and (iii) synthetic N fertilizers (IPCC, 2019c). The level of N₂O emissions per unit of N input depends on the composition of the N input (organic vs synthetic), the climate (wet vs dry) and the timing of the N application to soil (IPCC, 2019c; Venterea et al., 2012). Note that there is no N₂O emissions from the biological N fixation process (Rochette and Janzen, 2005).

Nitrogen excreted by livestock can either be directly applied to croplands or grasslands or be stored before application to croplands. During the storage period, nitrogen in manure is affected by the nitrification and denitrification processes (IPCC, 2019b). N₂O emissions are driven by manure storage practices through the control of temperature and humidity conditions (Chadwick et al., 2011; Chadwick, 2005; Pardo et al., 2015).

Finally, the production of synthetic fertilizers and especially the production of ammonium nitrate and urea are also responsible for N₂O emissions – along with CO₂ (Davidson and Kanter, 2014). Therefore, a comprehensive estimation of global N₂O emissions should consider all sources of direct, indirect and induced emissions from all agricultural activities.

Opportunities to reduce GHG emissions from the agricultural sector

Among all human activities, the Agriculture, Forest and Other Land-Use (AFOLU) sector plays a key role in environmental issues (Foley et al., 2011), and especially regarding climate change (Campbell et al., 2017). Being one of the first sector to be threatened by climate change consequences (IPCC, 2019d; Ray et al., 2019), the AFOLU sector is also responsible of 23% (12 Gt of CO₂eq.yr⁻¹) of all anthropogenic GHG emissions (IPCC, 2021). During the 1990-2000 period, global GHG emissions from the AFOLU sector have raised from 7.5 to 8.1 Gt of CO₂eq (Tubiello et al., 2014). These increasing emissions are driven by increased demand for agricultural products, together with changes in diets towards more land-demanding food diets (in particular with more livestock products). In the 1990-2010 period, the global population has increased of about 1.63 billion and the mean daily energetic consumption has increased by 130 kcal.capita⁻¹.day⁻¹ to reach 2353 kcal.capita⁻¹.day⁻¹ in the meantime (source FAOSTAT). This increasing demand in agricultural products has led to increased cropland soil fertilization (responsible of most N₂O emissions from the agricultural sector), in livestock population (responsible of most CH₄ emissions from the agricultural sector) and in the agricultural land surfaces

(responsible of large CO₂ emissions) (Dawson and Hilton, 2011; Thornton, 2010). The AFOLU sector faces, therefore, both the issues of feeding the increasing global population while mitigating climate changes (IPCC, 2019d).

However, the agricultural sector also shows unique opportunities to mitigate climate change either by reducing emissions or by increasing CO₂ removals from the atmosphere (Smith et al., 2008). Changes in farming practices towards (i) better soil fertilization management, (ii) better rice management system, (iii) optimized manure management systems and (iv) optimized animal feeding are put forward as practices to reduce GHG emissions in the crop and livestock production systems (Pellerin et al., 2015; Smith et al., 2008). Increasing soil organic carbon stocks in agricultural lands is considered as an option to remove atmospheric CO₂. Changes in agricultural practices by, (i) optimizing crop rotations, (ii) using cover crops, (iii) developing agroforestry or (iv) increasing organic matter return to soils (Fuss et al., 2018), are required to increase soil organic carbon stocks in agricultural lands. The potential of increasing organic carbon stocks in arable lands is estimated at 0.79-1.54 Gt C.yr⁻¹ (Amelung et al., 2020; Fuss et al., 2018) – which would represent 2.9-5.6 Gt CO₂eq removed from the atmosphere each year. However, adopting those farming practices – despite their individual potential to mitigate climate changes– might not be sufficient to reduce significantly global emissions from the agricultural sector. A French study showed that the application of ten practices without systemic changes in farming systems would only reduce GHG emissions from the agricultural sector by 10% at the scale of France (Pellerin et al., 2015). As a comparison the French low carbon national strategies aims at reducing GHG emissions from the agricultural sector by 19% in 2030 compared to 2015.

Two different pathways are often considered to reduce GHG emissions from the food production system: (i) changes in the demand side or (ii) changes in the supply side of the food system. Changing human diets towards reduction of livestock product consumption or more locally based diets is often put forward as an option to reduce GHG emissions in the AFOLU sector (Tilman and Clark, 2014). Livestock production is often criticized for the large amount of natural resources it requires, and especially lands (Steinfeld and Gerber, 2010). Therefore, reducing livestock products in human diets should free croplands and grasslands either for crop food production or for natural vegetation regeneration, in addition to reducing direct GHG emissions from the livestock sector (namely CH₄ and N₂O from enteric fermentation and manure management). In the same time, alternative farming systems are often brought forward to move the food production system towards more sustainable production (Ramankutty et al., 2019). Among those alternative farming systems, organic farming stands out as it is widely growing farming systems in terms of surface occupied (+31 million ha in the 1999-2019 period) and market (+91.3 billion euros in the same) (IFOAM, 2020).

Organic farming a promising option to mitigate climate change

Organic farming is often considered as a potential alternative to the current farming systems in order to face the global environmental and social issues of the 21st century (IFOAM EU Group, 2016; Reganold and Wachter, 2016). The International Federation of Organic Agriculture Movements (IFOAM) defines organic farming as *“a production system that sustains the health of soils, ecosystems and people. It relies on ecological processes, biodiversity and cycles adapted to local conditions, rather than use of inputs with adverse effect. Organic agriculture combines tradition, innovation and science to benefit the shared environment and promote fair relationships and a good quality of life for all*

involved” (IFOAM EU Group, 2016). This definition is often verified on fields, as evidences show benefits of organic farming for (i) biodiversity (Mondelaers et al., 2009; Tuck et al., 2014), (ii) water eutrophication (Tuomisto et al., 2012), (iii) water pollution, (iv) farmer incomes, (v) farmer and consumer health (Reganold and Wachter, 2016) and finally (vi) mitigating climate changes (IFOAM EU Group, 2016; Meier et al., 2015; Niggli et al., 2009; Scialabba and Mller-Lindenlauf, 2010).

Regarding climate change, there is two methods used to compare organic to conventional farming: (i) meta-analyses that capture the current differences between both farming systems and (ii) scenario modelling that try to estimate how these differences will evolve with the expansion of organic farming. The approach based on meta-analyses show lower greenhouse gas emissions (Lee et al., 2015; Mondelaers et al., 2009) and higher atmospheric CO₂ removals per unit of surface in organic farming compared to conventional farming. The ban of synthetic fertilizers in organic regulations is the main explanation of lower N₂O emissions in organic farming compared to conventional farming (Skinner et al., 2014). To compensate for the ban of synthetic fertilizers, organic farming practices generally adapt by applying more organic fertilizers than in conventional farming. This higher organic matter application to agricultural soils is responsible of higher soil carbon sequestration in organically managed soils compared to conventional ones (Gattinger et al., 2012). In addition, the different composition of organic amendments used in organic farming vs. conventional farming – especially with higher C/N ratio of crop residues in organic farming – seems to be also responsible of the higher soil organic carbon sequestration in organic farming (García-Palacios et al., 2018). Evidences are also reported of lower energy use in organic farming systems compared to conventional ones (Lee et al., 2015; Muller et al., 2017). This lower energy use is mainly explained by the ban of synthetic inputs that require a high amount of energy to be produced, such as synthetic fertilizers. Such decreased energy consumption in organic farming systems might potentially lead to GHG emissions reduction in the energy production sector. However, when measured per unit of products (i.e. yields), organic farming performances exhibit higher GHG emissions compared to conventional farming (Skinner et al., 2014). The reason for these higher GHG emissions per unit of product is the 20-30% lower yields in organic compared to conventional farming (Ponisio et al., 2015; Seufert et al., 2012). In scenarios of organic farming expansion at the global scale, lower crop yields may translate into expansion of croplands over other land uses resulting in additional GHG emissions (Alexander et al., 2015; Erb et al., 2016; Morais et al., 2021; Muller et al., 2017). Such comparison of organic and conventional farming impact on GHG emissions from the agricultural sector based on meta-analyses of field experiment does not totally capture differences between both farming systems (Meier et al., 2015). More precisely, such approach does not capture differences in N fertilisation between both farming systems and how this difference might evolve with the expansion of organic farming at large scales.

Several studies have estimated the overall impact of organic farming on GHG emissions compared to conventional farming based on scenario modelling (Morais et al., 2021; Muller et al., 2017). Results from scenario modelling might provide a more suitable approach to better capture differences between organic and conventional. However, modelling is based on assumptions and the choice of those assumptions is key to provide accurate estimates of the differences between the two farming systems. For instance, the study from (Muller et al., 2017) was based on the extrapolation of results from meta-analysis of field experiment (Badgley et al., 2007; Seufert et al., 2012) to estimate crop yields in organic farming. However, those meta-analyses are representative of a situation where organic farming covers less than 2% of the global agricultural area (IFOAM, 2020).

Recent studies on organic farming upscaling have shown that an increased share of organic farming in the agricultural area is likely to modify organic farming performances (Barbieri et al., 2021;

Smith et al., 2018). Organic farming expansion might lead to increased competition for organic fertilizing resources, thus resulting in systemic feedback that might affect crop yields and livestock population. Those systemic feedbacks due to organic farming expansion might modify the potential of organic farming systems to mitigate climate change. The systemic feedbacks that organic farming expansion creates on the global food production system and GHG emissions from the agricultural sector are discussed in the next section.

Organic farming expansion and systemic feedbacks

Organic farming has now regulation rules in 108 countries with a large variety, making it difficult to define organic farming globally (Seufert et al., 2017). However, all those regulations have in common the ban of synthetic agricultural inputs – such as pesticides and fertilizers. The expansion of organic farming will lead to the global ban of those synthetic agricultural inputs with uncertainty on the consequences on the food production system.

However, organic farming productivity is mostly impacted by the lack of fertilizing material, due to the ban of synthetic fertilizers (Muller et al., 2017). Nitrogen (N) availability represents a key issue in maintaining organic crop yields (Seufert et al., 2012). Organic farming relies on only three resources of nitrogen for crop fertilization, that are each limited: (i) atmospheric nitrogen deposition, (ii) biological nitrogen fixation by leguminous crops and (iii) farmyard manure application to soils (Lampkin et al., 2017). A higher share of leguminous crops is observed in organic crop rotations compared to conventional farming (Barbieri et al., 2017). However, the additional N from biological N fixation that this higher share of leguminous crops might bring would not be sufficient to fill the productivity gap between organic and conventional farming (Barbieri et al., 2019). Therefore, organic farming N fertilization require additional resources such as farmyard manure (Nowak et al., 2013; Oelofse et al., 2013). Manure is a limited resource which production is regionally concentrated due to the regional agricultural specialisation of livestock and crop production (Nesme et al., 2015; Peyraud et al., 2014; Schut et al., 2021). A global transition towards organic farming might lead to increasing competition for this resource (Barbieri et al., 2021; Smith et al., 2018), leading to reduced N availability for crops. Due to the difficult process that represents long distance manure transportation (Bartelt and Bland, 2007), the crop and livestock production segregation (Nesme et al., 2015) might lead to manure production surpluses in certain regions and increased competition for manure resources in other. Therefore, without global changes in livestock spatial repartition and density, organic farming expansion might face a strong increasing N deficiency and is likely to experience reduced productivity (Barbieri et al., 2021). Systemic changes in the food production system will be required in scenarios of large organic farming expansion in order to limit the food production reduction.

Such potential systemic changes in the food production system due to organic farming expansion have been capture by two recent studies (Barbieri et al., 2021; Smith et al., 2018). Those two studies were based on a similar modelling approach aiming at maximizing food production in scenarios of large organic farming expansion. The main difference between the two studies was the scale considered: (Smith et al., 2018) focused on England and (Barbieri et al., 2021) on the global scale. Both studies concluded to a significant drop of 40-56% in crop yields – which is much higher than the 20-30% drop observed in previous meta-analyses (Ponisio et al., 2015; Seufert et al., 2012). Profound changes in the livestock production system were also found in those studies, with a significant drop in the monogastric populations and a higher presence of ruminant livestock (Barbieri et al., 2021; Smith

et al., 2018). Those changes in the global food production system brings uncertainty on the GHG emissions budget of such scenarios of organic farming expansion.

Objectives and hypotheses

Main scientific questions and hypotheses

This dissertation aims at discussing the potential of global organic farming expansion to reduce agricultural GHG net emissions. This work is based on (i) estimating the global food production in scenarios of large organic farming expansion – considering all systemic feedbacks – and (ii) estimating GHG emissions in those scenarios. Global emissions in scenarios of large organic farming expansion will be compared to a baseline representing the current GHG emissions from the agricultural sector. In the baseline we assumed an equilibrium between food demand and food production, thus resulting in the absence of land-use change. Organic farming currently occupies less than 2% of the global agricultural lands (IFOAM EU Group, 2016), therefore we considered the current agricultural GHG emissions as a good proxy of the emissions from conventional farming of the planet. This work is based on a modelling approach coupling a global agricultural food production model – adapted to organic farming expansion – and models estimating GHG emissions from agriculture and related to land-use changes.

More precisely, we aim at answering the following question:

“What is the potential of organic agriculture to reduce net GHG emissions at the global scale in scenarios of large organic farming expansion?”

In order to answer this question, we aimed at answering four intermediate questions:

- 1. How will organic farming expansion change the global stocks of soil organic carbon in agricultural lands?*
- 2. How will organic farming expansion change global N₂O and CH₄ emissions on agricultural lands converted to organic farming?*
- 3. How will organic farming expansion affect land use, land-use changes and related GHG emissions?*
- 4. How will the overall GHG budget be affected by global organic farming expansion?*

Regarding those questions, we formulated several hypotheses for each of the three gases emitted from the agricultural sector:

- According to results from latest meta-analyses showing higher carbon sequestration rates under organic farming compared to conventional farming (García-Palacios et al., 2018; Gattinger et al., 2012), we expect SOC stocks to increase with expansion of organic farming. However, this increase of SOC stocks might be lower than what is observed in previous meta-

analysis of field experiment, due to a drastic yield reduction in organic farming, thereby resulting in reduction of soil carbon inputs.

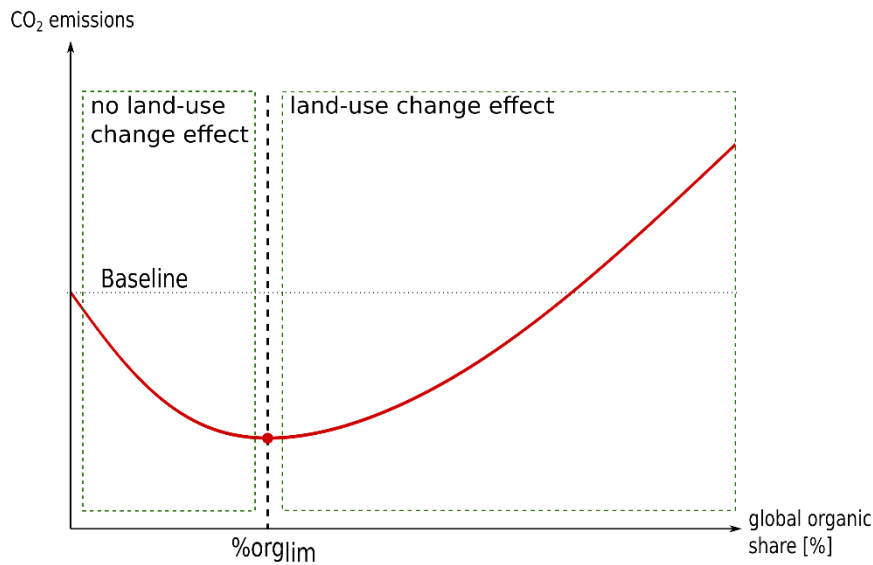


Figure 1: Expected evolution of the CO₂ emissions with the expansion of organic farming. %org_{lim} represents the share of organic farming under which the world could be fed without land-use change. The horizontal black dashed line represents the level of CO₂ emissions in the baseline.

- Previous studies have shown that, above a certain share of the global agricultural lands occupied by organic farming, organic farming expansion may require significant land-use changes (Barbieri et al., 2021; Erb et al., 2016). Above this share of organic farming (called %org_{lim}), food production on current agricultural lands may not be sufficient to feed the world (Barbieri et al., 2021). Therefore, we hypothesized that up to this %org_{lim}, land-use change would have little effect on CO₂ emissions. In contrast, above this %org_{lim}, land-use change would significantly increase CO₂ emissions (**Figure 1**). This %org_{lim} might vary according to which farming practices – and especially N fertilization practices – were implemented in organic farming.
- We hypothesized that the ban of synthetic fertilizers would lead to drastic reduction of N₂O emissions in scenarios of large organic farming expansion (**Figure 2**). However, above the previously mentioned %org_{lim}, the increase of croplands – required to feed the world – would bring additional N₂O emissions due to additional agricultural activities on those lands. Those additional N₂O emissions would make the reduction of overall N₂O emissions less drastic above %org_{lim}.

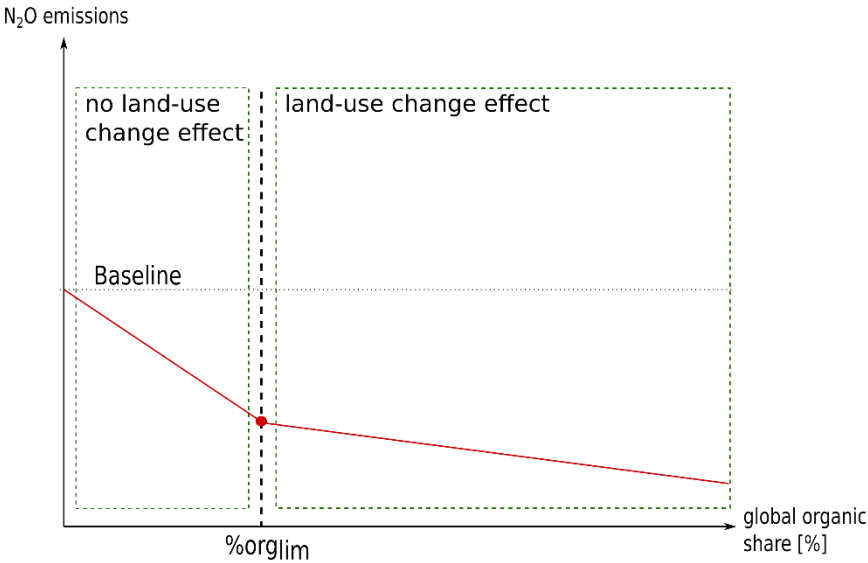


Figure 2: Expected evolution of the N₂O emissions with the expansion of organic farming. %org_{opt} represents the share of organic farming under which the world could be fed without land-use change. The horizontal black dashed line represents the level of N₂O emissions in the baseline.

- As a consequence of competition for N fertilizers, livestock feed production might be limited in scenarios of large organic farming expansion. As a consequence, livestock populations are expected to be reduced in those scenarios (Barbieri et al., 2019; Smith et al., 2018). We hypothesised that this livestock reduction would attenuate CH₄ emissions from the livestock production sector – meaning enteric fermentation and manure management. (Figure 3). Again, above the previously mentioned %org_{lim}, the increase of croplands – required to feed the world – would bring additional CH₄ emissions due to additional livestock production on those lands.

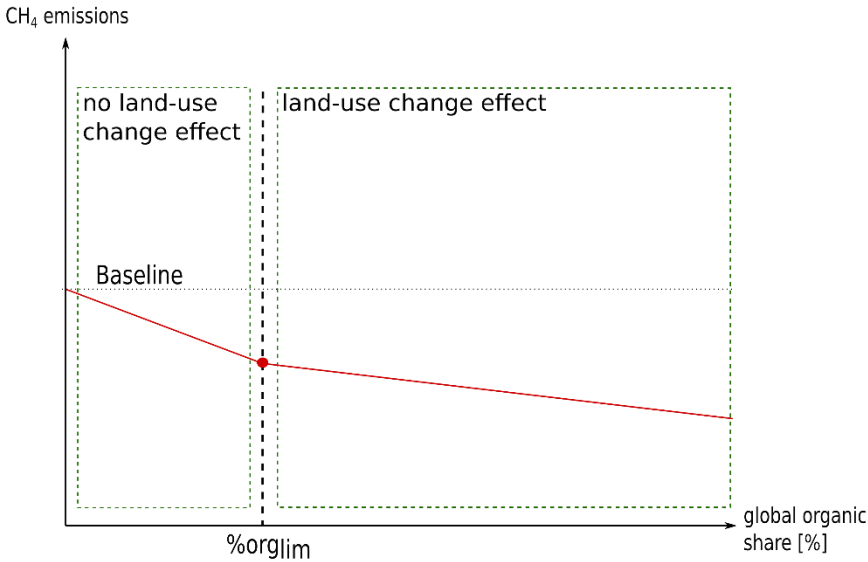


Figure 3: Expected evolution of the CH₄ emissions with the expansion of organic farming. %org_{opt} represents the share of organic farming under which the world could be fed without land-use change. The horizontal black dashed line represents the level of CH₄ emissions in the baseline.

Specific questions related to changes in GOANIM

GOANIM (Barbieri et al., 2021) provide opportunities to test various scenarios of organic farming expansion and their impact on the global food production. In this model, the differences between organic and conventional farming on crop rotations and crop yields have been included. However, due to the lack of studies providing information on global differences between organic and conventional livestock productivity and feeding strategies, such differences in the model had not been included so far. In a preliminary work, we explored such differences. This additional work comes with a specific scientific question:

- *What are the differences between organic and conventional livestock production in terms of productivity, feed rations and feed-use efficiency?*

This question comes with specific hypotheses:

- Livestock production in organic farming differs from conventional farming by lower animal productivity, and lower feed-use efficiency.
- We also expect that organic ruminant livestock feed ration will be composed of more forages compared to conventional ones. Therefore, organic ruminant livestock are less in competition with human food than their conventional counterparts.

Modelling objectives and options

In this section, we present the different modelling options that are available and we discuss their possible contribution to our scientific questions.

Options to estimate global CH₄ and N₂O emissions

Two main modelling approaches are possible to estimate CH₄ and N₂O emissions at large scales: (i) the bottom-up approach or (ii) the top-down approach. The bottom-up approach aggregates regional and source-specific data to estimate global N₂O and CH₄ emissions; while the top-down approach uses measurements of N₂O and CH₄ in models to estimate their sources (Nisbet and Weiss, 2010). If top-down provide accurate estimation of current CH₄ and N₂O emissions – and are often used to verify values estimated based on a bottom-up approach (Bergamaschi et al., 2015; Reay et al., 2012) – they are not fitted to estimate N₂O and CH₄ emissions in prospective scenarios such as the global expansion of organic farming. In such global prospective scenarios, bottom-up approaches and especially those provided by the IPCC guidelines are classical tools (Muller et al., 2017; Smith et al., 2019). Additionally the IPCC guidelines have already been used to estimate global N₂O and CH₄ emissions from the agricultural sector at the global scale (Carlson et al., 2016), providing a source of comparison in our estimation of the current N₂O and CH₄ emissions. For those reasons, we decided to use the IPCC guidelines in our estimations of N₂O and CH₄ emissions.

The IPCC guidelines offer three options to estimate CH₄ and N₂O emissions with an increasing precisions and data requirement between Tier 1, Tier 2 and Tier 3 (IPCC, 2019a). Tier 1 is the simplest approach suggested by the IPCC guidelines. It is based on robust default equations built upon regional and source-specific data (Hergoualc'h et al., 2021). Those equations are based on robust relationships

between national activity data – such as amount of nitrogen applied on lands or number of livestock animals – and regional or condition-specific emission factors (IPCC, 2019a). As defined in the IPCC guidelines, emission factors represent the amount of GHG emitted per unit of activity data (in kg of GHG emitted.unit of activity data⁻¹). Among all approaches suggested by the IPCC guidelines, the Tier 1 approach is the most commonly used to estimate N₂O and CH₄ emissions at the global and regional levels in agriculture (Carlson et al., 2016; Hong et al., 2021). The simplicity of the Tier 1 approach and its low requirement in data make it easily applicable in global studies. In studies estimating emissions in scenarios of large development of alternative farming systems (such as organic farming) this simple approach is an asset due to the lack of global data on the diversity of farming systems (Muller et al., 2017). However, this Tier 1 approach is often debated, especially regarding N₂O emissions from fertilizers application. In the IPCC guidelines, the relation between N₂O emissions and N fertilizers application is considered linear (IPCC, 2019c). However, recent study showed that this relation is rather exponential (Hoben et al., 2011; Philibert et al., 2012; Shcherbak et al., 2014), resulting in potential underestimation of N₂O emissions in highly fertilized lands (Makowski, 2019).

Tier 2 is based on the same methodological approach than Tier 1, but uses more precise emission factors, mostly based on country specific data (IPCC, 2019a). The estimation of country specific emission factors for each agricultural sector requires detailed country specific data. Such precision is often not available at the global scale – and especially for alternative farming systems (such as organic farming) – even though this approach has already been used to estimate livestock emissions at the global scale within the GLEAM model (Mottet et al., 2017).

Finally, Tier 3 is the most complex and precise approach of all three (IPCC, 2019a). It is based on country specific mechanistic models and estimation approved by the IPCC (Bannink et al., 2011). This method has been developed to allow countries to use specific methods to estimate their emissions with method adapted to their environmental and social conditions.

In our study, we chose to use the Tier 1 approach because it is easily applicable to alternative farming systems and because it has been used in past studies, thus providing sources of comparison for our own estimates.

Options to estimate global CO₂ emissions from change in SOC stocks

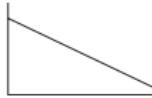
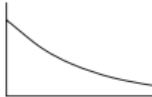
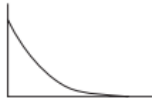

Emissions or removal of atmospheric CO₂ from changes in stocks of soil organic carbon (SOC) of agricultural lands are usually estimated using **Equation 1**:

$$\text{Equation 1 } CO_2 = \frac{\Delta SOC}{\Delta T} * \frac{44}{12}$$

Where ΔSOC (Mg C) is the variation of SOC stock in a given time period, ΔT is the time period over which the ΔSOC is measured or estimated. Variations of soil organic carbon stocks are converted into CO₂ emissions using the ratio of the molar masses of CO₂ and C (44/12). Modelling CO₂ emissions in scenarios of global organic farming expansions comes with choice of approach to estimate ΔSOC . The above mentioned Tier 1 approach allows to estimate ΔSOC for a finite period of time – usually 20 years – in scenarios of changes in farming practices (i.e. soil tillage, level of carbon input to soils) using a zero-order kinetic approach (**Table 1**) and default regional values (IPCC, 2006a, 2019e). This approach based on default regional values does not allow to capture the systemic feedbacks related to organic farming expansion and their effects on global SOC stocks in agricultural lands. More suitable approaches based on SOC dynamics model allow to estimate ΔSOC in scenarios of deep systemic

changes in farming systems (Plante and Parton, 2007; Smith et al., 2020). Such model generally estimates changes in SOC stocks by modelling the interactions between several active soil carbon pools according to pedo-climatic conditions, farming practices and level of soil carbon inputs. In those models, SOC stocks results from balance between the amount of soil carbon inputs and the amount of soil carbon mineralised. There is a large diversity of approaches to estimate the mineralisation level of soil organic carbon (**Table 1**).

Table 1: Different functions to simulate soil organic carbon mineralisation. The abbreviations describe the carbon (C) at the start (C₀) and at a certain time (t) step (C_t), the decomposition rate (k), the Michaelis–Menten constant (K_m) and the maximum reaction velocity for the process (V_m), the carbon demand by the microbes (X₀), the Monod constant (K_t) and the maximum growth rate (μ_{max}). The graphs show C_t in a time series for one set of arbitrary parameters. This table was retrieved from (Smith et al., 2020).

Approach	Equation	Graphical relation (C(t))	Example model	Publications
Zero-order kinetics	$C_t = C_0 - kt$			
First-order kinetics	$C_t = C_0 e^{-kt}$		RothC, ICBM	Jenkinson and Rayner (1977), Andr�n and K�tterer (1997)
Enzyme kinetics	$\frac{dC}{dt} = V_m \frac{C}{K_m + C}$		CLM, SEAM	Wieder et al. (2013), Wutzler et al. (2017)
Microbial growth	$-\frac{dC}{dt} = \mu_{max} \left(\frac{C}{K_t + C} \right) (C_0 + X_0 - C)$		NICA	Blagodatsky and Richter (1998)

Due to the lack of data required by the most complex approaches – such as the maximum velocity (V_m) in the enzyme kinetics approach or the maximum growth rate (μ_{max}) in the microbial growth approach (**Table 1**) – for organic farming context, such approach could not be used in our estimations of ΔSOC. Therefore, we chose to use a first-order kinetics model. More specifically, we chose to use the RothC model (Coleman et al., 1997; Martin et al., 2007) for the little amount of data it requires and its proved robustness at large scale and for different land cover – croplands and grasslands (Martin et al., 2021).

Options to estimate global land-use change

The land-use change processes result from complex interactions between a large variety of drivers such as (i) global food demand, (ii) global food productivity, (iii) variations of food products prices and (iv) food and land-use policies (Alexander et al., 2015; Meyfroidt et al., 2013). Those drivers, though distant both geographically and economically (Meyfroidt et al., 2013) are interconnected and, a forest regeneration policy in a given country could induce land-use changes abroad, leading to what is called land-use displacement (Meyfroidt et al., 2010). Similarly, a change in farming systems locally can induce higher agricultural land requirements abroad (Smith et al., 2019). The precise representation of the processes leading to land-use changes requires information on a large variety of drivers, their effects on one another and potential feedback effects (Meyfroidt et al., 2013).

Different modelling approaches have been developed to model the dynamic of land-use changes (Schaldach et al., 2011). Economic models such as GTAP (Corong and Tsigas, 2017) or MATSIM-LUCA (Forslund et al., 2020) are market-based models, where food demand, land productivity, global trade of food products and prices interact with each other. Integrated models – such as the IMAGE model (Bouwman and Kram, 2006) – combine an economic model to environmental processes. Those two different modelling approaches, by their complex representation of the global agri-food product market, require large quantity of economic and biotechnical data that are often poorly available regarding alternative farming system. In other models – such as GlobAgri (Le Mouël et al., 2018; Mora et al., 2020) – a more simple representation of the global agri-food product markets is considered. Those models estimate land-use changes based on mass balance between agri-food products availability and their uses (for food, feed and other uses). In those models, the mass balance is verified regionally and the agri-food products availability is estimated as balance between production, exports and imports. Those models represent the agri-food market only through variations of imports and exports with variations of crop yields or food demand, and does not consider prices in those variations, resulting in lower data requirement. Therefore, land-use change estimation in those more simple models is only driven by the regional food demand and land productivity (Lambin and Meyfroidt, 2011).

Options to estimate global GHG emissions from land-use change

The IPCC guidelines provide an approach to estimate GHG emissions from land-use changes (IPCC, 2006a). This approach estimates two sources of GHG emissions. *First*, CO₂ emissions from changes in organic carbon stocks that can be summarised by **Equation 2**.

$$\text{Equation 2 } CO_2 = \frac{\Delta OC}{\Delta T} * \frac{44}{12}$$

Where ΔOC (Mg C) is the variation of organic carbon stock (in soil and plant biomass) in a given time period, ΔT is the time period over which the ΔOC is measured or estimated. Variations of organic carbon stocks are converted into CO₂ emissions using the ratio of the molar masses of CO₂ and C (44/12). *Second*, the IPCC guidelines account for N₂O and CH₄ emissions due to the burning of natural ecosystems during the land-use change process.

The approach suggested by the IPCC guidelines has been spatialized in the Agro-ecological zone emission factor (AEZEF) model (Plevin et al., 2014). The AEZEF model, in addition to provide a spatially explicit version of the IPCC guidelines, also include more precise information on organic carbon stocks in the different land covers (Pan et al., 2011) and soil organic carbon mineralisation in the land-use change process (Poeplau et al., 2011), thus making the AEZEF model more robust than the tier 1 IPCC guidelines. Additionally, the AEZEF model has already been combined to different models estimating land-use changes such as GTAP (Plevin et al., 2014) and MATSIM-LUCA (Forslund et al., 2020). For those different reasons, we chose to use data from the AEZEF model to estimate GHG emissions due to land-use changes.

Overall modelling approach

In this dissertation, we aim at modelling emissions of three greenhouse gases (CO₂, CH₄ and N₂O) from agricultural activities and lands and land-use changes in scenarios of global organic farming expansion. To do so we used the GOANIM model (Barbieri et al., 2021) that estimates the global food production in scenarios of organic farming expansion. Then, we combined the GOANIM model outputs to three other models to estimate (i) N₂O and CH₄ emissions from agricultural activities, (ii) CO₂ emissions or removal from changes in SOC stocks, and (iii) land-use changes and related CO₂ emissions induced by those scenarios.

Description of the GOANIM model

GOANIM (Global Organic Agriculture Nitrogen Model) is a spatially explicit (5 arc-min resolution, i.e. ~10x10km at the equator) biophysical and linear optimisation model that simulates the cropland N budget in scenarios of global organic farming expansion – considering the flows of N between the atmosphere, cropland soils, grassland soils, livestock and human food (**Figure 4**). The cropland N budget and its effects on crop yields is estimated for a series of 61 crop species. As long distance transportation of organic fertilizers is difficult (Bartelt and Bland, 2007), the GOANIM model assumes that organic N fertilizers are produced and applied within the grid cell in which they are produced. Therefore, all N flows and the cropland N budget are estimated at the grid cell scale. Therefore, all N flows and the cropland N budget are estimated in each grid cell. Similarly, in order to respect the organic regulation aiming at a self-sufficiency of organic livestock farms (Lampkin et al., 2017), livestock feed are assumed to be produced within the grid cell where livestock are located and, livestock populations within each grid cell are limited by the feed availability in that grid cell. GOANIM aims at maximising the food production within each grid cell (from both crop-based and animal-based products). To do so it maximises the population of the 9 livestock species considered in order to (i) minimize the feed vs food competition and (ii) maximize N availability in croplands through manure application. This optimization module also allocates manure to the different cultivated plant species in order to maximise the amount of calories produced per unit of N applied.

We modified the first GOANIM version (GOANIM V1), as defined by (Barbieri et al., 2021). This new version of the GOANIM model (GOANIM V2) includes the following modification (the relative detailed method is presented in **Annex III**).

1. In **Chapter I**, we highlights differences between organic and conventional livestock feeding strategies and feed-use efficiency (Gaudaré et al., 2021). We included those differences to provide a more precise simulation of organic livestock in GOANIM.
2. We updated N losses estimates in agricultural systems using the new 2019 IPCC guidelines on manure management and nitrogen losses towards the environment (direct N₂O and N₂ emissions, N leaching and N volatilisation as ammonia, (IPCC, 2019c)).
3. Non-productive animals also consume feed and produce manure and, thus participate to both the feed-food competition and cropland fertilization. Therefore, we modified GOANIM so that it can include non-productive animals (for the 9

species considered) in the estimation of livestock feed requirements and N annual excretion rates.

4. The above-ground biomass of temporary pastures is not entirely cut or grazed by livestock animals and part of this above-ground biomass remain on field (Soussana and Lemaire, 2014). To account for temporary pastures above-ground biomass remaining on field, we set-up a threshold in temporary pasture fodders production available as feed.
5. There is a maximum grazing intensity – meaning the annual amount of grass removed from grassland by livestock animals – above which permanent grassland exploitation is not sustainable – meaning that there productivity might be reduced (Erb et al., 2016). We assumed that this limit was respected in organic farming. Therefore, we set-up a threshold in permanent grassland production available as feed

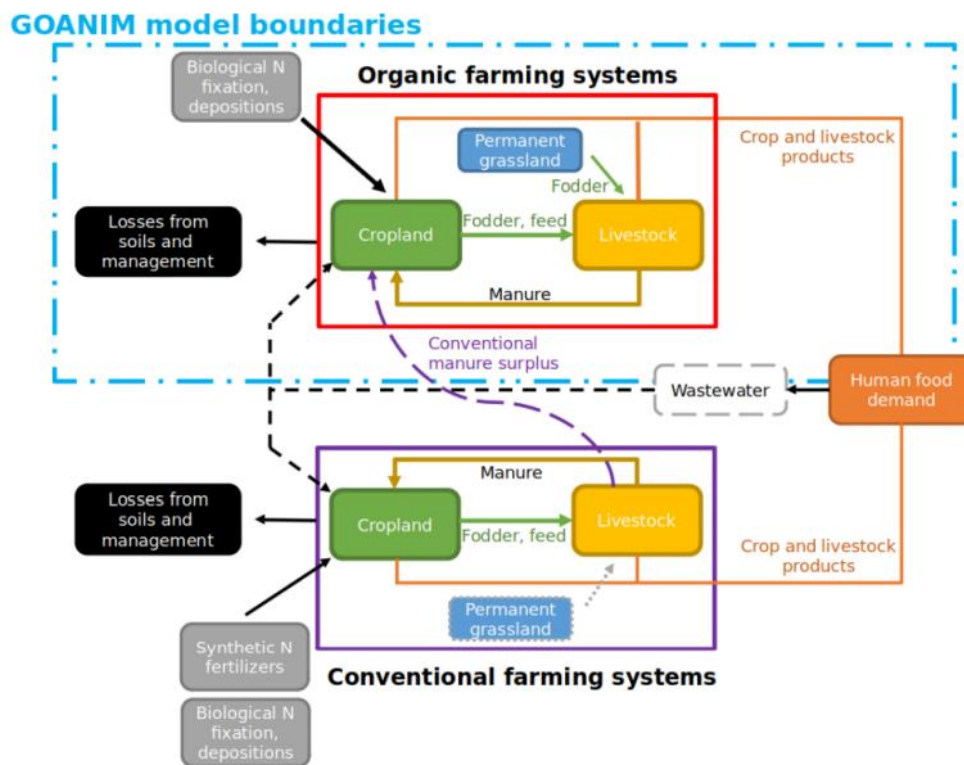


Figure 4: System definition of the GOANIM model represented by its boundaries, biomass and N flows as defined in (Barbieri et al., 2021).

Combination of GOANIM with other models

To estimate the N₂O and CH₄ emissions from agricultural activities and lands, we adapted the Tier1 approach of the 2019 IPCC guidelines refinement (IPCC, 2019b, 2019c) in a spatially explicit way – hereafter this adaptation is called the N₂O-CH₄ model. This model was used to estimate N₂O and CH₄ emissions from agricultural activities and lands in both the baseline and scenarios of large organic

farming expansion. As input data, this model requires (i) crop yields, (ii) crop harvested areas and (iii) livestock population. In scenario of global organic farming expansion, crop yields and livestock population were retrieved from the outputs of GOANIM (Figure 5), while the crop harvested areas were retrieved from (Barbieri et al., 2019)

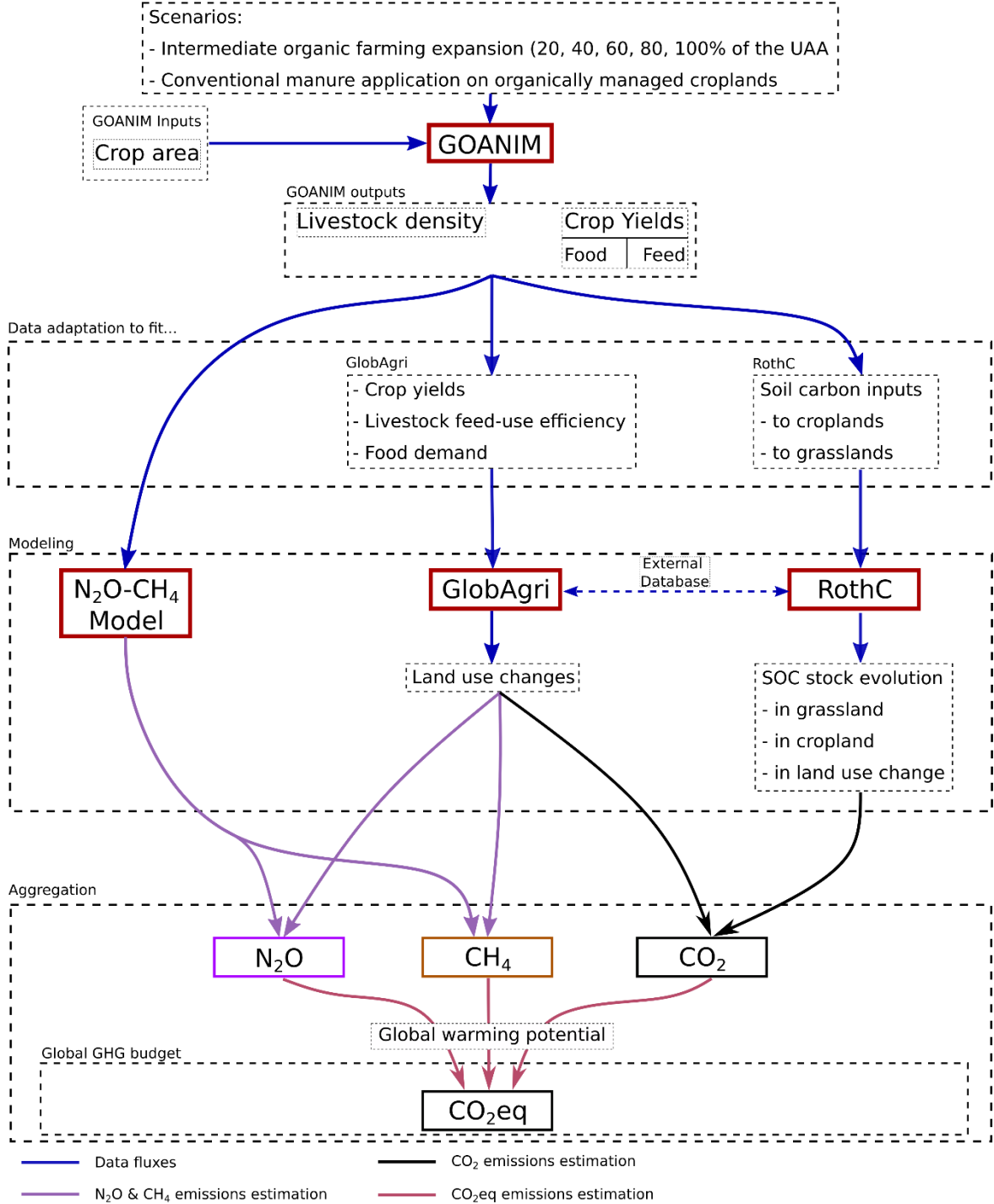


Figure 5: Conceptual framework of the general method used in this dissertation. Boxes in red represent the different models used. Boxes in black, brown and purple represent global CO₂, CH₄ and N₂O emissions respectively. Blue arrows represent fluxes of data between the different models. Pink arrows represent CH₄ and N₂O emissions estimations. Black arrows represent CO₂ emissions estimations.

We used the RothC model (Coleman et al., 1997; Martin et al., 2007) to estimate changes in soil organic carbon (SOC) stocks in both croplands and grasslands. RothC is a first order kinetic model (Smith et al., 2020) that estimates the soil organic carbon turnover according to soil carbon inputs, climate and soil conditions. RothC considers four active soil organic carbon pools: the resistant plant material pool (RPM), the decomposable plant material pool (DPM), the microbial biomass pool (BIO) and the humic pool (HUM). RothC estimates the carbon flows among those four pools as well as the amount of carbon mineralised from each pool, with a monthly time step. Input data for the RothC model are (i) soil carbon inputs, (ii) pedo-climatic conditions, (iii) soil covering period and (iv) initial SOC stocks. Soil and climatic data were retrieved from the harmonized world soil map database (Ruane et al., 2015) and the Agmerra dataset (Nachtergaele et al., 2009), respectively. Soil covering data were retrieved from (Sacks et al., 2010) and initial SOC stocks were retrieved from the AEZEF database (Gibbs et al., 2014). Soil carbon inputs were estimated by using GOANIM outputs on crop yields and livestock population to estimate carbon inputs from crop residues and manure, respectively (see **Chapter II, Figure 5**).

Land-use changes were estimated by first estimating the global cropland and grassland requirements using the GlobAgri-Agt model (Le Mouël et al., 2018; Mora et al., 2020). The GlobAgri-AgT model is a mass balance model that ensures equilibrium between regional resources and utilization of 22 agri-food products (for 14 regions), as well as equilibrium between total imports and exports of agri-food products globally. The main input data of the GlobAgri-AgT model are regional (i) crop yields (for 17 crop categories), (ii) livestock input-output ratios – meaning the amount of feed required for each unit of livestock product (for 5 livestock products) – and (iii) human diet (21 food categories). Crop yields were retrieved from GOANIM outputs (**Figure 5**). The livestock input-output ratios were estimated based on a combination of the livestock population estimated by GOANIM and the feed requirements used as input data to GOANIM. The regional human diets were estimated based on the assumption that the mean global food demand would fit the mean global food production estimated by GOANIM (see **Chapter III**).

The estimated land requirements were then converted into land-use changes based on the following assumptions:

1. Cropland expansion is likely to occur over grasslands (if the grassland area is sufficient in the given region).
2. If the grassland area is not sufficient to satisfy the need for cropland expansion, the remaining croplands are taken over forests.
3. Grasslands expansion occurs over forests and grasslands abandonment will lead to afforestation whenever pedo-climatic conditions are gathered.
4. Abandoned croplands are converted into grasslands.

We converted the estimated land-use changes into GHG emissions using the emission factors (in Gt CO₂eq.ha⁻¹.yr⁻¹) retrieved from the AEZEF database (Plevin et al., 2014). We also estimated additional N₂O and CH₄ emissions from agricultural activities on the additional croplands, by applying a mean per hectare N₂O and CH₄ emission rate estimated from the N₂O and CH₄ model (see **Chapter III**).

Finally, we combined the estimates from the three different models (N₂O-CH₄, RothC and GlobAgri-AgT) to estimate the overall GHG net emissions (expressed in Gg of CO₂ eq) from agriculture and for each of the considered scenarios of organic farming expansion (**Figure 5**). N₂O and CH₄ emissions were converted into emissions expressed in CO₂eq by using their respective global warming potential over 100 years: 298 and 25 respectively.

Outline of this PhD

The following dissertation will be structured as follows.

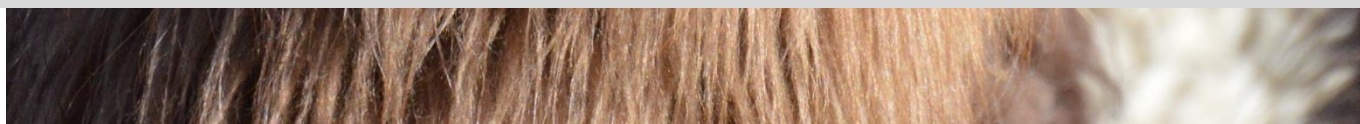
- **Chapter I** will discuss the systemic differences in terms of (i) productivity, (ii) feed ration composition and (iii) feed-use efficiency between organic and conventional farming. Results from this chapter were used to provide more precision in the simulation of the organic livestock production in GOANIM.
- **Chapter II** will discuss the effect of global organic farming expansion – and the related systemic feedbacks – on global agricultural SOC stocks. In this chapter, we combined the GOANIM model to the RothC model to estimate changes in SOC stocks in both croplands and grasslands, 20, 50 and 100 years after a global transition towards organic farming. We also tested the impact of cover crops and manure transfer from conventional to organic farming on SOC stock changes. Those estimations were made in scenarios covering different intermediate shares of organic farming expansion – meaning different shares of the global agricultural lands occupied by organic farming. Results obtained in this chapter were used to estimate CO₂ emissions from changes in SOC stocks in the chapter III.
- **Chapter III** will discuss the GHG emissions budget in scenarios of large organic farming expansion. In this chapter, we aggregated all GHG emission sources estimated, meaning (i) CH₄ and N₂O emissions from agricultural activities (based on the N₂O-CH₄ model), (ii) CO₂ emissions or removal from SOC stocks changes in agricultural lands (based on RothC) and (iii) GHG emissions from land-use changes (based on a combination of GlobAgri-AgT and the AEZEF database). In this chapter we discuss how systemic feedbacks due to organic farming expansion affects each GHG emission sources. We also discuss the response of the global GHG budget to scenarios of intermediate organic farming expansion, and how changes in farming practices (such as cover cropping) or in human diet (such as reduction of food waste and loss) impact the agricultural GHG budget globally.
- The **general discussion and conclusion** synthesises the results obtained in the three first chapters, put them in perspectives with previous studies. Finally, we discuss how this dissertation could be used in further studies to better estimate the sustainability of an organically managed world.



Chapter I: Comparing productivity and feed-use efficiency between organic and conventional livestock animals.

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In the previous chapter, we introduced the state of the art behind this dissertation, the objectives and the general methodology of this dissertation.

As mentioned in the previous chapter, GOANIM is at the core of this dissertation. GOANIM, alongside all model representing organic farming expansion scenarios, do not properly encompass the specificities of organic livestock management. This chapter represent an additional work aiming at making GOANIM more precise in its simulation of organic livestock production. In this chapter we realised a global comparison of organic and conventional livestock based on three indicators: productivity, feed ration composition and feed-use efficiency.

Abstract

Livestock animals play a key role in organic farming systems by providing nutrients for croplands through manure production and nutrient-dense food for human consumption. However, we lack global, synthetic view about livestock productivity in organic farming and about its differences with conventional farming. Here we fill this important gap of knowledge by providing a first global comparison highlighting differences between organic and conventional farming on animal productivity, feeding strategy and feed use efficiency in dairy cattle, pigs and poultry (both layers and broilers). We found (i) a 12% lower animal productivity under organic treatment, (ii) significant differences in feeding strategy, especially for organic dairy cattle fed with a lower proportion of concentrate and food-competing feed than in conventional systems, (iii) an overall 14% lower feed-use efficiency under organic treatment (-11 and -47% for organic dairy cattle and poultry broilers, respectively) compensated by (iv) a 46% lower human-food vs. animal-feed competition in organic dairy cattle. These results provide critical information on the sustainability of organic livestock management. They are also key for modelling global organic farming expansion while avoiding overestimation of organic farming production in upscaling scenarios.

Keywords

Organic farming, conventional farming, livestock production, feed-use efficiency, meta-analysis

Introduction

Scaling up organic farming is often considered as a promising option for a more sustainable food system (Reganold and Wachter, 2016). Global organic food sales were multiplied four-fold between 2001 and 2016, an increase driven by a strong consumer demand and constant policy support towards more sustainable forms of agriculture (Willer and Lemoud, 2018). Nevertheless, the sustainability of organic farming remains debatable, in particular due to its lower productivity compared to conventional – i.e., non-organic – farming (Reganold and Wachter, 2016; Seufert et al., 2012): on average, organic crops exhibit a 19 to 25% yield gap compared to conventional farming (De Ponti et al., 2012; Ponisio et al., 2015; Seufert et al., 2012). The effects of these crop yield gaps have been considered in organic farming upscaling scenarios in order to test the potential of that way of farming to meet global food security goals (Erb et al., 2016; Muller et al., 2017) and high environmental benefits.

However, none of those scenarios has considered consistent differences between organic and conventional livestock farming (Barbieri et al., 2019; Erb et al., 2016; Muller et al., 2017). This is likely due to the fact that, whereas some individual studies have compared the animal productivity and feed-use efficiency of organic and conventional farms (Röös et al., 2018; Van Wagenberg et al., 2017), no effort has been conducted so far to synthesize this information at the global scale. Such an important gap of knowledge is surprising due to the utmost importance of livestock animals for both food security and organic farming sustainability. On the one hand, livestock production provides rich food commodities with a high concentration of amino acids and nutrients (Mottet et al., 2017), contributes to replace synthetic fertilizers by animal manure (Watson et al., 2006) and fulfils a number of ecosystem services (especially when grass-fed). On the other hand, livestock production is a major anthropogenic driver of pollution and challenges food security through strong feed/food competition (Ertl et al., 2015; Laise et al., 2018a; Mottet et al., 2017; Wilkinson, 2011).

In this study, we aim to fill that important gap of knowledge by providing, synthesizing and comparing data on organic vs. conventional livestock production levels and feed use. In particular, we assess whether organic livestock farming differs from conventional in terms of animal productivity, composition of feed ration and feed-use efficiency. Because livestock feeding may have major consequences on feed/food competition, we paid specific attention to the composition of animal feed rations in organic vs. conventional farming systems and to feed use efficiency of animals fed on food-competing feeds. We hypothesized that organic livestock (i) are less productive and (ii) have a lower feed use efficiency, but - due to differences in feeding strategies - (iii) also have a lower use of food-competing feed than their conventional counterparts. Finally, we hypothesized that those results vary across animal functional types (mainly ruminants vs. monogastrics).

Material & Methods

Literature search and screening

The objective of our comparison was to evaluate whether organic and conventional farming systems differ in terms of livestock productivity, with a particular focus on feed-use efficiency and dietary composition. To do this, we searched for scientific papers comparing organic vs. conventional livestock productions and providing data on productivity as well as on feed rations. We included both research papers based on farm monitoring and those on experimental data. We focused our analysis on five main animal species –cattle, pigs, poultry, goats and sheep – as well as on three production types – meat, egg and milk. In order to identify suitable publications, we screened the "Web of Knowledge" and the "Scopus" portals using the following complex Boolean search:

((Organic OR Biological OR Ecological OR Sustainable OR conventional) NEAR/0 (Farm OR Agriculture OR Livestock OR Animal OR Husbandry OR system* OR management OR production OR dairy)) & ((Ruminant* OR monogastric*) OR (Beef OR Cattle OR Dairy OR Cow OR Heifer OR Calf OR Calves) OR Buffaloes OR Sheep OR Goat OR (Swine OR Pig) OR (Poultry OR Chicken OR Broiler OR Turkey OR Hen OR Duck OR Layer)) & (Feed OR "Life Cycle").*

The last search run was conducted on September 10th, 2020, yielding 2085 articles. These articles were further screened via a selection process based on three main steps in order to limit the number of papers to those that fulfilled our selection criteria (**Figure S1**). After a first selection based on title and abstract screening (in order to exclude off-topic papers), we screened 201 articles to select those that (i) specifically mentioned one organic system (either certified or in line with the definition of organic agriculture given in the *Basic Standard for Organic Production and Processing* of the International Federation of the Organic Agricultural Movement (IFOAM)) and one non-organic system that we defined as conventional, (ii) provided animal production and animal feed (either the entire feed ration or at least the share of concentrate feed) or the feed-use efficiency directly, (iii) reported data from animal or farm observation (national statistics and results from models were excluded) and (iv) had a number of observations (i.e. number of monitored animals) higher than 20. After this process, we retained 34 pertinent articles that referred to four livestock species and the three production types mentioned, covering 14 countries worldwide. Nevertheless, we only identified a limited number of papers that focused on beef cattle (three comparisons) and none on goats and sheep that fitted our selection criteria. Therefore, we finally excluded beef cattle from the analysis – i.e., we used only 37 comparisons from 31 papers to run our statistical analyses. Among the different livestock species, dairy cattle were the most highly represented (20 comparisons), followed by a much lower number of comparisons for pigs, broilers and layers (**Table 2**). Ruminant-related data were mainly taken from farm monitoring (18 comparisons out of 20 for dairy cattle), while monogastric-related data were mainly experimental. Developed countries are the most highly represented (31 comparisons), while only six studies were located in developing countries (**Table 2**). Studies selected were mainly located in Europe (25 comparisons) and the Middle-East (6 comparisons) (**Figure S2**). The complete list of studies is reported in **Table S1**.

We are aware of the reduced size of our dataset. This is mainly due to the fact that papers often report incomplete information, thereby not fulfilling our selection criteria. We tried to make up for this by directly contacting a number of authors in order to collect additional data, with a low share of response. Therefore, our dataset remained heterogeneous, meaning that we could not calculate all

of the requested variables for each article, hence leading to fluctuation in dataset size among the considered variables. Despite such shortcomings, our comparison represents the first attempt to globally quantify and compare livestock production performances between organic and conventional production farming based on the best available literature.

Table 2. Number of organic-to-conventional comparisons for each animal category, type of observation, country level of development and studied variable.

	Total no. comparisons	Type of observation		Level of development		Animal productivity	Feed-use efficiency		
		Experiment	Farm monitoring	Developed countries	Developing countries	Total feed	Concentrate feed	Food-competing feed	
Cattle dairy	20	2	18	19	1	19	18	19	6
Pig meat	7	7	0	5	2	7	6	6	6
Poultry egg	4	3	1	2	2	4	4	4	4
Poultry meat	6	5	1	3	3	6	6	6	4
All animals	37	17	20	29	8	36	34	35	20

Data extraction

In each selected paper, we extracted one or several pieces of information comparing one organic system and one conventional system in terms of animal productivity, feed ration and feed-use efficiency. We encountered cases where articles provided several different organic systems and/or several different non-organic systems. We therefore had to gather data in order to extract one or several comparisons. When one treatment for organic or non-organic treatments was compared to several of the other treatments, a mean was calculated with the other treatments in order to have only two treatments to compare. When several treatments of both organic and non-organic systems were present, treatments were combined (based on similar geographical position, breed or housing system) in order to make several comparisons.

We applied the following data extraction procedure: (1) when available, we recorded data reporting production quantities expressed as the amount of animal product per unit of time and per head. We considered the animal product to be the main product of the production type, i.e., animal by-products (e.g. meat from reformed dairy cattle) are not considered. Animal production quantities were expressed as energy corrected milk (ECM), kg of egg and kg of live weight gain. When not available, production was calculated to fit the previous units (see **Annex I**); (2) when available, feed ration composition was recorded as the amount of dry matter per unit of time and per head for each feed type. Data were sometimes in the form of fresh weight: we converted such data to dry matter (DM) equivalents using dry matter coefficients retrieved from the Feedipedia and Feedtables databases (see **Annex I**). When the detailed feed ration composition was not available, composition in terms of forage and concentrate was recorded; (3) we recorded feed-use efficiencies expressed as the ratio between production quantity and feed intake, although other authors express feed-use efficiency as the ratio between feed intake and production (Mottet et al., 2017; Wilkinson, 2011). Because both formulas represent a good feed-use efficiency indicator (Laisse et al., 2018a), we decided to use the former for easier interpretation and greater comparability with crop input use efficiency. If feed-use efficiency was not available, we calculated it using the data recorded in the two previous steps.

Different authors question whether calculating feed efficiency as the ratio of production to total feed ingested is an appropriate indicator. These same authors instead suggest calculating independent feed-use efficiency as the ratio between production and specific feed items, e.g., concentrate or food-competing feed (Ertl et al., 2015; Mottet et al., 2017; Wilkinson, 2011). These two other feed-use efficiency indicators are important in order to understand the impact of livestock production on feed/food competition. We therefore also recorded feed-use efficiencies based on concentrate and food-competing feeds when available.

Feed-use efficiency is commonly calculated as a mass ratio (Mottet et al., 2017) (**Equation 3**).

$$\text{Equation 3 } \textit{feed use efficiency} = \textit{kg of animal product} / \textit{kg of ingested feed (expressed in dry matter)}$$

Nevertheless, since energy and protein are two important nutritional human and animal components, feed-use efficiency is often calculated as the ratio between production expressed in energy and crude protein (CP) and the energy or protein ingested as feed (Ertl et al., 2015; Mottet et al., 2017; Wilkinson, 2011). Similarly, we recorded the energy and crude protein feed-use efficiency for all feed categories when available (**Equation 4**, **Equation 5**).

$$\text{Equation 4 } \textit{Energy feed use efficiency} = \textit{MJ in animal product} / \textit{MJ in feed}$$

$$\text{Equation 5 } \textit{Energy feed use efficiency} = \textit{kg CP in animal product} / \textit{kg CP in feed}$$

In addition to those efficiency indicators, we recorded the net feed-use efficiency defined as the ratio of the energy (or protein) available for human consumption in the animal product to the energy (or protein) available for human consumption in the feed ration. Although several authors suggested different calculation methods for this indicator, we used the method developed by (Laisse et al., 2018a) because it is the only one that provides a detailed classification of feed products with their corresponding human-edible energy and protein content. Since no proof of differences in energy and protein content between organically-produced and conventionally-produced food is clearly available (Srednicka-Tober et al., 2016), we used the same coefficients to estimate animal food product energy and protein content (following (Laisse et al., 2018a).

Statistical analysis

In our comparison, we used the non-organic treatment as the control. To estimate productivity and feed use efficiency differences between organic and conventional systems, we calculated as an effect size the organic-to-conventional log response-ratios (Makowski et al., 2017) for both productivity and feed-use efficiency. We then tested whether the mean effect size was significantly different from zero using a linear weighted mixed-effect model. The production type (e.g., dairy cows, poultry broilers) was set as a fixed factor, whereas we used a dummy variable representing each paper ID number as a random factor. The absence or the poorly reporting of variance values in the selected papers did not allow to follow the common study-weighting procedure – meaning weighting each study by the inverse of its variance. However, alternative procedures are possible for example by weighting each study by its number of observations (i.e. the number of monitored animals in our case) (Beillouin et al., 2019; Letourneau et al., 2011; Philibert et al., 2012). In addition, we compared the results obtained following this statistical procedure with results based on simpler statistics using non-

weighted means. Note that this last approach does not account for the often greater accuracy of studies that report data from large number of monitored animals.

Since livestock management differs across animal species and production types and since organic practices may vary depending on the geographical location, we disaggregated our dataset according to the different (i) livestock species, (ii) production types (meat, milk or eggs) and – for each of them – (iii) type of data (experimental vs. on-farm observations) and (iv) geographical locations (developed vs. developing regions). We then run our statistical analyses for each sub-group. Note that the developed vs. developing country grouping is common when comparing organic to conventional farming (Barbieri et al., 2017; Seufert et al., 2012). Dairy cattle data was additionally disaggregated according to (i) the duration of animal monitoring (i.e. over the whole year vs. over the lactation period) and (ii) the monitored entity (herd vs. individual cows).

To compare whether the two systems differ in terms of the entire feed rations, we run a permutational analysis of variance (non-parametric MANOVA) using a Euclidean dissimilarity index and 999 permutations to compute the significance tests. In addition, we tested the presence of significant differences between organic and conventional farming in the use of each single feed category by using a non-parametric Kruskal-Wallis test – due to the non-normal distribution, tested through a Shapiro-Wilk test and residual check plots. All analyses were run on R x 64 3.5.1, using lmer4 (Bates et al., 2019) and vegan packages (Oksanen et al., 2019).

Results

Animal productivity in organic vs. conventional systems

Our results show that overall productivity per animal is 12% ($\pm 5\%$) lower in organic compared to conventional farming (**Figure 6**). Despite high variability in the effect-sizes across animal species - especially for pigs and poultry layers (**Figure 6**) - all livestock species exhibit a lower productivity in organic vs. conventional farming. Among all livestock types, dairy cattle productivity, with a difference of -14% in organic compared to conventional farming, is the only one that reveals a significant difference. Note that similar results were observed by using non-weighted means – although with lower uncertainties – (**Figure S3**) or when breaking down our dataset into research experiment vs. farm monitoring (**Figure S4**). Exception for this are dairy cows and poultry broilers for which experiment-based results yield no difference between organic and conventional management whereas lower organic productivity was reported in farm-based studies (**Figure S4**). Note also that by breaking down our dataset into developed vs. developing countries (**Figure S5**), we found lower organic productivity in developed countries compared to conventional – in particular for dairy cows and poultry broilers. These results are in line with the statement that organic farming may perform well in many developing regions while drop in productivity is higher in regions with high conventional productivity (De Ponti et al., 2012; Kniss et al., 2016; Rigby and Cáceres, 2001).

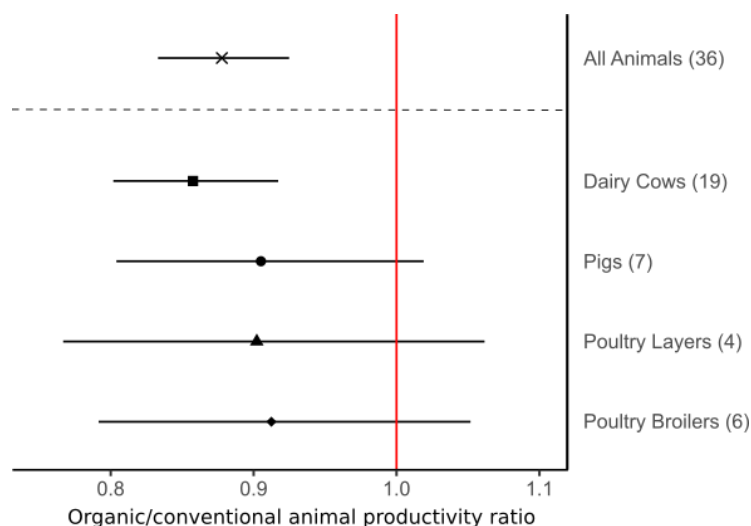


Figure 6. Organic-to-conventional animal productivity ratios. Values are the weighted means of organic-to-conventional ratios with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one (meaning no differences between organic and conventional animal productivity). A ratio higher than one represents cases where organic farming has higher productivity than conventional farming.

Several factors may explain the observed productivity gaps, such as (i) use of less productive animal breeds, (ii) higher vulnerability to animal diseases and parasites, in particular for monogastrics and (iii) difference in feeding strategies, in particular for ruminants (longer grazing period, lower energy and protein density of the feed ration, higher share of fodder in the feed ration) (Röös et al., 2018; Van Wagenberg et al., 2017). Our dataset did not make it possible to confirm any differences in the use of animal breeds and in vulnerability to diseases and parasites between organic and conventional farming systems, but it allowed to highlight differences in feed ration composition (see next section).

Feed ration composition in organic vs. conventional farming

Our results show that differences in animal feed ration composition are small for poultry, moderate for pigs and large for dairy cows when all eight of the detailed feed categories (**Table S2**) are considered (**Figure 7a**). These differences between organic and conventional were consistent independently of whether feed rations are expressed in mass (**Figure 7**), energy or protein (Figure S6).

More precisely, we found that the share of grassland products and hay is higher in organic than in conventional dairy feed rations (63 vs. 44%, respectively). Similarly, the share of legume grains was higher in organic rations (**Table S2**). In contrast, organic rations exhibit a lower share of non-legume grains (e.g., cereal grains: 21 vs. 38%), non-legume by-products (e.g., wheat middling: 6 vs. 8%), and legume by-products (e.g., soybean cakes: 0 vs. 3%). These differences might be explained by a longer grazing season in organic dairy farming compared to conventional (Van Wagenberg et al., 2017), a higher occurrence of legume grains in organic crop rotations (Barbieri et al., 2017), especially in Europe, and a reluctance to use processed, costly concentrates such as legume and non-legume by-products. All these explanatory factors are clearly in line with the recommendations of organic regulations aimed at a high degree of self-sufficiency of organic livestock farming (Lampkin et al., 2017). As mentioned before, moderate differences were observed between organic and conventional pig ration composition, with organic rations containing more legume grains (16 vs. 9%), on the one hand, and the absence of feed from the ‘other concentrate’ category in organic rations, on the other

hand. The ‘other concentrates’ represent 3% of the conventional pig ration and contain feed such as synthetic amino acids. These synthetic amino acids are banned in organic livestock feed rations, thereby probably contributing to the observed lower animal productivity (Wu et al., 2007) as reported in Figure 6.

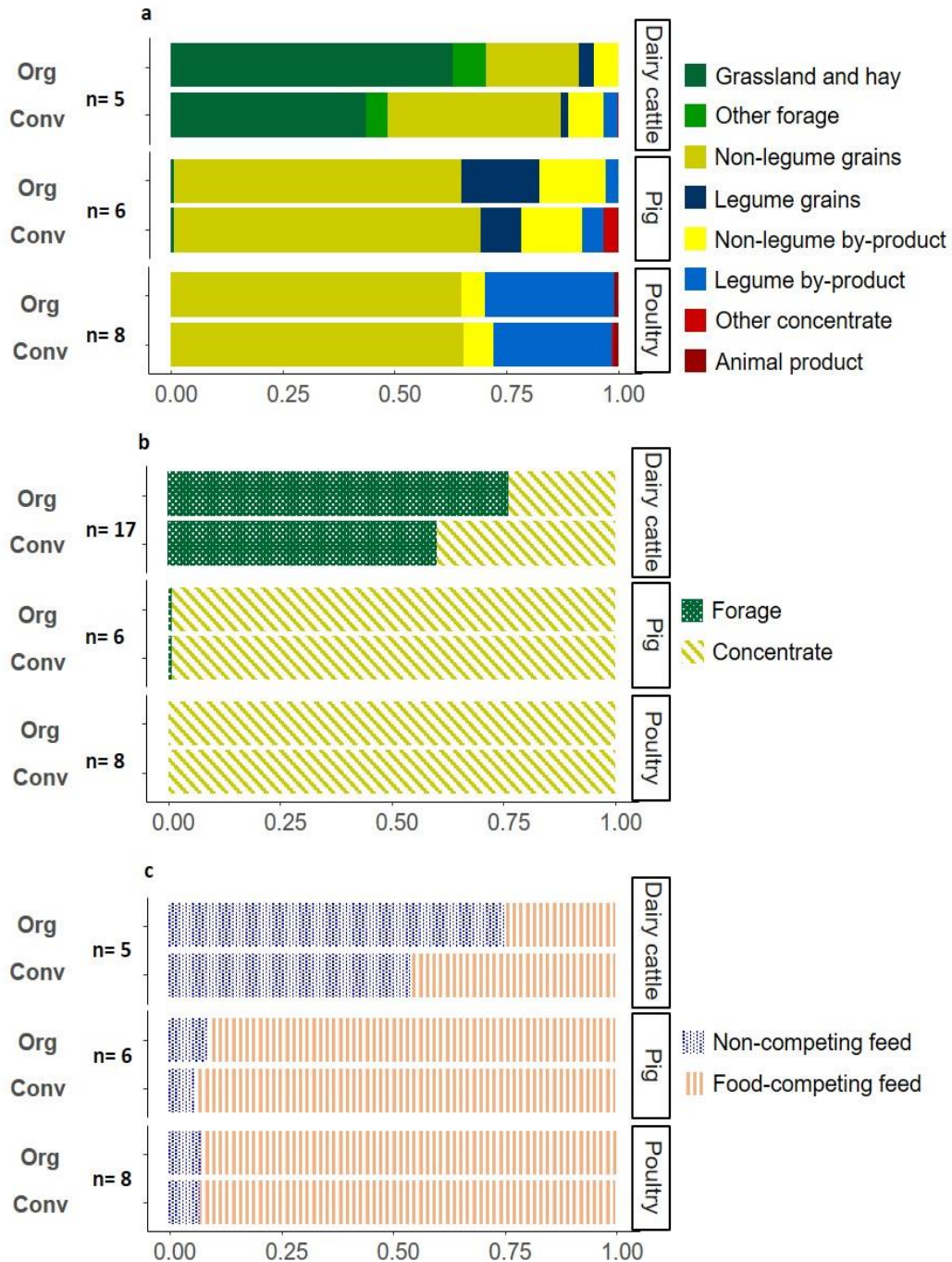


Figure 7. Animal feed rations composition in organic and conventional farming systems for three livestock species. Horizontal bars represent the share of each feed category as a fraction of the total feed ration (expressed in kg of dry matter). The composition of the feed ration is expressed based on eight detailed feed categories (a) or clustered as forage vs. concentrate feed (b), or as food-competing vs. non-competing feed (c). ‘Org’ and ‘Conv’ refer to organic and conventional farming, respectively. The number of studies supporting each comparison is given at the left of the horizontal bars.

When considering feed rations expressed in terms of forage vs. concentrate feed (**Figure 7b**), we found that rations of organic dairy cattle contain significantly more forage products than for conventional dairy cattle (76 vs. 60%, respectively), a result confirmed when expressing feed rations in energy and protein (**Table S3** and **Table S4**). Organic farmers often use a higher share of fodder to feed their animals due to (i) the low availability of organic concentrate feed (lower diversity and higher prices than for conventional ones) (Escribano, 2018; Flaten and Lien, 2009), and (ii) organic regulation requirements that set a minimum share of forage in ruminants' diets (Lampkin et al., 2017). This higher use of forage and limited utilisation of concentrates probably contribute to the productivity gap between organic and conventional dairy cattle found in **Figure 6** (Aguerre et al., 2011).

Finally, when considering feed rations expressed in terms of food-competing vs. non-competing feed (**Figure 7c**), we found a 45% lower share of food-competing feed in the organic dairy cattle feed ration compared to conventional livestock feeding (25% vs. 46% respectively). Similar results are found when considering the energy and protein feed ration (**Table S3** and **Table S4**). However, no differences can be observed regarding pigs and poultry production, with approximately 92% of the ration potentially competing with human food in both organic and conventional farming (**Table S2**).

Feed-use efficiency in organic vs. conventional farming

Our results show that feed-use efficiency (the ratio of the amount of animal product to the animal feed intake), when calculated over the entire feed ration, is 14% ($\pm 8\%$) lower in organic compared to conventional farming (**Figure 8a**). This lower feed use efficiency in organic compared to conventional is especially significant for dairy cattle ($-11\% \pm 9\%$) and poultry broilers ($-47\% \pm 10\%$). Similar results were observed by using non-weighted means (**Figure S7**) – although with smaller uncertainties –, when feed-use efficiency is calculated based on the energy and protein feed ration (**Figure S8**) or when disaggregating our dataset into studies based on research experiment vs. farm monitoring (**Figure S9**).

The lower feed-use efficiency for organic dairy cattle may be partly explained by differences in feeding strategies. We found a higher share of rough forages in animal diets in organic compared to conventional farming (**Figure 7**). Forage based diets are known to be often less balanced than grain based diets (Brito and Silva, 2020; Voelker et al., 2002), leading to reduced milk yield. However, in those forage based diets, the negative effect of lower milk yield on feed-use efficiency might be compensated (though not completely) by a lower feed intake: as rough forages are less digestible, they require more space and time in the cow's rumen, leading to lower ingestion of other feeds (Voelker et al., 2002). Milk yield reduction can be exacerbated if feeding animals with rough forages comes with more grazing. Indeed, grazing costs more energy to the animals than other feed intakes, leading to reduced energy availability for milk production (Kaufmann et al., 2011). Although our dataset did not provide information on grazing management between organic and conventional dairy cows, we found both a reduced milk yield and a higher forage share in the organic dairy rations compared to conventional ones. Therefore, lower feed-use efficiency for organic dairy cattle (**Figure 8a**) may be explained by a lower animal productivity due to a coarser and less energetic forage-based feed ration (**Figure 7**).

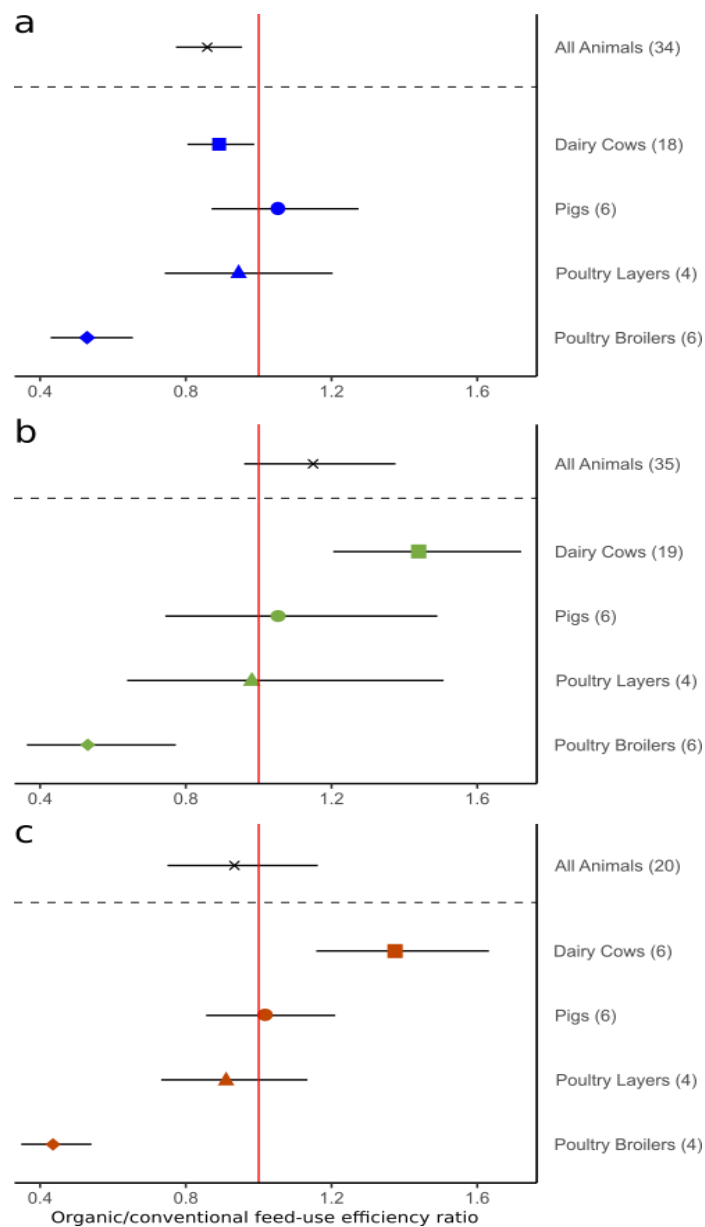


Figure 8. Organic-to-conventional animal feed-use efficiency. Feed-use efficiency is calculated based on the entire feed ration (a), on concentrate feed (b), and on food-competing feed (c). Values are weighted means of organic-to-conventional ratio with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming.

In contrast, the difference in feed-use efficiency for poultry broilers cannot be explained by a difference in animal productivity (which was non-significantly different in organic vs. conventional farming, see **Figure 6**). Data on poultry life span showed a 45% longer lifespan for organic vs. conventional poultry broilers in our database. This result is in agreement with organic regulations that do not allow broiler slaughtering before 81 days (Rezaei et al., 2018). Consequently, organic broilers need to be fed over a longer time, which leads to lower feed-use efficiency. When controlling slaughter age (two of our comparisons were based on an experiment where organic and conventional poultry were both slaughtered at the same age), similar feed-use efficiencies were found between organic vs. conventional (data not shown) thus confirming effect of slaughter age.

Interestingly, our results show that these differences between organic vs. conventional farming are modified when feed-use efficiency was calculated based on concentrate feed or on food-competing feed. Concentrate feed-use efficiency generally exhibited a higher - although not significant - value for organic animals (**Figure 8b**). In particular, organic dairy cattle are 44% ($\pm 23\%$) more efficient in their use of concentrate feeds than their conventional counterparts (**Figure 8b**), a result explained by the lower concentrate consumption in organic dairy cattle production (**Figure 7b**). We found a similar result when feed-use efficiency was expressed in terms of food-competing feed, with organic dairy cattle being 37% ($\pm 26\%$) more efficient in their use of food-competing feed compared to their conventional counterparts (**Figure 8c**). In contrast, for pigs and poultry, feed-use efficiency does not significantly change when calculated based on the entire feed ration, the concentrate feed or the food-competing feed (**Figure 8**), a result explained by those animals being mainly fed with concentrate, food-competing feeds (**Figure 7**). Finally, by breaking down our dataset into developed vs. developing countries we found a consistent – although rarely significant – greater feed-use efficiency in developed countries (**Figure S11**). This result is probably related to more precise feeding management in developed countries, as well as to scarce data regarding developing countries.

Discussion

When comparing the sustainability, profitability and food security impacts of organic compared to conventional farming systems, the yield gap between the two systems is a key issue (Connor, 2008; Gattinger et al., 2012; Reganold and Wachter, 2016; Skinner et al., 2014). To the best of our knowledge, this study is the first global comparison to provide quantification of the productivity gap between organic and conventional livestock production. More importantly, we provide here a first comparison of organic vs. conventional livestock's feed ration composition and feed-use efficiency in a systemic way. By calculating partial feed-use efficiencies based on concentrate and food-competing feed, our analysis also provides critical values to assess the impact of organic livestock production on the feed/food competition in a food security context.

Feeding strategies and animal productivity are closely related. A higher forage-to-concentrate ratio often result in lower animal productivity (Aguerre et al., 2011), whereas the use of synthetic amino acids often promotes animal growth (Eriksson et al., 2010). Our results show similar trends, with (i) lower animal productivity under organic compared to conventional farming and (ii) differences in the feed ration composition that likely impact animal productivity. Different feeding strategies contribute to the differences we found in feed-use efficiency as well, although the main driver probably also lies in the management practices applied (such as age at slaughter and reproduction cycle management).

Our results have different implications for the development of organic farming and for assessing its potential to deliver food in a sustainable manner. *First*, the overall lower productivity of organic animals contrasts with the observed increasing consumption of livestock products at the global scale, especially in developing countries (Tilman and Clark, 2014). Therefore, farming the planet organically would make it difficult to satisfy animal product demand, thus reinforcing the global mitigation of animal product demand as a key leverage factor to achieve global food security (Erb et al., 2016; Muller et al., 2017). *Second*, our results highlight how the organic vs. conventional livestock affect and contribute to the feed/food competition. Livestock production uses one-third of the global cereal production (Foley et al., 2011), with considerable implications for human food supply. An increase in the feed-use efficiency of food-competing feed is essential to reduce cereal use by livestock

animals and to enhancing global food security. Providing indicators and data on the impact of organic farming on feed/food competition is therefore highly needed to assess its potential to ensure food security. Our results show that this impact strongly depends on the animal species and type considered. Organic poultry is less efficient in its use of food-competing feed (improvement of this might come from the selection of breeds more adapted to organic conditions (Röös et al., 2018)), whereas the opposite is observed for dairy cattle (that strongly rely on forage products for feeding). Those results are in line with the outcomes of scenarios that explore more sustainable ways of managing livestock production globally (Röös et al., 2016; van Zanten et al., 2016). Most of those scenarios converge on the need to feed ruminants a grass-based diet in order to alleviate the feed/food competition. Our results show that organic dairy cattle management already apply those recommendations. *Third*, the forage-rich diets of organic dairy cattle that we highlighted is highly consistent with previous studies showing a higher share of temporary pasture in organic crop rotation compared to conventional ones (Barbieri et al., 2019, 2017). Rotated, temporary pastures have been reported to have environmental benefits – especially in terms of carbon sequestration – (Dumont et al., 2019) thus helping to offset part of livestock greenhouse gas emissions. Therefore, by being more often grass-based than in conventional farming, organic dairy systems contribute to more sustainable and climate-friendly ways of farming.

Note however that the significance of our results must be balanced with their limitations. The scientific literature on feed-use efficiency between organic and livestock production remains limited and often provides incomplete data (on variance or detailed feed ration), with some consequences for our study implications. *First*, weighting studies by their internal variance was made impossible, thus preventing to account for individual study accuracy and precision. However, weighting studies by their number of observations is a satisfactory alternative that we applied here and similar results were obtained by using weighted and non-weighted methods, thus confirming the robustness of our approach. *Second*, though we consider geographical variability by disaggregating our dataset between developed vs. developing countries, we could not consider more regional variability. Our data set is mainly focused on Europe and Middle East (**Figure S2**), and this specificity must be accounted for when using our results. Clearly, more results are needed from developing countries to better capture effects of organic management in those regions. *Finally*, some livestock categories are under-represented in the literature, with a very limited number of studies on small ruminants and on beef cattle production, thus preventing to extend considerably our study beyond the four livestock species and types considered here. For instance, based on the very few data available in the literature (in Italy and in India, (Buratti et al., 2017; Singh et al., 2010), we found that the productivity gap between organic and conventional animals was lower (and closer to zero) for beef than for dairy systems. This result is in line with the fact that, at least in Europe, beef systems are often managed less intensively (whether organic or conventional) than dairy systems. Therefore, these dataset limitations must be accounted for when using our results as inputs in global models that explore the consequences of organic farming upscaling and its impacts on food security and the environment. If these limitations are taken into consideration, our results could be of strong interest for models exploring such upscaling scenarios - such as the BioCBioBaM (Erb et al., 2016) or the SOL models (Muller et al., 2017) - which currently consider no differences between organic and conventional livestock production. Implementing our results in those models will improve their accuracy about feed demand and animal product supply.

Finally, the limited size of our dataset highlights the need for more standardised procedures when comparing and reporting data concerning organic and conventional livestock production and feeding strategies, e.g., by detailing the animal feed ration composition. In addition, a unified

classification of feed products and their potential to be used in human nutrition (currently and considering technological improvements in energy and protein extraction for human use) would be a big help to calculate appropriate food-competing feed-use efficiencies (Laisse et al., 2018a; Mottet et al., 2017). Adopting a production system approach in studies reporting animal feed use (e.g., by detailing animal number of lactations or herd replacement rate) would be of great benefit to consider the different factors that influence animal productivity and system feed-use efficiency.

Conclusion

This first global comparison on organic vs. conventional livestock production highlights a clearly lower level of animal productivity and feed-use efficiency of organic compared to conventional livestock farming. Differences in productivity are likely to be explained by differences in feeding strategies for which we provided some evidence. Differences in feed-use efficiency are likely to be explained by differences in livestock system management (such as herd structure and slaughter age) in addition to feeding effects. Such findings may result in more land required by organic livestock farming compared to conventional farming to achieve the same level of animal production. Notwithstanding, our results also show that organic dairy cattle are less in competition with human food production due to their higher food-competing feed-use efficiency, with strong implication for land use and human food production. Even though additional research efforts are needed to consolidate our findings, those are key to understanding and assessing the impact that organic livestock upscaling may have on global food security and farming sustainability.

Conflicts of interest

The authors declare no competing interests.

Acknowledgment

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Data availability

The authors declare that the main data supporting the findings of this study are available within the article and its Supplementary Information files. Extra data are available from the corresponding authors upon request.

Authors' contributions

U.G., T.N. and S.P. designed the study; U.G. collected the data and performed the statistical analysis; all authors were involved in the interpretation of results and contributed to writing and revising the manuscript

Chapter II: Soil organic carbon stocks potentially at risk of decline in an organically farmed world

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In the previous chapter, we highlighted differences between organic and conventional livestock. These differences were implemented in the latest version of GOANIM alongside other modifications. In this chapter, we combined this new version of GOANIM to the RothC model in order to estimate changes in soil organic carbon stocks of agricultural lands due to organic farming expansion. We used this combination to test different scenarios of organic farming expansions based on: the share of agricultural lands occupied by organic farming, the use of cover crops in organic farming and the application of conventional manure in organic farming.

Abstract

Increasing soil organic carbon (SOC) stocks in agricultural lands is key to mitigate climate change and, organic farming is often considered as a promising option to do so. So far, evidence of higher SOC stocks in organic farms compared to conventional farms reflects situations where organic farming occupies small fractions of agricultural areas, with access to ample amounts of organic fertilising resources – access that might be reduced with organic farming expansion. Using a modelling approach, we estimated global SOC stocks following a 100% conversion to organic farming of global agricultural lands. We found that (i) global soil carbon inputs would be reduced by 39% in croplands and not changed in grasslands, leading to a (ii) 6, 8 and 10% global SOC stock reduction in agricultural lands 20, 50 and 100 years after that transition, respectively. These results suggest that organic farming expansion might reduce its potential to mitigate climate change through soil carbon sequestration. This potential might be maintained when appropriate practices – such as enhanced soil cover cropping – are implemented to alleviate nitrogen limitations and boost carbon inputs to soils.

Keywords

Organic farming, Soil organic carbon stocks, Soil carbon inputs, Global scale, Modelling

Introduction

The agricultural sector is responsible for 23% of global anthropogenic greenhouse gas (GHG) emissions (Foley et al., 2011; IPCC, 2021). Meanwhile, it offers unique opportunities to mitigate climate change through carbon sequestration in agricultural soils. The potential of arable lands to sequester carbon has been estimated at 0.79-1.54 Gt C.yr⁻¹ (Amelung et al., 2020; Fuss et al., 2018), a value equal to 11% of global anthropogenic GHG emissions. While arable lands have lost up to half of their organic carbon stocks since the industrial revolution (Lal, 2004a), agricultural practices could help increase soil organic carbon stocks, by increasing soil carbon inputs or by reducing soil carbon mineralisation (Paustian et al., 2016).

Organic farming is often presented as a way of farming that helps increase soil carbon sequestration and soil organic carbon (SOC) stocks (Clark and Tilman, 2017). Meta-analyses of field experiments have shown that organically managed soils have higher SOC stocks (+3.5 Mg C.ha⁻¹) and soil carbon sequestration rate (+0.45 Mg C.ha⁻¹.yr⁻¹) than conventional ones (Gattinger et al., 2012; Seufert and Ramankutty, 2017). These results are largely explained by higher soil carbon inputs in organic systems through both enhanced manure application rates and the use of more complex crop rotations with higher frequency of temporary pastures and cover crops (Barbieri et al., 2017), resulting in higher plant-based organic carbon inputs to soils.

However, organic farming occupies less than 2% of the global utilized agricultural area (UAA, (IFOAM, 2020). Evidence provided by meta-analyses therefore represent situations where organic materials are abundant for fertilisation of organically managed soils (Nowak et al., 2013). In contrast, the expansion of organic farming might generate an increased competition for fertilising resources, possibly resulting in a reduction of soil carbon inputs and soil carbon sequestration rate. A recent study has shown that organic farming upscaling to 100% of the UAA would lead to a 56% crop yield reduction due to severe nitrogen (N) limitation (Barbieri et al., 2021) – a significant drop compared to the 20-30% yield reduction previously reported by field-based meta-analyses (Ponisio et al., 2015; Seufert et al., 2012). This drop is mostly due to the ban of synthetic N fertilizers in organic guidelines that reduces both the range of N fertilization resources (e.g., crop residues, livestock manure) and their global availability with large consequences for soil fertilisation – a result confirmed by recent studies highlighting N fertilisation limitation in organic farming upscaling scenarios (Billen et al., 2021; Erb et al., 2016; Muller et al., 2017). Organic farming expansion is thus likely to have major consequences for soil carbon inputs as crop residues and as fertilising materials, potentially resulting in large changes in SOC stocks.

Capturing those systemic feedbacks of organic farming expansion on N availability is key to get accurate estimates of soil carbon inputs in scenarios of large organic farming upscale. Additionally, considering both croplands and grasslands is needed to get unbiased estimates of SOC sequestration due to possible horizontal carbon transfers between croplands and grasslands (Leifeld et al., 2013; Nesme et al., 2021). Finally, adopting a spatially explicit approach is highly relevant to account for the spatial variability in soil carbon inputs, soil mineralisation rates and initial SOC stocks. We addressed these knowledge gaps by combining (i) GOANIM, a spatially explicit model simulating cropland N cycle, crop productivity and livestock populations under scenarios of large organic farming expansion (Barbieri et al., 2021) with (ii) RothC, a dynamic, first order kinetic model simulating carbon dynamics in soils (Coleman et al., 1997; Martin et al., 2007). We used GOANIM outputs about livestock manure and crop residue production to estimate carbon fluxes between croplands, grasslands and livestock, and to estimate soil carbon inputs (SCI) in scenarios of large organic farming expansion (for

both croplands and grasslands). We then used the estimated SCI as an input to RothC to simulate the changes in SOC stocks under different time horizons. We assessed different scenarios combining (i) variations in organic farming practices (cover cropping, use of conventional manure on organic croplands) and (ii) variations in the level of organic farming expansion globally, each compared with a baseline scenario of no changes in agricultural practices.

Organic farming encompasses a diverse set of farming practices, depending on regional regulations, farming contexts and markets. Although all organic regulations are gathered under the ban of synthetic fertilisers (Seufert et al., 2017), organic farms exhibit ample variability in the way this ban is translated into farming practices (Kirchmann et al., 2016; Ponisio et al., 2015; Puech et al., 2014). In particular, organic farms may adopt cropping practices that are known to improve soil carbon sequestration (e.g. cover cropping, agroforestry). In this study, we will consider situations of simple organic farming practices, thereby excluding cropping practices that would provide additional soil carbon sequestration (see Methods). This conservative attitude is not meant to provide a normative view on organic farming. Instead, it is meant to provide estimates that can serve as references to envision additional and complementary cropping practices. This conservative definition of organic farming in the GOANIM model led to a drastic reduction of cropland production (-56%) and livestock population reduction (- 20 % in livestock units) in a fully organically managed world (Barbieri et al., 2021), with a large shift towards ruminant animal species. In such a scenario, we hypothesized that both SCI and SOC stocks would be negatively affected by a global transition to organic farming, with potential modulations when accounting for additional organic farming practices – such as cover cropping.

Material & Methods

The objective of this study was to estimate the potential impact of global organic farming expansion on soil organic carbon stocks. To do so, we used a modelling approach to estimate the SOC stock changes in scenarios of global organic farming expansion compared to the currently observed SOC stocks (that we considered as those in conventional farming and hereafter called the baseline). The modelling approach was based on two separate steps, as explained below.

First, we estimated the soil carbon inputs (SCI) in both the scenarios of large organic farming expansion and in the baseline for croplands and grasslands in a spatially explicit way (5 arcmin resolution, i.e. $\sim 10 \times 10 \text{ km}$ at the equator). In both the organic scenarios and the baseline, we estimated the SCI as a sum of (i) the amount of carbon that is returned to agricultural lands as plant residues (crop-based and grass-based residues) and (ii) the amount of carbon excreted by animals as farmyard manure (FYM) applied to lands after accounting for C losses during manure storage. The SCI estimates for the organic farming scenarios were computed using outputs from the GOANIM model (Barbieri et al., 2021). GOANIM is a spatially explicit (5 arcmin resolution) linear optimisation model that simulates nitrogen flows to and from croplands and grasslands under scenarios of organic farming upscaling. GOANIM calculates cropland N budget and its effects on crop yield for 61 crop species. The optimising module of GOANIM is designed to maximise food availability at the global scale (from both crop-based and animal-based products) by spatially optimising the global livestock population and the N allocation from animal manure to the different considered crops. We used the latest version of GOANIM (see **Annex III**), accounting for (i) differences in feed rations and feed use efficiency between organic farming and conventional farming (Gaudaré et al., 2021), (ii) the 2019 refinement of the IPCC guidelines

values on manure management and nitrogen losses (as direct N₂O emissions, nitrate leaching and ammonia volatilisation) and (iii) representation of non-productive, young animals.

Second, we used those estimated SCI in the RothC (Coleman et al., 1997; Martin et al., 2007) model to estimate changes in SOC stocks in the organic farming scenarios, considering only annual crops (which represents 45 of the 61 crops in GOANIM, thereby assuming no changes in carbon inputs to soils for perennial crops). RothC is a model that estimates soil organic carbon turnover in both croplands and grasslands according to SCI, soil covering, climate and soil conditions. RothC considers four active soil organic carbon compartments: the resistant plant pool (RPM), the decomposable plant pool (DPM), the microbial pool (BIO) and the humic pool (HUM). An additional inert organic matter (IOM) pool is considered but the latter is supposed to be constant over time in RothC; it is thus assumed unchanged in the organic scenarios vs. in the baseline, and is not included in the equations below. RothC estimates the carbon flows among the four active compartments as well as the amount of carbon mineralised from each compartment, with a monthly time step and through first order kinetic equations. In this study we used the continuous formulation of RothC (Martin et al., 2007) summarized in **Equation 6**.

$$\text{Equation 6 } SOC'(t) = \rho(t) * A * SOC(t) + B(t)$$

Where $SOC'(t)$ represent the derivative of SOC with respect of time, $SOC(t)$ represent the SOC stocks at time t . A is a 4x4 matrix representing the mineralisation and carbon flows among the four active soil organic carbon pools. $\rho(t)$ is the decomposition rate modifier and depends on the climatic, edaphic and soil covering conditions. Note that soil covering affects SOC dynamics by reducing its mineralisation rate in RothC. We assumed similar rates of soil organic carbon stabilisation and mineralisation in both the organic scenarios and the baseline – a rather conservative estimate due to lack of consistent data, despite preliminary evidence of more active carbon cycling in organically managed soils (Lori et al., 2017). Spatially explicit climatic data were retrieved from the AgMERRA dataset (Ruane et al., 2015) combined with the Penman equation to estimate potential evapotranspiration. Spatially explicit data on soil clay content were retrieved from the harmonized world soil database (Nachtergaele et al., 2009). Finally, spatially explicit soil covering data for all crops considered were extracted from (Sacks et al., 2010). $B(t)$ represents the soil carbon inputs at time t and was estimated using **Equation 7**:

$$\text{Equation 7 } B(t) = [(a_{dpm} \ a_{rpm} \ a_{bio} \ a_{hum})_{crop\ residues}^T * (1 - \%FYM) + (a_{dpm} \ a_{rpm} \ a_{bio} \ a_{hum})_{farmyard\ manure}^T * \%FYM] * b_t$$

Where a_{dpm} , a_{rpm} , a_{bio} and a_{hum} are four coefficients (in %) that define the composition of the carbon inputs to soils between the four active soil organic carbon pools for both crop residues and farmyard manure. Here, a_{dpm} , a_{rpm} , a_{bio} and a_{hum} were parametrised as follow: (0.6,0.4,0,0) for crop-based residues, (0.4,0.6,0,0) for grass residues and (0.49,0.49,0,0.02) for farmyard manure. $\%FYM$ (in %) represents the share of farmyard manure in total soil carbon inputs and b_t represents the total soil carbon inputs at time t (in t C.ha⁻¹).

Soil carbon input (SCI) estimation

For both the organic scenario and the baseline, we estimated the annual SCI using **Equation 8**:

$$\text{Equation 8 } SCI = AgC * \% Recycled + BgC + FYM_{applied}$$

Where SCI represents the inputs of organic carbon to either cropland or grassland soils (in t C.ha⁻¹.yr⁻¹). *AgC* and *BgC* (in t C.ha⁻¹.yr⁻¹) are respectively the above and belowground plant carbon biomass. *%Recycled* (in %) represents the percentage of the *AgC* that remains on field. In croplands the *%Recycled* data were extracted from the GOANIM model(Barbieri et al., 2021). In grasslands, *%Recycled* represents the non-grazed carbon share of the entire grassland biomass production. Finally, *FYM_{applied}* (in t C.ha⁻¹) is the carbon from farmyard manure applied to cropland or grassland soils. We assumed that biomass quality and its related carbon stabilisation and mineralisation properties were similar in both the organic scenarios and the baseline due to inconsistent data in the literature(García-Palacios et al., 2018). We estimated *AgC* and *BgC* using **Equation 9** and **Equation 10**:

$$\text{Equation 9 } AgC = Yield * 0.5/HI$$

$$\text{Equation 10 } BgC = AgC * RS$$

Where *HI* and *RS* represent the crop-specific harvest index (unit-less) and the root-shoot ratio (unit-less), respectively, for each of the considered 45 crop species. Both *HI* and *RS* values were retrieved from Monfreda et al. 2008(Monfreda et al., 2008) and Smil et al. 1999(Smil, 1999). *Yield* refers to the crop yields (in tons DM.ha⁻¹) as retrieved from Monfreda et al. 2008(Monfreda et al., 2008) (for the baseline) or from the GOANIM model (for the organic scenarios)(Barbieri et al., 2017). To convert the estimated dry matter production in C, we used a 0.5 coefficient value (in t C.t DM⁻¹).

In order to account for possible uncertainties in input data, we tested the sensitivity of the RothC outputs to variations in SCI values. We considered two possible sources of uncertainty in SCI values related to crop and grass biomass production and to biomass allocation to above- vs. below-ground plant compartments. Uncertainties in SCI were explored by a ±20% variation in the carbon biomass production of both croplands and grasslands, modulated by a variation in root-shoot ratio (*RS*) for croplands (see **Annex II**).

FYM_{applied} was estimated using **Equation 11** and **Equation 12**:

$$\text{Equation 11 } FYM_{applied} = \frac{C_{ex} * (1 - \beta)}{HA}$$

$$\text{Equation 12 } C_{ex} = \sum_a VS_a * Pop_a$$

Where *C_{ex}* (in tC.yr⁻¹) is the total amount of carbon excreted by the livestock population as farmyard manure and *HA* is the total harvested area (ha). *β* represents the share of *C_{ex}* that is not applied to the agricultural lands. In croplands, *β* represents the share of *C_{ex}* that is left on pasture during animal grazing, used for non-agricultural purposes (e.g., as fuel) and is lost during the manure management process. In grasslands, *β* the share of *C_{ex}* that is not left on pasture during animal grazing. *β* was estimated following the 2019 IPCC guidelines refinement (IPCC, 2019b). The amount of carbon lost in the manure management process was estimated according to Bareha et al., 2021. In equation (7), *Pop_a* is the livestock population (in heads) for each of the nine considered animal species *a*. *VS* (in tC.head⁻¹.yr⁻¹) is the amount of volatile solid carbon excreted per animal and per year (see **Annex II**).

We made sure that the VS excretion would remain in a range of 10 to 50% of the total C ingested by livestock animals (Soussana and Lemaire, 2014). This helped to close the carbon cycle within both the organic scenarios and the baseline, thereby avoiding any overestimation of soil carbon inputs.

Additional soil carbon input from cover crops

The observed higher share of cover crops in organic crop rotations – compared to conventional ones – may bring additional SCI in the organic scenarios (Barbieri et al., 2017). To the best of our knowledge, there is no global, spatially-explicit database about SCI from cover crops. The use of cover crops is limited by agronomic and pedo-climatic conditions. Based on a previous meta-analysis on the extent of cover-crops, we considered that cover cropping could be potentially applied on 25% of global croplands (Poeplau and Don, 2015). Therefore, we considered two situations for the organic scenarios: (i) a reference situation without cover crops, i.e. the cropland soils remain bare between main crops (as simulated in the 100% REF organic scenario) and (ii) a situation with a use of cover crops between main crops to avoid bare soil on 25% of the organically managed croplands (named the organic 25% cover crops (CC) scenario). For this second situation, we estimated the additional SCI from cover crops using **Equation 13**. Meanwhile, we assumed that there were no cover crops in the baseline.

$$\text{Equation 13 } SCI_{cc,i,month} = \frac{1.87}{GMBSP} * \frac{Yield_{plant,i}}{Yield_{plant,world}}$$

Where $SCI_{cc,i,month}$ (in t C.ha⁻¹.month⁻¹) is the soil carbon input from cover crops in country i per month of cover cropping. The 1.87 value (in t C.ha⁻¹.yr⁻¹) is the global annual mean of soil carbon input from cover crops estimated by Poeplau and Don, 2015. We divided this 1.87 value by the estimated global mean time of cover crop presence in the baseline ($GMBSP$, expressed in month). To account for the variability of cover cropping productivity among countries – that is driven by climatic and farming factors (Justes, 2012) – we multiplied this global mean cover-cropping biomass production by the ratio of the country specific mean yield ($Yield_{plant,i}$) to the global mean yield ($Yield_{plant,world}$) for the most productive crop species between wheat and maize in the country.

RothC parametrisation

We used RothC assuming carbon pools to be at steady state in the baseline. This needed assumption translates into a steady state assumption for climatic conditions and soil carbon inputs over the years for both organic farming scenarios and the baseline. Although partly unrealistic, this assumption is consistent with the though experiment of large organic farming expansion that we report in this study. To remain in line with this steady state assumption in the baseline, we first estimated the SCI that are required to keep baseline SOC stocks at their current level (SCI_0) by using the method developed by Martin et al., 2007 and summarized in **Equation 14**.

$$\text{Equation 14 } SCI_0 = (I_4 - F) * SOC^*$$

Where SCI_0 is the carbon inputs (in t C.ha⁻¹.yr⁻¹) required to maintain SOC stocks at their current level. F is a 4x4 matrix representing the mineralisation and carbon flows among the four active soil organic carbon pools. F values depend on the climatic, edaphic and soil covering conditions. SOC^* is the current active (i.e. not comprised in the IOM pool) SOC stocks that is assumed to be at the

equilibrium (in either croplands or grasslands). Total SOC stocks were retrieved from the AEZEF dataset (Gibbs et al., 2014) that provides estimates of soil organic carbon stocks for croplands, grasslands and forestlands on the first 30cm of topsoils per country and for 18 agroecological zones (**Figure S12**). SOC^* was estimated after subtracting the IOM content which was estimated using the Falloon, 2000 equation.

To estimate the SCI in the organic farming scenarios (SCI_1), we corrected SCI_0 by the ratio of SCI_{org} to $SCI_{baseline}$ (RCI) as detailed in **Equation 15**.

$$\textbf{Equation 15 } SCI_1 = SCI_0 * RCI = SCI_0 * \frac{SCI_{org}}{SCI_{baseline}}$$

Where SCI_{org} and $SCI_{baseline}$ are the soil carbon inputs for the organic farming scenarios and the baseline, respectively, estimated using the methods presented in the previous sections. We used SCI_1 as input in the RothC model to estimate the changes in SOC stocks in the organic farming scenarios – 20, 50 and 100 years after a global conversion to this farming system – using **Equation 6**. We assumed constant climate data over the simulation periods. This assumption is disputable given current and future climate change, but it remains consistent with our thought experiment that consists in exploring situations of drastic expansion of organic farming. Further studies that are beyond the scope of this article would be needed to account for future climate scenarios. The estimated SCI_1 is expressed in $tC \cdot ha^{-1} \cdot yr^{-1}$, though RothC requires monthly data. We assumed that the annual soil carbon inputs were equally between the twelve months.

In order to account for the observed difference in crop rotations between organic and conventional farming (Barbieri et al., 2017), we ran RothC in the organic farming scenarios for each of the 45 considered crop species separately, and then, estimated a weighted mean of SOC stocks according to crop species harvested areas, as detailed in **Equation 16**.

$$\textbf{Equation 16 } SOC_{t,mean} = \frac{\sum_i SOC_{t,i} * HA_i}{HA_{total}}$$

Where $SOC_{t,mean}$ is the weighted mean of SOC stocks at time t and $SOC_{t,i}$ is the SOC stocks estimated by the run of RothC for each specific crop i , HA_i represents the harvested area of crop i in the organic farming scenario and HA_{total} is the total harvested area (all crop considered). HA_i and HA_{total} were retrieved from Barbieri et al. 2019 (Barbieri et al., 2019).

Results

Carbon flows to agricultural soils in an organic world

We found a global 43% reduction (with a sensitivity range between 26 and 54%, see Methods) in the total SCI to croplands for the 100% organic farming scenario (hereafter called REF 100% organic scenario) compared to the baseline and no change for the global SCI to grasslands (**Table 3**). In croplands, the massive drop of SCI is primarily due to (i) a 39% reduction in plant-based residues returned to the soil (-1 PgC.yr^{-1}) followed by (ii) a 68% reduction in farmyard manure application rate ($-0.23 \text{ PgC.yr}^{-1}$) in the REF 100% organic scenario compared to the baseline. The reduction in plant-based residues returns is mainly due to a 51% reduction of annual crop dry matter production, partially attenuated by a lower dry matter yield reduction for temporary pastures (-26%), resulting in an overall 47% reduction of cropland biomass production (**Table S6**). The reduction in manure application rate is mainly due to a 66% reduction in the livestock population, as well as changes in animal types and in regional location of livestock populations.

Table 3: Global soil carbon inputs (PgC.yr^{-1}) for croplands and grasslands under the REF 100% organic scenario and the baseline.

	Soil C inputs to croplands			Soil C inputs to grasslands		
	Plant-based residues	Manure	Total	Grass residues	Manure	Total
<i>Baseline</i>	2.5	0.34	2.8	17.1	0.33	17.4
<i>REF 100% organic scenario</i>	1.5	0.11	1.6	17.2	0.1	17.3
<i>Ratio organic/baseline</i>	0.61	0.31	0.57	1.01	0.29	1.00
<i>Difference organic - baseline</i>	-1	-0.23	-1.2	+0.1	-0.23	-0.1

These global reductions in soil carbon inputs mask large variations among world regions (**Figure 9** and **Figure S13**). In some specific regions – such as Central Africa or Russia – soil carbon inputs are increased in the 100% REF organic scenario compared to the baseline (**Figure 9a**). This is explained by higher inputs as plant-based residues (**Figure 9b**) due to (i) high manure application rates that help to sustain high crop yields in organic farming (**Figure 9c**) and (ii) high share of carbon fixing crops – such as temporary pastures – in organic rotations (Barbieri et al., 2019, 2017). Note, that in other regions – such as Northern Brazil – the increase in plant-based residues resulting from more frequent carbon fixing crops in organic rotations is offset by a drop in farmyard manure application, resulting in reduced soil carbon inputs to cropland soils.

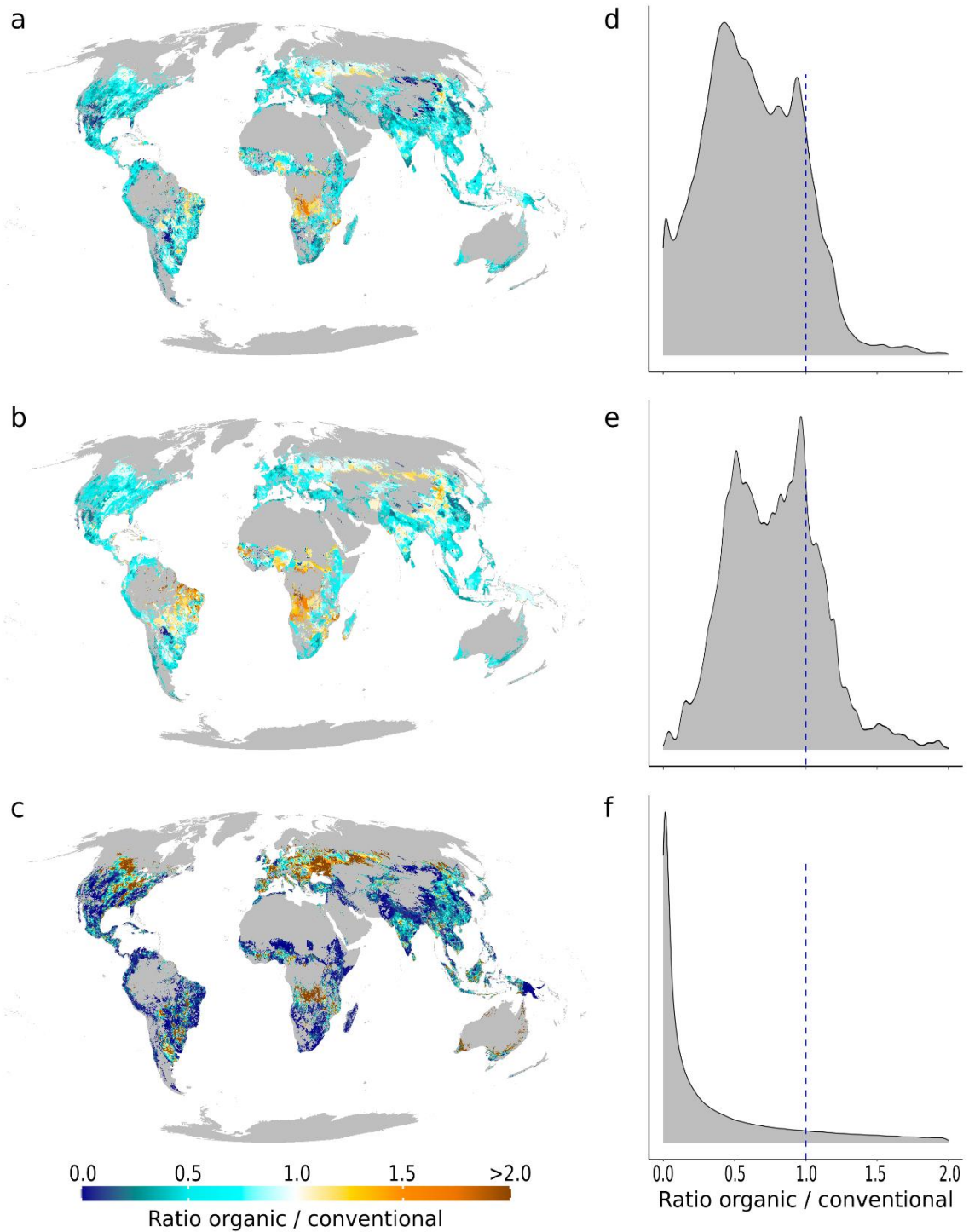


Figure 9: Annual organic-to-conventional ratios of soil total carbon inputs (panels a and d), plant-based residue (panels b and e) and farmyard manure (panels c and f) inputs to cropland soils, reported as global maps (a, b & c) and density curves (d, e & f). In the density curves, the blue dashed line indicates the value 1.

In grasslands – unlike to croplands – we found that regional increase in manure application rate is associated to a reduction of grass residue inputs to soils and consequently to a SCI reduction (**Figure S13**). This is mainly explained by the fact that a higher manure application often means higher grazing intensity, which leads to higher grass residue removal as livestock feed.

SOC stocks changes in an organically farmed world

We found that the transition to organic farming would result in a 6, 8 and 10% (with an uncertainty range of 5-13, 7-20 and 9-16%) SOC stocks reduction in agricultural lands (croplands plus grasslands) after 20, 50 and 100 years, respectively, compared to the baseline (**Table 4**). This reduction represents an overall loss of -13 PgC from agricultural soils in the first 20 years after that transition – resulting from -7 and -6 PgC losses from croplands and grasslands, respectively (**Figure 10**).

Table 4: Global changes in SOC stocks (PgC) for grasslands, croplands and total agricultural land (i.e. grasslands and croplands combined) after 20, 50, and 100 years. Ratios and differences between the organic and the baseline are indicated.

		<i>Global soil organic carbon stocks (PgC)</i>		
		20 years	50 years	100 years
Croplands	<i>Baseline</i>		76	
	<i>REF 100% organic scenario</i>	69	65	62
	<i>Ratio organic/baseline</i>	0.9	0.86	0.81
	<i>Difference organic - baseline</i>	-7	-11	-14
Grasslands	<i>Baseline</i>		121	
	<i>REF 100% organic scenario</i>	115	115	116
	<i>Ratio organic/baseline</i>	0.95	0.95	0.96
	<i>Difference organic - baseline</i>	-6	-6	-5
Total agricultural lands	<i>Baseline</i>		197	
	<i>REF 100% organic scenario</i>	184	180	177
	<i>Ratio organic/baseline</i>	0.94	0.92	0.90
	<i>Difference organic - baseline</i>	-13	-17	-20

Again, these global estimates mask spatial variations among world regions (**Figure 10**). Some regions (such as India and Mexico) would experience a decrease in their cropland SOC stocks while others (such as central Africa) would experience an increase (**Figure 10b** and **Figure 10c**) – a result largely explained for both croplands and grasslands by regional variations in soil carbon inputs (**Figure 9** and **Figure S13**).

In grasslands, we found a global SOC stock reduction (-6 PgC in the first 20 years) while no reduction was observed in total SCI. This result is explained by the spatial variability of the response of SOC stocks to SCI variations (**Figure S14**), due to differences in pedo-climatic conditions, initial SOC stock values, and composition of SCI (grass residues vs. farmyard manure).

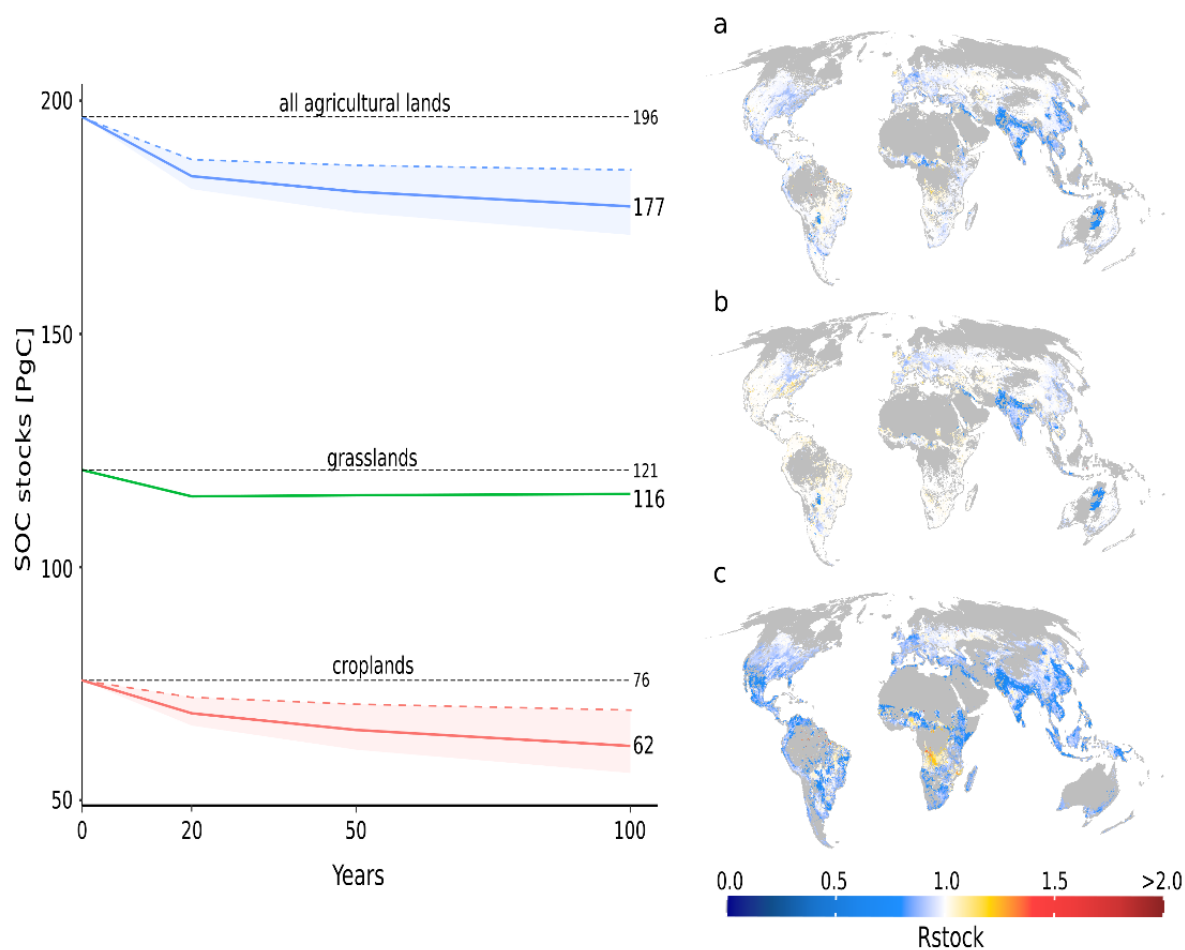


Figure 10: Global changes in soil organic carbon (SOC) stocks (PgC) over time, and maps of the SOC stock ratios (R_{stock}) between the REF 100% organic scenario and the baseline at 20 years. Changes in SOC stocks and spatial distribution are reported for croplands (red line, panel c), grasslands (green line, panel b), and croplands plus grasslands combined (blue line, panel a). A scenario variant where 25% of organically managed croplands are covered by cover-crops is also considered (see below and Methods) and the resulting changes in SOC stocks for croplands and the combination of croplands and grasslands are represented by the red and blue dashed lines respectively (called the organic 25% CC scenario). Values at the right end of each curve represent the global SOC stocks 100 years after transition to organic farming. The shaded area around each curve lies between the upper and lower values obtained through the sensitivity analysis of soil carbon input values (see Methods). The black dashed lines represent the global SOC stock for croplands, grasslands and both combined in the baseline.

We also found that SOC stocks would be drastically reduced in the first 20 years after transitioning to organic farming ($-0.5 \text{ \%} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ on average) whereas the SOC reduction would slow down afterwards ($-0.2 \text{ \%} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ on average) (Figure S15). The slowing decrease after 20 years can be explained by the spatial variability in the pace of SOC stock changes due to differences in pedo-climatic conditions – modulated by variations in soil carbon inputs and their composition. For instance, in tropical regions, the SOC stock reduction is fast in the first 20 years and then slows down afterwards. This is in contrast with northern regions – such as Northern Canada and Russia – where the reduction in SOC stocks remains slow throughout the considered 50 years.

The potential of cover crops to improve SOC stocks in organic farming

Covering soils by catch and cover-crops – to protect soils from erosion, to maintain year round carbon inputs to the soil, to recycle nutrients or to control pests and weeds – is common practice that many organic farmers implement (Barbieri et al., 2017). Based on a previous meta-analysis on the extent of cover-crops, we considered that cover cropping could be potentially applied on 25% of global croplands (Poepflau and Don, 2015). Accordingly, we simulated soil carbon inputs and changes in SOC stocks under a scenario where cover crops are used to avoid bare soil in 25% of organically managed croplands (hereafter called the organic 25% CC scenario, see Methods).

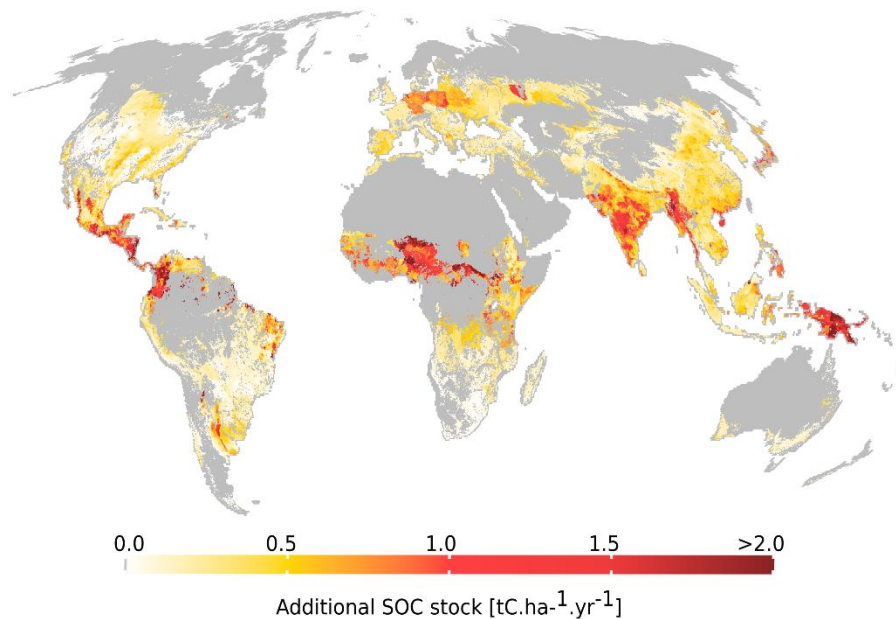


Figure 11: Additional SOC stocks per ha [tC.ha⁻¹.yr⁻¹] due to cover cropping in the organic 25% CC scenario compared to the 100% REF organic scenario.

Our results show that the use of cover crops could increase SOC stocks by +0.29 tC.ha⁻¹.yr⁻¹ on average over the 50 first years (+0.47 tC.ha⁻¹.yr⁻¹ over the 20 first years) in the organic 25% CC scenario compared to the 100% REF organic scenario. This additional SOC stock in the organic 25% CC scenario comes along with (i) an additional SCI of +0.07 tC.ha⁻¹.yr⁻¹ on average (which represents an additional global SCI of +0.11 PgC.yr⁻¹, **Figure S16**) and (ii) an additional soil covering effect that reduces SOC mineralisation. We also found that the increase in SOC stock would be higher in tropical regions (**Figure 11**), with about +1.5 tC.ha⁻¹.yr⁻¹ in Southern Asia, and sub-Saharan Africa. However, this additional SOC stock would not be sufficient to fully compensate the estimated SOC stock reduction in the 100% REF organic scenario compared to the baseline. In the organic 25% CC scenario, SOC stocks in croplands and grasslands combined would be 5, 6 and 7% lower than those in the baseline at 20, 50 and 100% respectively - representing a loss of 9.5 PgC over the first 20 years (**Table S7**).

Intermediate scenarios of organic farming expansion

Because converting the whole agricultural area to organic farming is a rather drastic thought experiment, we also explored more realistic scenarios of intermediate conversion to organic farming. We found that global SOC stocks (in croplands and grasslands combined) would exhibit a linear reduction with increasing share of the UAA under organic farming, without the use of cover crops (**Figure 12**). SOC stocks are reduced by 1.3, 2.6, 3.9, 5.2 and 6.5% with 20, 40, 60, 80 and 100% of the UAA under organic farming and at 20 years compared to the baseline. We observe the same linearity in the reduction of SOC stocks in croplands (**Figure S17**) and in grasslands (**Figure S18**). For both croplands and grasslands, the linear reduction of SOC stock is explained by the linear reduction of the soil carbon inputs with increasing share of the UAA under organic farming (**Table S8**). This linearity in SOC stock changes is translated spatially, with similar regional trends in the scenario with 20% (**Figure 12**) and 100% (**Figure 10a**) of the global UAA under organic farming.

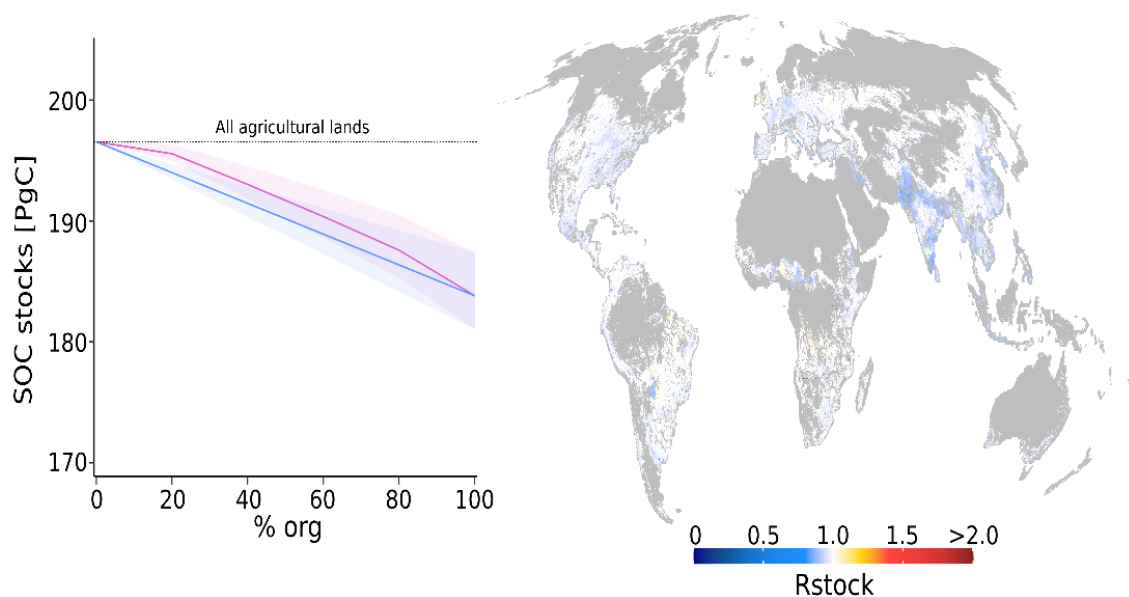


Figure 12: Global changes in agricultural (croplands and grasslands combined) SOC stocks (PgC) 20 years after conversion to organic farming when considering various shares of UAA converted to organic farming. The pink and blue lines represent situations with and without conventional manure surplus application on organic croplands, respectively. The dotted black line represents global SOC stocks in the baseline. The shaded area around each curve represents the model response to the variation of soil carbon input values (see Methods). The map represents the ratios of SOC stocks between the 20% of global UAA under organic farming scenario with conventional manure and the baseline, 20 years after conversion to organic.

So far, we did not consider the fact that conventional manure surplus – meaning all conventional manure that is in excess compared with conventional cropland N requirements – is often applied on organically farmed lands. Using conventional manure surplus as an additional, external source of organic fertilising material on organically managed croplands – a practice sometime implemented by organic farmers (Nowak et al., 2013; Oelofse et al., 2013) – would change the evolutions of SOC stocks (**Figure 12**). Twenty years after the conversion to organic farming, and in a situation with 20% of the global UAA under organic farming, agricultural SOC stocks would be close to those reported in the baseline. Above 20% of the UAA under organic farming, we found a positive and

constant effect on global SOC stocks in case conventional manure is used in organic farming. Up to 80% of the global UAA under organic management, global SOC stocks remain higher in the situation where conventional manure surplus is applied on organic croplands compared to the situation where it is not. Of course, this effect disappears when 100% of the UAA is converted to organic farming as no more conventional manure is produced.

Again, the use of conventional manure surpluses on organically managed croplands would affect the spatial variations of SOC stocks. Some regions – such as the UK, Northern India and Northern China – would see their cropland SOC stocks increase compared to the baseline. In those same regions, SOC stock would decrease in a scenario with 20% of the UAA under organic farming without conventional manure application compared to the baseline. This regional effect is explained by the uneven geographic distribution of conventional manure surpluses at the global scale (**Figure S19**), with major consequences for soil carbon inputs. This transfer of fertilising resource from conventional to organic farming would boost SOC stocks in organically managed croplands by (i) increasing the carbon inputs to organic cropland soils and (ii) stimulating organic crop biomass production – due to an additional N fertilization – resulting in further increase in soil carbon inputs as crop residues. However, the effect of an increased soil carbon input to organic croplands would be globally compensated by an equivalent reduction of soil carbon input in conventional croplands – due to the transfer of organic material from conventional to organic farming. Therefore, this transfer of fertilising resource from conventional to organic farming would boost global SOC stocks only by increasing organic croplands biomass and thus, increasing the global soil carbon inputs.

Discussion and conclusion

Organic farming is often considered as a potential option to mitigate climate change through enhanced soil carbon sequestration (Clark and Tilman, 2017; Gattinger et al., 2012). We provide here a first estimate of the change in global SOC stocks in both croplands and grasslands – accounting for possible transfers of carbon between these two land uses – under scenarios of global expansion of organic farming.

Contrary to what is sometimes claimed (IFOAM EU Group, 2016), our results show that agricultural global SOC stocks would decrease in such scenarios. This SOC stock reduction is mostly due to drastic reduction in global soil carbon inputs (SCI), especially on croplands. These unexpected results are in strong contrast with previous results on the carbon sequestration potential of organic farming based on field observations at the local scale (Gattinger et al., 2012). These results highlight that the estimation of the potential of soil carbon sequestration in scenarios of organic farming offtake cannot be based only on the extrapolation of local field observations without considering whole-system effects. Put differently, the contrast between observed or experimental carbon sequestration data and our modelling results illustrates that simulating the geographic expansion of organic farming systems needs to consider the systemic feedbacks that go along with organic farming expansion itself (Nesme et al., 2021). In particular, special attention must be paid to the availability of N fertilising resources and their effects on crop biomass production (Barbieri et al., 2021; Smith et al., 2018).

Nevertheless, a panel of additional cropping practices could be explored, in addition to those we considered in the organic farming scenarios we simulated, which could attenuate this modelled SOC stock reduction. We found that the use of cover crops would help to limit SOC stock reduction by both increasing SCI and reducing SOC mineralisation (Lal, 2015; Mazzoncini et al., 2011). Other practices – such as agroforestry – may have a similar impact on SOC stocks, and their potential use in

organic farming system is yet to be studied. Because the estimated SOC stock reductions result mainly from N deficiency in many organic croplands, cropping practices that would enhance N availability for plants are likely to improve soil carbon sequestration. Higher biological N fixation by leguminous crops or cover crops in organic rotations – by increasing their frequency (including as relay crops), their fixation rate or their biomass return to soils – could help achieve that objective by increasing N availability for other crops (Smith et al., 2008). An additional benefit from improved crop rotations is the reduction in nitrate leaching (Abdalla et al., 2019) and thereby the conservation of N resources in soils for plant uptake. Another source of N for organically farmed lands comes from possible import of animal manure from conventional farms (Nowak et al., 2013), going along with a transfer of carbon. This transfer of organic fertilising materials brings on indirect carbon inputs by stimulation of crop biomass production. Similarly, using external fertilising organic materials – such as urban compost, green wastes, food industry by-products or eventually sewage sludge – could provide N to soils on top of providing additional soil carbon inputs. Many regulatory and social barriers exist for the use of some of those external materials, in particular regarding sewage sludge (Tanase et al., 2017), making more detailed studies needed about those products. Modelling the benefits brought by this extensive set of additional cropping practices was beyond the scope of this study. However, our results suggest that making organic farming more climate beneficial will require some of these additional practices and enhanced circularity in organic farming systems (Morais et al., 2021).

Modelling variations in soil organic carbon stocks in contrasted farming scenarios at the global scale comes with some methodological choices and related limitations. In particular, the SOC stocks were modelled using RothC, a model that has proved its potential to accurately simulate SOC changes at the local (Falloon and Smith, 2002) and large (Martin et al., 2021) scales, but that requires some specific modelling assumptions. Among them, we had to assume that carbon stocks in the baseline are at the equilibrium. It is likely that this assumption does not always reflect the reality (Chen et al., 2015; Meersmans et al., 2011) which may have implications for our findings. However, through additional analysis, we found evidence that the error brought by this assumption was negligible (see Supplementary Information). We found only a 1% reduction of global croplands SOC stocks after 100 years compared to the initial croplands SOC stocks, when SOC stock in the baseline were not considered at the equilibrium. This suggests that our equilibrium assumption is acceptable when considered at the global scale. Another limitation may be related to the fact that the soil organic carbon mineralisation we estimated goes along with a nitrogen mineralisation (Cai et al., 2016), a factor we did not consider in our study. This may lead to a slight over-estimation of SOC stock reduction due to over-estimate of reduction in soil carbon inputs compared to the baseline.

In addition, our modelling requires a series of input data, each affected by its own uncertainties. The complexity of the GOANIM and RothC models and limited knowledge about several aspects of input data makes the quantification of uncertainties very difficult. However, the SOC stocks we estimated were determined over long periods (20, 50 and 100 years). Long term averages show reduced errors on estimated variables due to reduced aggregation effects by the input data – especially the climate data (Kuhnert et al., 2017). In addition, this study is based on the comparison of organic farming to a baseline, that are both affected by the same errors and uncertainties. Therefore, concentrating the analysis on the ratios (or differences) of organic to conventional estimation helps to reduce errors and uncertainties.

The lack of knowledge on input data also affects the estimation of the potential of cover crops to increase SOC stocks. To the best of our knowledge, information on (i) potential areas available for cover cropping, (ii) spatially explicit species composition of the cover crops and (iii) cover crops biomass

production are not (or poorly) available. The potential additional SOC stocks offered by cover crops that we found in our study ($0.29 \text{ tC}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$) is very similar to the 0.32 value reported in a recent meta-analysis (Poepflau and Don, 2015). This suggests that, despite the limitations of our data, our estimate remains solid.

Finally, this study provides important information to estimate the potential of organic farming to reduce greenhouse gas (GHG) emissions from agriculture. Accurate estimates of changes in soil organic carbon stocks, along with N_2O and CH_4 emission estimation, is key to estimate the net GHG emissions of scenarios for organic farming upscaling (Tuomisto et al., 2012). Latest studies comparing organic vs. conventional farming impacts on GHG emissions at the global scale used an upscaling method of SOC stock differences based on field observations (Muller et al., 2017; Tuomisto et al., 2012). Further studies, comparing organic to conventional impacts on GHG emissions might consider our results in their methodology.

Conflicts of interest

The authors declare no competing interests.

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Data treatment & code availability

All analyses were made using R x64 3.5.3. GOANIM was used in its most recent version deposited in a public repository (https://github.com/Pie90/GOANIM_public). For RothC we used the cin_month and runExplicitSol functions from the RothC package (Martin, 2018) to respectively estimate SCl₀, and SOC stock evolution across time.

Authors' contributions

U.G., M.K., S.P. and T.N. designed the study; U.G. performed the modelling work, with the help of P.B. for the GOANIM model and M.K. and M.M. for RothC. All authors were involved in the interpretation of results and contributed actively to writing and revising the manuscript.

Chapter III: The global effect of organic farming expansion on GHG emissions.

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In the previous chapter, we found that converting agricultural lands to organic farming would lead to reduced global soil organic carbon stocks of croplands and grasslands. Such results differ from those provided by meta-analyses of field experiment, such highlighting the need of systemic approaches to estimate the sustainability of organic farming expansion. In the following chapter, we combine GOANIM to the IPCC guidelines and the GLobAgri-AgT model to estimate N₂O, CH₄ and CO₂ emissions from the agricultural sector in organic farming expansion scenarios. We used this combination of models to estimate the GHG budget of different scenarios accounting for intermediate level of organic farming expansion, cover crops effect on soil organic carbon stocks and reduced food waste and losses.

Abstract

Reducing emissions in the AFOLU sector is a key lever to reach greenhouse gas (GHG) emission mitigation goals. Organic farming is often considered as a promising option to reduce GHG emissions in the food production sector. However, previous estimations of the potential of organic farming to reduce GHG emissions globally did not account for deep systemic changes that would come along with organic farming expansion – such as increased competition for organic fertilizers. Using a modelling approach, we estimated the global GHG budget of different scenarios of organic farming expansion accounting for different shares of the global agricultural land under organic management (20, 40, 60, 80 and 100%) and based on the assumption that human food demand will adapt to the food supply. We found a 56% increase in agricultural GHG emissions in a fully organically managed world compared to current emissions (i.e. the baseline). We found that this increase in GHG emissions is mainly due to land-use changes (+ 3.7 Gt CO₂eq.yr⁻¹) and losses of agricultural soil organic carbon stocks (+2.3 Gt CO₂eq.yr⁻¹), partly compensated by a reduction of N₂O and CH₄ emissions (-3.1 Gt CO₂eq.yr⁻¹). We also found that a 20% conversion of global agricultural lands towards organic farming (together with adapted human food diets) would reduce GHG emissions by 70% compared to the baseline. More generally, we found a non-linear response of GHG emissions to the share of global agricultural lands occupied by organic farming, suggesting the existence of an optimal organic farming share (here estimated at 20%) that minimizes agricultural GHG emissions. This optimum might differ if appropriate practices are implemented in organic farming to improve (i) soil carbon sequestration (such as cover cropping), or (ii) if changes in human food diets are favoured.

Keywords

Organic farming, GHG emissions, Land-use change, Global scale, Modelling

Introduction

The agriculture, forest and other land uses (AFOLU) sector is responsible of 23 % of global anthropogenic greenhouse gas emissions (IPCC, 2021). Emissions in the AFOLU sector are due to both (i) agricultural activities – with CH₄ and N₂O emissions from soil, manure and livestock management alongside CO₂ emissions from fossil use and soil carbon losses – (ii) and the expansion of agricultural lands over natural ecosystems – with CO₂ emissions due to biomass and soil organic carbon (SOC) loss, and N₂O and CH₄ emissions due to biomass burning. Changes in cropping and husbandry practices – such as reduced tillage, improved crop rotations or optimised animal feeding – show some large potential to reduce emissions from the AFOLU sector (Smith et al., 2008). At the scale of France, a recent study has shown that adjusting cropping and husbandry practices without changing farming system management, location or productivity level, would help achieve only 10% reduction of current agricultural GHG emissions (Pellerin et al., 2015). Therefore, more systemic changes of the food production sector are expected, for instance through the generalisation of alternative farming system such as organic farming (Foley et al., 2011; Ramankutty et al., 2019; Tilman and Clark, 2014).

Organic farming is often presented as a potential alternative to achieve drastic reduction in GHG emissions in the AFOLU sector (Muller et al., 2017; Niggli et al., 2009; Reganold and Wachter, 2016). At the field scale, and based on meta-analysis of field experiments, evidence has been provided that organic farming reduces N₂O emissions (-434 kg CO₂eq.ha⁻¹.yr⁻¹, (Skinner et al., 2014)) and increases soil carbon sequestration (+0.45 Mg C.ha⁻¹.yr⁻¹ (Gattinger et al., 2012)) compared to conventional farming. Studies based on the extrapolation of local results reported in meta-analyses of field experiments have estimated a potential 3 to 40% reduction of GHG emissions in scenarios of global organic farming expansion (Muller et al., 2017; Niggli et al., 2009). However, those meta-analyses relate to data collected in situations where organic farming occupies small share of agricultural lands (IFOAM, 2020). While organic fertilisers are relatively easy to source by organic farms in those contexts (Nowak et al., 2013), expansion of organic farming might lead to more severe competition for these fertilising materials. Such competition might reduce the amount of fertilizers applied on organically managed land, thus possibly impacting the potential of organic farming to reduce agricultural GHG emissions – especially N₂O emissions (Smith et al., 2019). In addition, lower yields observed in organic farming compared to conventional farming (-20-30% (Ponisio et al., 2015; Seufert et al., 2012)) may lead to increased requirements of agricultural lands to feed the world, resulting in GHG emissions due to land-use change that may offset the benefits reported in field-based meta-analyses. Capturing those systemic effects related to organic farming expansion is key to get accurate estimate of the real potential of organic farming to attenuate agricultural GHG emissions.

To the best of our knowledge, no study has been conducted to estimate GHG emissions in scenarios of large organic farming expansion, especially by accounting for systemic feedbacks induced by organics expansion. To address this gap of knowledge we used a modelling approach combining GOANIM, a spatially explicit (~10x10km at the equator) model simulating cropland N cycle, crop productivity and livestock populations under scenarios of large organic farming expansion (Barbieri et al., 2021) with three other models: (i) a model adapted from the Tier 1 approach of the IPCC guidelines that estimates N₂O and CH₄ emissions due to agricultural activities (IPCC, 2019a) – hereafter called the N₂O-CH₄ model – (ii) RothC, a first order kinetic SOC dynamic model (Coleman et al., 1997; Martin et al., 2007) and (iii) GlobAgri-AgT, a partial equilibrium model that estimates regional land requirements in different food demand and productivity scenarios (Le Mouël et al., 2018; Mora et al., 2020). GOANIM outputs on livestock densities and crop yields were used as inputs in the three other models. We based

our use of GlobAgri-AgT on the assumption that the global human food demands would change to fit the global food production as estimated by the GOANIM model. The N₂O-CH₄ and RothC models were used to spatially estimate N₂O, CH₄ and CO₂ emissions of from agricultural lands. We used the GlobAgri-AgT model outputs on land requirements for 14 world regions to estimate regional land-use changes induced by the expansion of organic farming. We combined these regional land-use changes with emissions factors (in Gt of CO₂ eq.ha⁻¹) adapted from the AEZEF model (Plevin et al., 2014) to estimate GHG emissions due to land-use change. We used this model combination to assess different scenarios combining (i) variations in the level of organic farming expansion globally and (ii) variations in organic farming practices (e.g. cover cropping), each compared with a baseline involving no changes in current agricultural practices. We also tested scenarios where food wastes were reduced by 50% and 100%.

Organic farming encompasses a diverse set of farming practices, depending on regional regulations, farming contexts and markets. Although all organic regulations are based on the ban of synthetic fertilisers (Seufert et al., 2017), organic farms exhibit ample variability in the way this ban is translated into farming practices (Kirchmann et al., 2016; Ponisio et al., 2015; Puech et al., 2014). In this study, we defined organic farming as the simple ban of synthetic fertilisers, with minimal changes in the type of crops grown in rotations and moderate yield losses due to pest and diseases, without more ambitious changes in soil management (i.e. through intercropping or soil cover cropping). This conservative attitude is not meant to provide a normative view on organic farming. Instead, it is meant to provide estimates that can serve as references to envision additional and complementary cropping practices.

This study is based on the recent evidence that global and regional expansion of organic farming is likely to lead to strong competition for nitrogen (N) fertilising resources (Barbieri et al., 2021; Smith et al., 2018). The ban of synthetic N fertilizers within organic farming regulation limits the diversity of N fertilizers and their availability – such as crop residues and animal manure – resulting in severe N limitations for cropland fertilization (Billen et al., 2012; Erb et al., 2016; Muller et al., 2017). Recent simulations performed with the GOANIM model (and by using the same conservative definition of organic farming) have shown that the full conversion of global agricultural lands to organic farming would lead to a drastic -57% reduction of global cropland production (**Annex II**) – due to lower N availability for crops – and drop in livestock population (-66% in livestock units) – with large shift towards ruminant animal species. Such global changes have numerous impacts on global GHG emissions. On the one hand, reduced N fertilization and livestock population is expected to lead to a reduction of global N₂O and CH₄ emissions. On the other hand, reduction of cropland productivity is expected to lead to increased requirements of global agricultural lands, resulting in additional GHG emissions from land-use changes and agricultural activities. We thus hypothesized that GHG emissions from land-use changes would overcome the reduction of N₂O and CH₄ emissions, resulting in increased GHG emissions in a fully organically managed world compared to the baseline.

Methods

General framework

We aimed at estimating the global agricultural GHG emissions in scenarios of organic farming expansion at the global scale. To do so, we used a modelling approach in order to estimate (i) N₂O and CH₄ emissions from agricultural activities, (ii) CO₂ emissions and removal from changes in agricultural land SOC stocks and (iii) GHG emissions from land-use changes. We compared the GHG emission estimates of each organic farming expansion scenario to the current GHG emissions – hereafter called the baseline. This modelling approach was based on the combination of four different models, using the following steps.

First, we estimated the global agricultural production, in scenarios of large organic farming expansion, by using the GOANIM model (Barbieri et al., 2021). GOANIM is a spatially explicit (5 arc-min resolution, i.e. ~10x10km at the equator) linear optimisation model that simulates N flows to and from croplands and grasslands under scenarios of organic farming upscaling. GOANIM calculates croplands N budgets and their effects on crop yields for a series of 61 crop species. The optimising module of GOANIM is designed to maximise food availability at the global scale (from both crop-based and animal-based products) by spatially optimising the global livestock population and the N allocation from animal manure to croplands. We used the latest version of the GOANIM model (see **Annex III**).

Secondly, we estimated spatially explicit N₂O and CH₄ emissions in both the organic farming scenarios and the baseline by using a modelling adaptation of the Tier 1 approach of the IPCC guidelines (IPCC, 2019a, 2019b, 2019c, 2019e) – hereafter called the N₂O-CH₄ model. In the organic scenarios, we used the main GOANIM outputs on (i) crop harvested areas, (ii) crop yields and (iii) livestock densities as inputs of the N₂O-CH₄ model.

Then, we estimated the CO₂ emissions from changes in agricultural SOC stocks using the estimations provided in **Chapter II** of this dissertation by combining the GOANIM model outputs to the RothC model (Coleman et al., 1997; Martin et al., 2007). RothC estimates soil organic carbon turnover in both croplands and grasslands according to soil carbon inputs, climate and soil conditions. RothC estimates the carbon flows among four active soil organic carbon compartments as well as the amount of carbon mineralised from each pool, with a monthly time step and using a first order kinetic equation.

Finally, we estimated regional land requirements in scenarios of global organic farming expansion by combining the GOANIM outputs on crop and livestock production to the GlobAgri-AgT model (Le Mouél et al., 2018; Mora et al., 2020). GlobAgri-AgT is a mass balance model that ensures equilibrium between regional resources and utilization of each agri-food product, while respecting global equilibrium between total imports and exports of each of those products. In each region, lands used for crop production are limited in their expansion according to their potential suitability for crop production – retrieved from the GAEZ database (Fischer et al., 2021).

Most studies comparing organic to conventional farming energy consumption concluded to a lower consumption under organic farming (Lynch et al., 2011; Muller et al., 2017; Reganold and Wachter, 2016; Tilman and Clark, 2014). This lower energy consumption in organic farming is mainly due to the ban of energy-intensive synthetic fertilizer and pesticide inputs. To the best of our knowledge, we found no global information showing a difference between organic and conventional farming on-farm energy consumption – meaning GHG emissions due to on-farm fossil fuel consumption (for engines and building) or GHG emissions for the production of on-farm electric energy

used. Therefore, we assumed that a transition towards organic farming would not impact GHG emissions due to on-farm energy use.

All other GHG emission pathways considered are detailed in the following sections.

Estimation of CH₄ and N₂O emissions

The N₂O-CH₄ model is an adaptation of the IPCC guidelines (IPCC, 2019e, 2019b, 2019c) that spatially estimates N₂O or CH₄ emissions for five agricultural emitting sectors – for both the baseline and the organic farming scenarios. Those emitting sectors are (i) livestock enteric fermentation, (ii) paddy rice, (iii) farmyard manure uses, (iv) crop residues and (v) synthetic N fertilizers application. The N₂O-CH₄ model can be summarized by **Equation 17** for all emitting sectors.

$$\text{Equation 17 } Emissions_i = A_i * EF_i$$

Where $Emissions_i$ (in kg gas.yr⁻¹) represents the emissions in sector i , A_i (in unit adapted for each sector, i.e. livestock heads, ha or kg N) represents the activity in sector i and EF_i is the emission factor for each sector i (in kg gas.unit of $A^{-1}.yr^{-1}$).

CH₄ emissions from livestock enteric fermentation

We estimated CH₄ emissions due to livestock enteric fermentation, using spatially explicit livestock densities (in heads) for nine different species as activity data in **Equation 17**. In the baseline, livestock densities were retrieved from spatially explicit livestock densities map for nine species (Robinson et al., 2014). In scenarios of global organic farming expansion, we retrieved livestock densities from the GOANIM outputs (in heads of producing animals) corrected by the fraction of producing animals over the entire livestock population (in heads/heads of producing animals). The enteric fermentation emission factors (in kg CH₄.head⁻¹.yr⁻¹) for each of the nine species considered were retrieved from the default values in table 10.11 of the 2019 IPCC guidelines (**Table S13**,(IPCC, 2019b)). Because organically managed ruminants are generally fed with more roughages than their non-organic counterparts (Gaudaré et al., 2021), their enteric fermentation is likely to be higher (Patra, 2012). However, consistent and global data are missing to get an accurate estimate of the difference between the two management systems. Therefore, we assumed similar CH₄ emission factors for enteric fermentation in both organic vs. non-organic systems, although this remains a fairly optimistic assumption.

CH₄ emissions from paddy rice management

We estimated CH₄ emissions from paddy rice by using rice harvested areas (in ha) as activity data in **Equation 17**. In the baseline, we retrieved rice harvested areas from (Monfreda et al., 2008). In scenarios of global organic farming expansion, crop harvested areas in the organic farming scenarios were adapted from (Monfreda et al., 2008) corrected by differences in crop rotations between organic farming and conventional farming (Barbieri et al., 2019, 2017). In paddy rice management, CH₄ emission factor (in kg CH₄.ha⁻¹.yr⁻¹) was estimated using the tier 1 approach from the IPCC guidelines (IPCC, 2019e) and summarized in **Equation 18**:

$$\text{Equation 18 } EF = (EF_c + SF_w + SF_p + SF_o) * t$$

Where EF (in $\text{kg CH}_4 \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$) is the emission factor for rice cultivation, EF_c (in $\text{kg CH}_4 \cdot \text{ha}^{-1} \cdot \text{day}^{-1}$) is the default emissions factor from continuously flooded fields without organic amendments, retrieved from table 5.11 of the 2019 IPCC guidelines (IPCC, 2019e), SF_w (unitless) is the scaling factor due to water management during the cultivation period, SF_p is the scaling factor due to pre-cultivation water management and SF_o is the scaling factor due to organic amendments. SF_w , SF_p and SF_o were retrieved from tables 5.12, 5.13 and 5.14 of the 2019 IPCC guidelines (IPCC, 2019e) respectively. SF_o depends on the amount of organic amendments applied on soil. For both the baseline and the organic scenarios, we retrieved organic amendments values (in $\text{t DM} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$) from estimations made in **Chapter II** of this dissertation. t is the rice cultivation period (in days). Spatially explicit information on cultivation periods, water management in the cultivation period and the pre-cultivation period were retrieved from (Carlson et al., 2016).

N₂O emissions from farmyard manure uses

We estimated N_2O emissions for the three uses of farmyard manure defined by the IPCC (IPCC, 2019b): (i) manure left on pasture during the grazing period, (ii) manure management systems and (iii) manure applied on croplands. For all three uses, we used the amount of N (in kg N) in each farmyard manure use as activity data in **Equation 17**. We estimated the spatially explicit amount of N in each manure use based on **Equation 19**, **Equation 20** and **Equation 21**.

$$\text{Equation 19 } N_{pasture} = \sum_{a,r} Pop_{a,r} * Nex_{a,r} * \%P_{a,r}$$

$$\text{Equation 20 } N_{management} = \sum_{a,r} Pop_{a,r} * Nex_{a,r} * \%M_{a,r}$$

$$\text{Equation 21 } N_{croplands} = \sum_{a,r} Pop_{a,r} * Nex_{a,r} * \%M_{a,r} * (1 - \%lost_{a,r})$$

Where $N_{pasture}$, $N_{management}$ and $N_{croplands}$ represent the amount of N (in $\text{kg N} \cdot \text{yr}^{-1}$), left on pasture during grazing, in manure management systems and applied on croplands respectively. $Pop_{a,r}$ (in heads) is the livestock population for species a and region r , $Nex_{a,r}$ (in $\text{kg N} \cdot \text{head}^{-1} \cdot \text{yr}^{-1}$) is the annual N excretion rate per animal. In the baseline, the annual N excretion rates were retrieved from default values in tables 10.19 and 10A.5 of the 2019 IPCC guidelines (**Table S10**, (IPCC, 2019b)). In the organic farming scenarios, the annual N excretion rates were estimated based on annual mass conservation between feed N intake on the one hand and N outputs in livestock biomass and manure production on the other hand. $\%P_{a,r}$ and $\%M_{a,r}$ are the share of the excreted manure left on pasture during the grazing period and stored in manure management systems, respectively. $\%P_{a,r}$ and $\%M_{a,r}$ were retrieved from the default values in tables 10A.6 to 10A.9 of the 2019 IPCC guidelines (**Table S10**, (IPCC, 2019b)). In each region, and for each livestock species, the sum of $\%P_{a,r}$ and $\%M_{a,r}$ should equal one. $\%lost_{a,r}$ is the share of N lost during manure management through direct N_2O and N_2 emissions, NO_3 leaching, and NH_3 volatilization. $\%lost_{a,r}$ was retrieved from default values in table 10.21 to 10.23 in the 2019 IPCC guidelines (IPCC, 2019b).

Direct N_2O emissions from N in manure applied to grasslands and croplands were estimated using emissions factors (in $\text{kg N}_2\text{O-N} \cdot \text{kg N}^{-1}$) retrieved from default values in table 11.1 of the 2019 IPCC guidelines (IPCC, 2019c) – using the specific value for rice lands and accounting for differences between wet and dry climates (**Annex III**). Indirect N_2O emissions were estimated using the default values of

leaching and volatilization fraction (in kg N.kg N⁻¹ and kg NH₃-N/NO_x-N.kg N⁻¹, respectively) and the default emission factors (in kg N₂O-N.kg N⁻¹ and kg N₂O-N.kg NH₃-N/NO_x-N⁻¹ respectively) provided by table 11.3 of the 2019 IPCC guidelines (IPCC, 2019c). N₂O-N emissions were converted to N₂O emissions by using the ratio of molar masses. Direct N₂O emissions from N in manure management systems was estimated using emissions factor (in kg N₂O-N.kg N⁻¹) retrieved from default values in table 10.21 of the 2019 IPCC guidelines (IPCC, 2019c) – using the specific value for each manure management systems. Indirect N₂O emissions from manure management systems were estimated using the default values of leaching and volatilization fraction in manure management systems (in kg N.kg N⁻¹ and kg NH₃-N/NO_x-N.kg N⁻¹, respectively) retrieved from default values in table 10.22 and the default emission factors (in kg N₂O-N.kg N⁻¹ and kg N₂O-N.kg NH₃-N/NO_x-N⁻¹ respectively) provided by table 11.3 of the 2019 IPCC guidelines (IPCC, 2019c, 2019b).

CH₄ emissions from manure management

We estimated CH₄ emissions from manure management systems (IPCC, 2019b). The amount of manure in manure management systems (in kg DM) was used as activity data in **Equation 17**. We estimated the spatially explicit amount of manure in manure management systems based on **Equation 22**.

$$\text{Equation 22 } MA_{management} = \sum_{a,r} Pop_{a,r} * MAex_{a,r} * \%M_{a,r}$$

Where $MA_{management}$ represents the amount of manure (in kg DM.yr⁻¹) in manure management systems. $Pop_{a,r}$ (in heads) is the livestock population for species a and region r , $MAex_{a,r}$ (in kg DM.head⁻¹.yr⁻¹) is the annual manure excretion rate per animal. In the baseline, the annual manure excretion rates were retrieved from default values in table 10.13 of the 2019 IPCC guidelines (**Table S10**, (IPCC, 2019b)). In the organic farming scenarios, the annual manure excretion rates were estimated based on **Equation S5**. $\%M_{a,r}$ is the share of excreted manure stored in manure management systems, and was retrieved from the default values in tables 10A.6 to 10A.9 of the 2019 IPCC guidelines (**Table S10**, (IPCC, 2019b)).

CH₄ emissions from manure management systems were estimated using emissions factors (in kg CH₄.kg DM⁻¹) retrieved from default values in table 10.14 of the 2019 IPCC guidelines (IPCC, 2019b) – using the specific value for each manure management system and livestock species.

N₂O emissions from crop residues remaining on fields

We estimated the N₂O emissions from crop residues remaining on fields by using the amount of N in those crop residues (in kg N) as activity data in **Equation 17**, which was estimated following **Equation 23**:

$$\text{Equation 23 } N_{residues,remaining} = \sum_c Yield_c * HA_c * [N]_c * \%Recycled_c$$

Where $N_{residues,remaining}$ is the amount of N in crop residues remaining on fields (in kg N.yr⁻¹), $Yield_c$ (in t DM.ha⁻¹.yr⁻¹) is the crop yield for crop species c , HA_c (in ha) is the harvested area of crop species c , $[N]_c$ is the N concentration of crop residues biomass (in kg N.t DM⁻¹) and $\%Recycled_c$ is the share of the overall crop residues production that remains on field. $Yield_c$ and HA_c were retrieved from (Monfreda et al., 2008) in the baseline, and from GOANIM outputs for the organic farming scenarios

(Barbieri et al., 2021). $[N]_c$ was retrieved from (Monfreda et al., 2008) and (Smil, 1999). $\%Recycled_c$ was retrieved from (Liu et al., 2010; Sheldrick et al., 2003; Smil, 1999).

To estimate direct N_2O emissions from crop residues remaining on field, we used the emission factors (in $kg\ N_2O-N.kg\ N^{-1}$) as defined in table 11.1 of the 2019 IPCC guidelines (IPCC, 2019c) – using the specific value for rice lands and accounting for differences between wet and dry climates. Indirect N_2O emissions were estimated using the default values of leaching and volatilization fraction (in $kg\ N.kg\ N^{-1}$ and $kg\ NH_3-N/NOx-N.kg\ N^{-1}$, respectively) and the default emission factors (in $kg\ N_2O-N.kg\ N^{-1}$ and $kg\ N_2O-N.kg\ NH_3-N/NOx-N^{-1}$ respectively) provided by table 11.3 of the 2019 IPCC guidelines (IPCC, 2019c). N_2O-N emissions were converted to N_2O emissions by using the ratio of molar masses.

N_2O and CH_4 emissions from crop residues burning

We estimated the N_2O and CH_4 emissions from crop residues burning by using the amount of crop residues dry matter burned (in $kg\ DM.yr^{-1}$) as activity data in **Equation 17**. The amount of crop residues burned was estimated following **Equation 24**:

$$\text{Equation 24 } DM_{residues,burned} = \sum_c Yield_c * HA_c * \%burned_c$$

Where $DM_{residues,burned}$ is the amount of crop residues (in $kg\ DM.yr^{-1}$) burned, $Yield_c$ (in $t\ DM.ha^{-1}.yr^{-1}$) is the crop yield for species c , HA_c (in ha) is the harvested area of crop c and $\%burned_c$ is the share of the overall crop residues production that is used for burning. $Yield_c$ and HA_c were defined as mentioned previously. $\%burned_c$ was retrieved from the default values in table 2.4 from the 2006 IPCC guidelines (IPCC, 2006a).

To estimate N_2O and CH_4 emissions from crop residues burning, we used the emission factors (in $kg\ N_2O.kg\ DM^{-1}$ and $kg\ CH_4.kg\ DM^{-1}$ respectively) that were retrieved from default values in table 2.5 of the 2006 IPCC guidelines (IPCC, 2006a).

N_2O emissions from synthetic N fertilizer application

We estimated N_2O emissions from synthetic N fertilizers by using the amount of N from synthetic fertilizers applied on croplands (in $kg\ N.yr^{-1}$) as activity data in **Equation 17**, which was retrieved from (Mueller et al., 2012). Direct emissions from synthetic N application were estimated using emissions factors (in $kg\ N_2O-N.kg\ N^{-1}$) retrieved from default values in table 11.1 of the 2019 IPCC guidelines (IPCC, 2019c) – using the specific value for rice lands and accounting for differences between wet and dry climates. Indirect N_2O emissions were estimated using the default values of leaching and volatilization fraction (in $kg\ N.kg\ N^{-1}$ and $kg\ NH_3-N/NOx-N.kg\ N^{-1}$, respectively) and the default emissions factor (in $kg\ N_2O-N.kg\ N^{-1}$ and $kg\ N_2O-N.kg\ NH_3-N/NOx-N^{-1}$ respectively) provided by table 11.3 of the 2019 IPCC guidelines (IPCC, 2019c). N_2O-N emissions were converted to N_2O emissions by using the ratio of molar masses.

CO₂ emissions or removals from changes in agricultural SOC stocks

We estimated the annual net CO₂ emissions due to changes in soil organic carbon (SOC) stocks in both grasslands and croplands using **Equation 25**.

$$\text{Equation 25 } E_{CO_2} = \frac{\Delta SOC}{20} * \frac{44}{12}$$

Where E_{CO_2} (in Gt CO₂.yr⁻¹) represents the CO₂ net emissions due to changes in SOC stocks and ΔSOC (in t C) is the variation of global, agricultural SOC stocks between an organic farming scenario (at 20 years) and the baseline, as estimated in **Chapter II** of this dissertation for both croplands and grasslands. 44/12 is a dimensionless factor representing the ratio of molar masses used to convert SOC stocks variation into CO₂ emissions.

Land requirements estimation

In the section we provide the method use to estimate the amount of lands (grasslands and croplands) required to feed the world in scenarios of global organic farming expansion – hereafter called land requirements. To estimate global and regional land requirements we used the GlobAgri-AgT model. The GlobAgri-AgT model estimates regional cropland and grassland requirements in different scenarios of crop productivity and diets changes. The GlobAgri-AgT model is based on the balance between resources and utilisation for each agri-food product and in each world region, as defined in **Equation 26**.

$$\text{Equation 26 } Prod_{i,r} + Imp_{i,r} - Exp_{i,r} = Food_{i,r} + Feed_{i,r} + Oth_{i,r} + Waste_{i,r} + VStock_{i,r}$$

Where i is one of the 22 agri-food products and r one of the 14 regions considered in the model (**Table S14**). On the left-hand side of **Equation 26** $Prod$ (in t FM.yr⁻¹) represents the domestic production, Imp (in t FM.yr⁻¹) the imports and Exp (in t FM.yr⁻¹) the exportations. On the right-hand side, $Food$ (in t FM.yr⁻¹) is the domestic food consumption, $Feed$ (in t FM.yr⁻¹) the feed consumption, Oth (in t FM.yr⁻¹) the other uses, $Waste$ (in t FM.yr⁻¹) the waste (before retailing) and $VStock$ (in t FM.yr⁻¹) the stock variations. In our study, other uses and stock variations were set-up at a zero value.

For crop-based agri-food products (17 crop categories), $Prod_{i,r}$ is defined using **Equation 27**.

$$\text{Equation 27 } Prod_{i,r} = Surf_{i,r} * Yield_{i,r}$$

Where $Surf_{i,r}$ (in ha) and $Yield_{i,r}$ (in t FM.ha⁻¹) are the harvested area and yield of crop i in region r respectively. In the baseline, $Yield_{i,r}$ was retrieved from the GlobAgri-AgT database (Mora et al., 2020). In the organic farming scenarios, $Yield_{i,r}$ was estimated using **Equation 28**.

$$\text{Equation 28 } Yield_{i,r} = \frac{\sum_p Yield_{p,i,r} * HA_{p,i,r}}{\sum_p HA_{p,i,r}}$$

Where $Yield_{p,i,r}$ (in t DM.ha⁻¹) was retrieved from GOANIM outputs and represent the yield of each plant species p (from the 61 crop species considered in GOANIM, **Table S9**) of the plant category i (as defined in the 17 crop categories in the GlobAgri-AgT model, **Table S14**). $HA_{p,i,r}$ (ha) is the harvested area of each plant species p of the plant category i and was retrieved from (Barbieri et al., 2019). $Yield_{i,r}$

was adapted to fit the GlobAgri-AgT model requirements – meaning yields expressed in tons of fresh matter per ha – by using the inverse dry matter ratio retrieved from Feedipedia¹.

For each region, $Feed_{i,r}$ is defined using **Equation 29**.

$$\text{Equation 29 } Feed_{i,r} = \sum_l \beta_{l,i,r} * Prod_{l,r}$$

Where $\beta_{l,i,r}$ (in kg.FM.kg FM⁻¹) is the annual ratio of feed intake from crop category i to livestock production l , for region r . $Prod_{l,r}$ is the annual livestock (in kg FM) and was retrieved from the GlobAgri-AgT database (Mora et al., 2020). In the baseline, $\beta_{l,i,r}$ was retrieved from the GlobAgri-AgT database (Mora et al., 2020). In the organic farming scenarios, $\beta_{l,i,r}$ was estimated using **Equation 30**.

$$\text{Equation 30 } \beta_{l,i,r} = \frac{\sum_{p,a} Consumed_{p,a}}{\sum_a Pop_a * Prod_a}$$

Where $Consumed_{p,a}$ (in kg FM.head⁻¹) represents the amount of plant species p (in plant category i) consumed by livestock species a (from the 9 livestock species considered in GOANIM) included in production l (as defined in the 5 livestock products in the GlobAgri-AgT model). $Consumed_{p,a}$ was estimated using the GOANIM outputs about cropland production for feed use. Pop_a and $Prod_a$ represent the livestock population (in heads) and the livestock production (in kg FM.head⁻¹) for each animal a and livestock production l . Pop_a was retrieved from the GOANIM outputs. $Prod_a$ was retrieved from the FAOSTAT database² for ruminants and pigs, and from (Cobb-Vantress, 2015; Ross Aviagen, 2014) for poultry production. We made the assumption that livestock products were not used in organic livestock feeding (Gaudaré et al., 2021).

GlobAgri-AgT estimates the regional cropland and grassland areas required to provide enough food for the global human population according to regional crop yields and human food diets. In the baseline the human food diets were retrieved from the GlobAgri-AgT database (Mora et al., 2020). Evidences show that organic farming expansion might not be feasible without deep changes in human food diets (Erb et al., 2016; Morais et al., 2021). Additionally, there is evidence of different food purchase behaviours of organic food consumers (Baudry et al., 2019). Therefore, we assumed that the global human food diets would evolve with organic farming expansion. However, due to the lack of data on potential changes in human diets with organic farming expansion, we assumed that regional human diets will adapt so that that the mean global food demand fits the mean global food production as estimated by GOANIM. We thus estimated regional food diets so that they would respect two conditions: (i) the mean global food demand should have the same caloric composition than the global food production and (ii) regional caloric consumption level should be maintained – in other word we assumed the per capita daily caloric intake to be constant in each region. The mean global food demand caloric composition was estimated using **Equation 31**.

$$\text{Equation 31 } \%E_{org,f} = \frac{E_f}{\sum_f E_f}$$

Where $\%E_{org,f}$ represents the caloric share of each agri-food product f considered in GlobAgri-AgT in the total caloric intake (in kcal.cap⁻¹.day⁻¹) in the adapted organic diet. E_f represents the total calories produced in the REF 100% organic scenario for each agri-food product f , retrieved from the GOANIM outputs.

¹ <https://feedipedia.org/>

² <https://www.fao.org/faostat/>

Regional diets were then estimated using **Equation 32**.

$$\text{Equation 32 } Diet_{org,f,r} = Diet_{b,f,r} * \frac{\%E_{org,f}}{\%E_{b,f}} * E_{correction,r}$$

Where $Diet_{org,f,r}$ represents the organic food demand for each agri-food product f in each region r and $\%E_{b,f}$ represents the caloric share of each agri-food product f in the mean global food demand (in kcal.cap⁻¹.day⁻¹) in the baseline. $E_{correction,r}$ is a regional caloric correcting factor (dimensionless) to maintain the regional daily energetic intake similar in the baseline and in the adapted organic diets.

GlobAgri-AgT, estimates the regional land required to answer the regional agri-food products demand. Croplands requirements is limited regionally to a given area suitable for cropping, as defined in **Equation 33**

$$\text{Equation 33 } Surf_r \leq \overline{Surf}_r$$

Where $Surf$ (in ha) is the cropland requirements area and \overline{Surf}_r (in ha) is the upper limit of land suitable for cropping in each region. In each region r , cropland required area is limited to a maximum cropping area \overline{Surf}_r . When the cropland required area this maximum cropping area in one region, the uses not covered by the local production are covered through trade, by following two steps. First, the considered region decreases its export market shares; second, if not sufficient, the region increases its imports. Changes in regional exports and imports must respect a global equilibrium between total global imports and total global exports as defined in **Equation 34**.

$$\text{Equation 34 } \sum_r Imp_{i,r} = \sum_j Exp_i$$

The GlobAgri-AgT model has been specifically designed for the Inra/Cirad foresight study Agrimonde-Terra: Land use and food security in 2050. (Mora et al., 2020) report the main results of Agrimonde-Terra. Supporting data for Mora et al. (2020) are available on the INRAE data repository (<https://data.inrae.fr/dataset.xhtml?persistentId=doi:10.15454/RMCZTW>). In this chapter, we use the same initial data as Agrimonde-Terra but scenarios are completely different.

Land-use changes estimation

In the previous section, we explained how we combined the GOANIM and the GlobAgri-AgT models to estimate agricultural land requirements in scenarios of global organic farming expansion. These agricultural land requirements need to be translated into land-use changes to estimate their related GHG emissions. We assumed that the change of agricultural lands requirements is translated in an equivalent change in agricultural land use – meaning the estimated regional land requirements changes correspond to regional changes in land-use area, resulting in land-use change. We based our land-use changes estimation based on three main assumptions. *First*, croplands area expansion will first occur on grasslands and, if necessary, on forests. *Second*, we assumed that abandoned croplands will be turned into grasslands. *Third*, we assumed that abandoned grasslands will be afforested whenever pedo-climatic conditions allow afforestation.

More in details, we estimated land-use changes in each of the 14 regions defined in GlobAgri-AgT by using the decision process summarized in **Figure 13** and based on **Equation 35** and **Equation 36**.

Equation 35 $\Delta Total = Total_{org} - Total_b$

Equation 36 $\Delta Crop = Crop_{org} - Crop_b$

Where $Total_{org}$ and $Total_b$ (in ha) are the total regional agricultural lands (sum of croplands and grasslands) used in the organic scenario and the baseline, respectively. $Crop_{org}$ and $Crop_b$ (in ha) are the regional cropland areas (sum of croplands and grasslands) used in the organic scenario and the baseline, respectively.

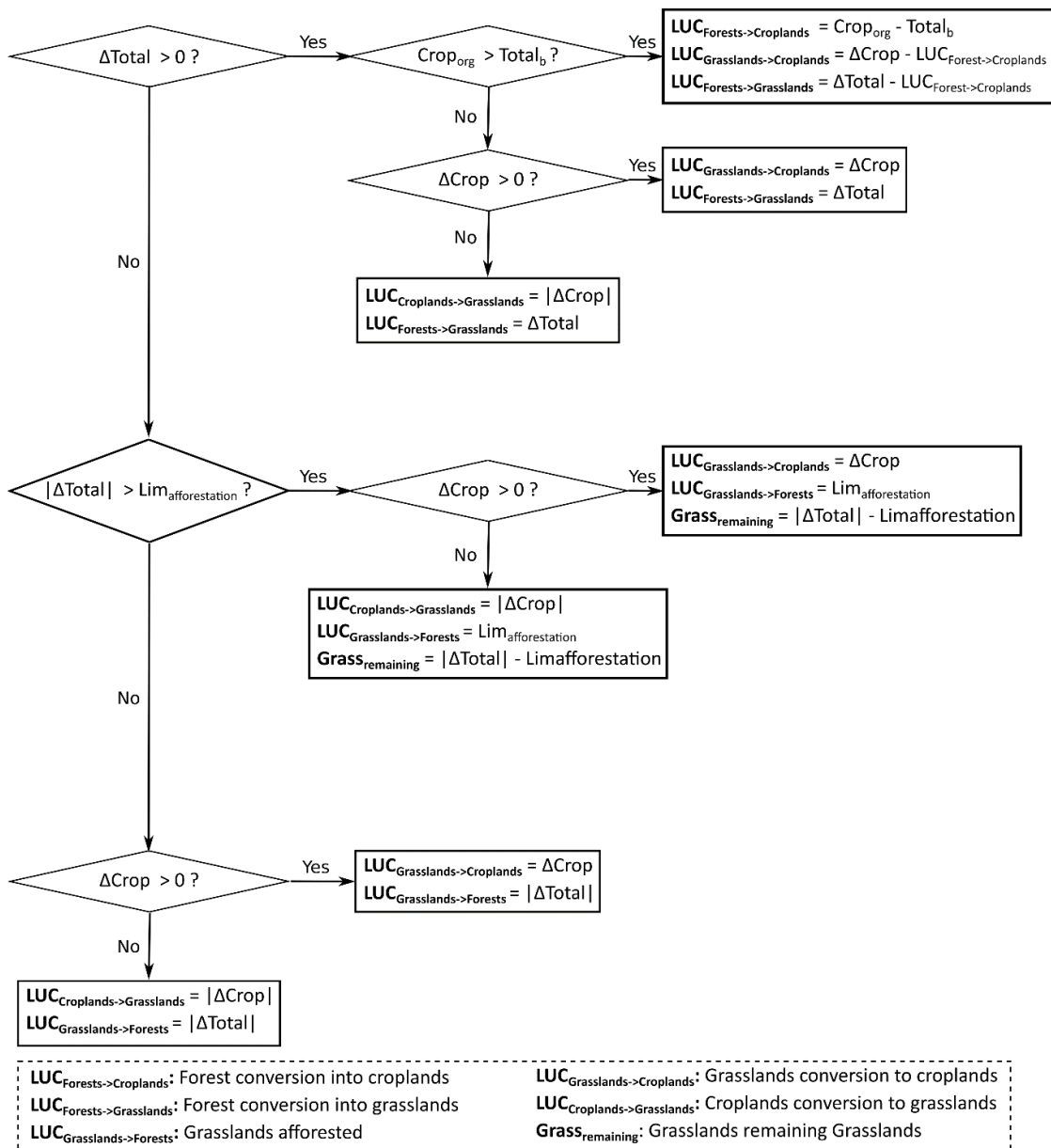


Figure 13: Decision process to estimate regional land-use changes. $\Delta Total$ and $\Delta Crop$ are defined in Equation 35 and Equation 36, respectively. $Lim_{afforestation}$ represents the pedo-climatic potential area for afforestation (Bastin et al., 2019).

As reported by several studies, there is evidence of high uncertainty on the estimation of grassland areas and grassland use in India (Bouwman et al., 2005; Chang et al., 2016; Fetzel et al., 2017; Petz et al., 2014). As grasslands expansion is the first source of land-use changes – through deforestation (Gibbs et al., 2010; Herrero et al., 2013), based on our approach, a misestimating of

grassland areas might lead to misestimating of land-use changes and related GHG emissions. In India, we found a potential +18 Gt CO₂eq.yr⁻¹ due to the uncertainty on initial grassland areas – representing a 46% increase in the agricultural GHG emissions in a fully organically managed world scenario. Due to lack of accurate and validated data on grassland areas in India, we assumed that current grassland areas in this region would be sufficient to cover grassland and cropland requirements in scenarios of global organic farming expansion. In other word, we assumed no deforestation in India induced by the expansion of organic farming.

GHG emissions from land-use changes

We estimated GHG emissions from land-use changes, by using land-use change areas (in ha) estimated in the previous section as activity data in **Equation 17** for all types of land-use changes in each of the 14 regions considered in GlobAgri-AgT. The regional emission factors for each type of land-use change were estimated using **Equation 37**.

$$\text{Equation 37 } EF_{luc,r} = \frac{\sum_{AEZ} EF_{AEZ,luc,r} * Area_{AEZ,r}}{\sum_{AEZ} Area_{AEZ,r}}$$

Where $EF_{luc,r}$ is the emission factor (in Gt CO₂eq.ha⁻¹.yr⁻¹) for a given land-use change luc in region r as defined in GlobAgri-AgT. $EF_{luc,r}$ represents the CO₂ emission or removal from changes in organic biomass (sum of living biomass, dead organic biomass and soil organic biomass) as well as N₂O and CH₄ emissions from biomass burning. $EF_{AEZ,luc,r}$ is the emissions factor (in Gt CO₂eq.ha⁻¹.yr⁻¹) for a given agroecological zone AEZ and a given land-use change in region r . $EF_{AEZ,luc,r}$ values were retrieved from the AEZEF model (Plevin et al., 2014). $Area_{AEZ,r}$ is the total area of croplands or grasslands (in ha) in a given agroecological zone in region r and was estimated using global maps of current cropland and grassland areas (Ramankutty et al., 2008).

The expansion of croplands over the other land uses comes with additional agricultural activities. Inversely, a reduction of croplands areas would come with a reduction of agricultural activities. Those variation of agricultural activities results in a variation of N₂O and CH₄ emissions and must therefore be accounted for. To simulate these variation of N₂O and CH₄ emissions, we used the regional variation of croplands (Δ Crop) as activity data in **Equation 17**. Regional mean emission factors (in Gt CO₂eq.ha⁻¹.yr⁻¹) for both N₂O and CH₄ were estimated based on **Equation 38**:

$$\text{Equation 38 } EF_r = \frac{Total_Emission_r}{Area_r}$$

Where EF_r is the regional mean emission factor (in Gt CO₂eq.ha⁻¹.yr⁻¹) in region r , $Total_Emission_r$ is the total emissions of both CH₄ and N₂O (in Gt CO₂eq.yr⁻¹, as estimated using the N₂O-CH₄ model) in region r and $Area_r$ represents the total cropland areas (in ha) in region r .

In **Chapter II**, we estimated changes in SOC stocks in scenarios of transition towards organic management of croplands and grasslands. Such changes in SOC stocks (and the related CO₂ emissions or removal) are only representative of conversion of the land management towards organic farming, and should not be considered when croplands or grasslands are converted in other land uses. Therefore, for all croplands or grasslands converted into another land use, we estimated the amount of CO₂ that should have been emitted or removed, if those lands had remained within the same land-use but managed organically. We considered this amount of CO₂ emitted or removed as avoided emissions or removal due to land-use change.

Upstream GHG emissions and GHG aggregation

Finally, we estimated CO₂ and N₂O emissions from the production process of synthetic N fertilizers in the baseline by using the IPCC guidelines on chemical industries emissions (IPCC, 2006b). Based on **Equation 17**, we used the amount of ammonia (tons) and nitric acid (tons) produced for synthetic N fertilizers as activity values. Values for global ammoniac and nitric acid production we converted from FAOSTAT data on global urea and anhydrous ammonia production, respectively. We converted urea production into ammonia production using a 0.57 coefficient (in t ammonia.t urea produced⁻¹). Assuming that all anhydrous ammonia was converted into nitric acid, we converted anhydrous ammonia into nitric acid using a 1.85 coefficient (in t nitric acid.t anhydrous ammonia⁻¹). We used an emission factor of 2 (in t CO₂.t ammonia⁻¹) for ammonia production and 0.005 (in t N₂O.t nitric acid⁻¹) for nitric acid production (IPCC, 2006b). Note that, due to the lack of consistent data, we assumed that GHG emissions are similar downstream in the food chains – meaning in the food transport, packaging and retailing process – for both organic and non-organic products.

All CO₂, CH₄ and N₂O emissions were aggregated using their respective global warming potential over 100 years (1, 25 and 298 respectively).

Scenarios definition

We estimated the GHG budget of several scenarios of global organic farming expansion. Because converting the whole agricultural area to organic farming is a rather drastic thought experiment, we also explored more realistic scenarios of intermediate conversion to organic farming – meaning scenarios where organic farming occupies a limited share of the global agricultural lands (20 to 80%). In those scenarios we estimated $Yield_{i,r}$, $\beta_{i,i,r}$ and $Diet_{o,f,r}$ as defined in **Annex IV**. Additionally, we considered two situations for all scenarios: (i) a reference situation where cover crops are not considered in the estimation of SOC stocks changes (see **Chapter II**) and (ii) a situation where the effect of using cover crops between main crops to avoid bare soil on 25% of the organically managed croplands is considered in the estimation of SOC stocks changes (see **Chapter II**). Finally, as reducing food waste in retailing systems and households represent key levers to improve global food availability, we explored three situations for each scenario: (i) a situation where food wastes are not reduced, (ii) a situation where food waste are reduced by 50% and (iii) a situation where food wastes are reduced by 100% (see **Annex IV**).

Results

Conversion of agricultural lands to organic farming and related GHG emissions

We found that N₂O emissions would be reduced by 60% (-1.1 Gt CO₂eq.yr⁻¹) in a scenario of full conversion of agricultural lands to organic farming (hereafter called the REF 100% organic scenario) compared to the baseline. This strong reduction was observed for all N₂O emitting sectors (**Figure 14**), with a specific disappearance of emissions from synthetic fertilizers due to the ban of those inputs in organic farming regulations. We found a 51%, 45% and 41% reduction in N₂O emissions from manure left on pasture, applied to croplands and managed in storage systems, respectively, that are mostly explained by a 44% reduction (**Table S15**) in the amount of N excreted by animals – itself driven by a 66% reduction in the livestock population (expressed in livestock units). As the share of manure excreted and left on pasture or managed in storage facilities varies from one region to another (IPCC, 2019b), changes in the spatial distribution of the livestock population in the REF 100% organic scenario compared to the baseline affect the global mean N₂O emission intensity per unit of N excreted by animals (37% lower in the REF 100% organic farming scenario compared to the baseline). Finally, we found a 55% reduction in N₂O emissions from crop residues left on fields and a 57% reduction in N₂O emissions from crop residues burning, some results largely explained by the 49% reduction in crop yields (in t DM.ha⁻¹) that we found globally (see **Annex II**).

We also found that CH₄ emissions would be reduced by 60% (-2 Gt CO₂eq.yr⁻¹) in the 100% REF organic scenario compared to the baseline (**Figure 14**). This large drop in CH₄ emissions is in great part due to the drastic 62% reduction in CH₄ emissions from enteric fermentation that we found. This cut in enteric fermentation is mostly explained by the 66% reduction in the livestock population (expressed in livestock units) that we found previously (see **Annex IV**), partially compensated by a higher share of ruminants (representing 94% of the global livestock population when expressed in livestock units) in the REF 100% organic scenario compared to the baseline (where ruminants represent 72% of the global livestock population) (**Table S15**). We found a nearly 100% reduction in CH₄ emissions from manure management. Such drastic reduction is explained by (i) a 66% reduction of manure excretion (in tons of volatile solids), together with a transition towards livestock species that have lower emitting factors (in kg CH₄.t VS⁻¹, (IPCC, 2019b)). The 31% reduction of the rice harvested area due to differences in crop rotations in organic farming compared to conventional farming (Barbieri et al., 2019, 2017) – along with a 43% reduction of organic fertiliser application on lands (see **Chapter II**) – results in a 37% reduction in CH₄ emissions from paddy rice managed organically compared to the baseline. Finally, the 49% reduction in crop production that we found is the main explanation of the 57% reduction in CH₄ emissions from crop residues burning.

As a result, we found a 60% reduction emissions of both N₂O and CH₄ combined either expressed globally (-3.1 Gt CO₂eq.yr⁻¹) or as mean per hectare emissions (-2 t CO₂eq.ha⁻¹.yr⁻¹) compared to the baseline. This global mean reduction of per hectare emissions masks spatial variations. In some regions – such as Canada, Russia and Australia – we found increased N₂O and CH₄ emissions per hectare (**Figure S20**), driven by increased livestock population (expressed in livestock units), thus indicating higher agricultural intensity in the REF 100% organic scenario compared to the baseline. In contrast, regions experiencing a reduced livestock population in the REF 100% organic scenario – such as Central America and India – showed decreased N₂O and CH₄ emissions.

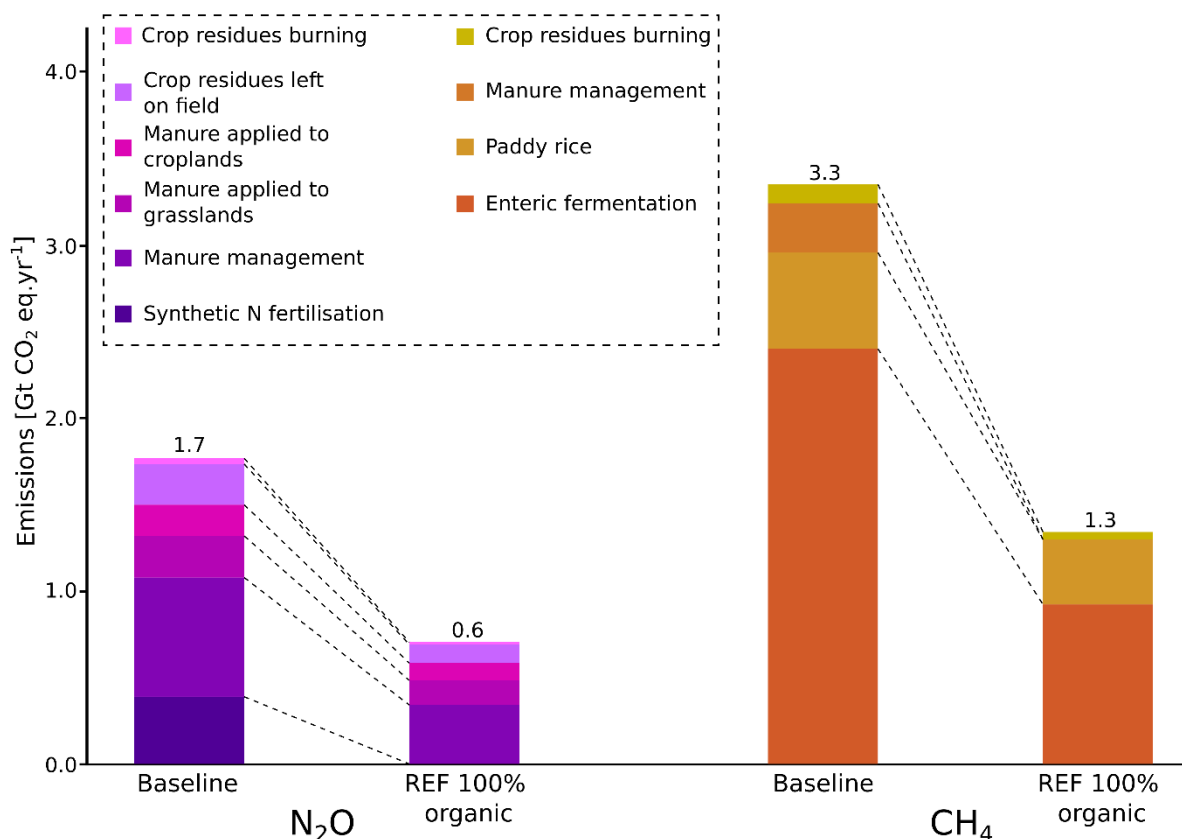


Figure 14: Changes in global N₂O and CH₄ emissions between the 100% REF organic scenario and the baseline. Emissions are expressed in Gt CO₂eq.yr⁻¹ for all emitting sectors. The numbers on top of each bars represent the cumulative emissions (all sectors combined) for both gases. Dotted black lines represent the changes of each emitting sector.

Functional units have critical role when comparing GHG emissions from different production systems. If normalised by caloric production (i.e., if expressed in kcal of crop and livestock products combined), we found that agricultural N₂O and CH₄ emissions combined would be reduced by only 10% (-406 kg CO₂eq.kcal produced⁻¹.yr⁻¹). This result is explained by the 57% reduction in total caloric production that we found in the REF 100% organic scenario compared to the baseline – decomposed in a 57% reduction in the crop energy production (**Table S15**) and an 80% reduction in the livestock energy production. However, this reduction in caloric production is compensated by a higher share of the total energy dedicated to human food in the REF 100% organic scenario (77%) compared to the baseline (56%), resulting in a 35% reduction of GHG emissions (N₂O and CH₄ combined) when expressed per kcal of food produced globally (-251 kg CO₂eq.kcal of food⁻¹.yr⁻¹).

In **Chapter II**, we found a reduction of global SOC stocks in both croplands and grasslands – mainly explained by a reduction of soil carbon inputs. We estimated that such reduction of global SOC stock would result in 1.2 and 1.1 Gt 1.2 and 1.1 Gt CO₂eq.yr⁻¹ from croplands and grasslands respectively.

To summarize, in the REF 100% organic scenario, (i) N₂O emissions are reduced by -1.1 Gt CO₂eq.yr⁻¹, (ii) CH₄ emissions are reduced by -2 Gt CO₂eq.yr⁻¹ and there are additional CO₂ emissions from SOC stocks reduction in croplands (+1.2 Gt CO₂eq.yr⁻¹) and grasslands (+1.1 Gt CO₂eq.yr⁻¹). All gases considered, this result in a reduction of -0.8 Gt CO₂eq.yr⁻¹ from the agricultural sector, which would represent a 16% reduction compared to the baseline.

In addition, we found that the GHG emissions from the chemical process of fertilizer production that are induced by the use of synthetic fertilizers would be 0.09 Gt CO₂eq.yr⁻¹. Added to the emissions from the agricultural sector, this would lead to a global reduction of 0.9 Gt CO₂eq.yr⁻¹ in the REF 100% organic scenario, which would represent an 18% reduction compared to the baseline.

Land requirements and land-use changes in a fully organic world

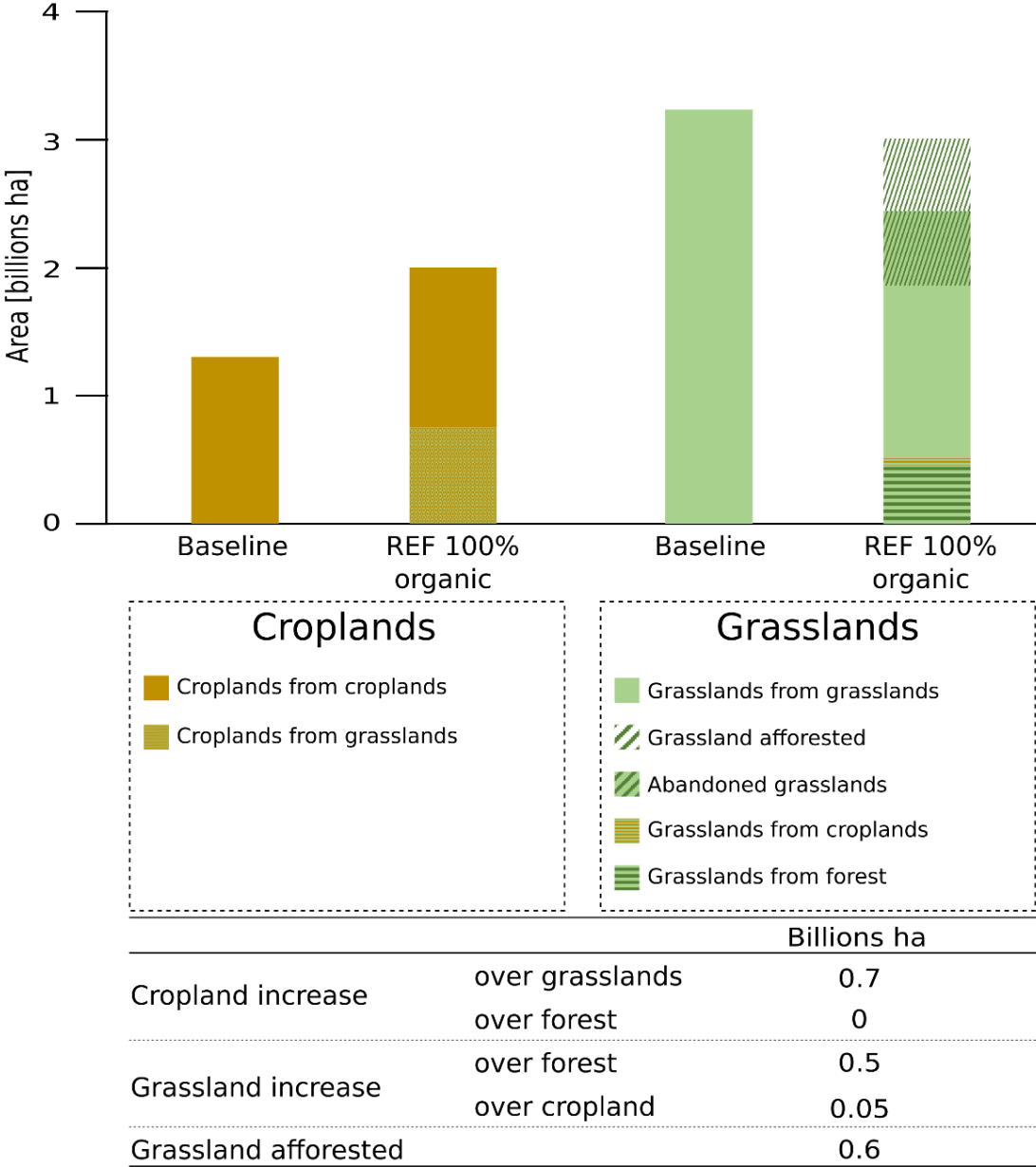


Figure 15: Global cropland and grassland requirements and land-use changes in the REF 100% diets adapted organic scenario and the baseline. The brown bars represent the cropland requirements (in billion ha) and the green bars the grassland requirements (in billions ha) for both the organic scenario and the baseline.

We found a 58% increase (+0.7 billion ha) in cropland requirements in the REF 100% organic scenario with regional adapted organic diets (see Methods) – hereafter called the REF 100% diets adapted organic scenario - compared to the baseline (Figure 15). Such increase in cropland

requirements is explained by an increased competition for N fertilizers. We found that, in addition to the ban of synthetic fertilizers, we found that the amount of N from manure applied on croplands was reduced by 48% (**Table S15**), thus resulting in 57% reduction of cropland productivity. These increased cropland requirements resulted in a 0.7 billion ha of croplands expansion over grasslands – with an additional 0.01 billion ha of croplands expansion over forest. In contrast, we found a 41% lower (-1.3 billion ha) grassland requirements, which is driven by the reduction of livestock products in the adapted organic diets compared to the baseline diets (**Table S16**), partially compensated by the higher share of fodder in organic livestock feed rations (Gaudaré et al., 2021). These decreased grassland requirements resulted in a 1.1 billion ha of grassland abandonment – with 49% of it available for afforestation – and, as mentioned above, a conversion of 0.7 billion ha of grasslands in croplands. However, as land-use changes were estimated regionally, in some regions we found some grassland expansion over forests (see below), resulting in a 0.5 billion ha of forests converted into grasslands globally. For similar reasons, we found 0.05 billion ha of croplands would be turned into grasslands.

Again, these global changes mask regional variabilities (**Figure S21**). While most regions experience similar land requirements than globally, we found noticeable variations in specific regions. In Oceania, we found increased grassland requirements, resulting in the expansion of 0.3 billion ha of grasslands over forest. These high grassland requirements is due to (i) a 59% higher regional demand of small ruminant meat (**Table S16**) in the adapted organic diets compared to the baseline diets, combined with (ii) important exports of small ruminant meat from this region (the Oceania region represents currently 90% of the global small ruminant meat export). Such high grassland requirements was also observed in China, although at a lesser extent, largely explained by the increased demand for small ruminant meat.

Those global land-use changes would result in several fluxes of GHG. *First*, we found large atmospheric CO₂ removal mostly due to afforested grasslands (-4.1 Gt CO₂eq.yr⁻¹), complemented by some croplands conversion to grasslands (-0.2 Gt CO₂eq.yr⁻¹). *Second*, GHG emissions from forest conversion to grasslands and croplands would lead to a massive emission of 4.6 Gt CO₂eq.yr⁻¹ while grasslands conversion to croplands would result in 2.8 Gt CO₂eq.yr⁻¹ emission. We also found that agricultural activities on the additional 0.7 billion ha of croplands would be responsible of 1 Gt CO₂eq.yr⁻¹. Finally, the correction made on CO₂ emissions from changes in SOC stocks due to the conversion of current agricultural lands towards organic farming (see Methods) accounted for 0.5 Gt CO₂eq.yr⁻¹. Putting all those GHG emissions together, we found that land-use changes would result in net GHG emissions of 3.7 Gt CO₂eq.yr⁻¹.

Global GHG budget in a fully organic world

We found that the REF 100% diets adapted organic scenario would increase global agricultural GHG emissions by 56% compared to the baseline (+2.9 Gt CO₂eq.yr⁻¹) (Figure 16). This would result from the addition of the net decrease of GHG emissions on current agricultural lands (-0.8 Gt CO₂eq.yr⁻¹) and the net increase of GHG emissions due to land-use changes (+3.7 Gt CO₂eq.yr⁻¹).

Again, the global GHG increase in the REF 100% diets adapted organic scenario compared to the baseline masks regional variabilities (Table S17). We found that in Oceania, GHG emissions would increase by 2500%, mainly due to GHG emissions from forest conversion to grasslands (+ 2.8 Gt CO₂ eq) that represents 83% of the regional emissions in the REF 100% diets adapted organic scenario. Other regions show important increase of GHG emissions such as West Africa (+443%), Europe (+208%) and China (+166%). In contrast, we found a 623% reduction of GHG emissions in the Former Soviet Union, mainly explained by large increase of forest lands over grasslands (-0.9 Gt CO₂ eq), added to smaller increase of grasslands over croplands (-0.1 Gt CO₂ eq).

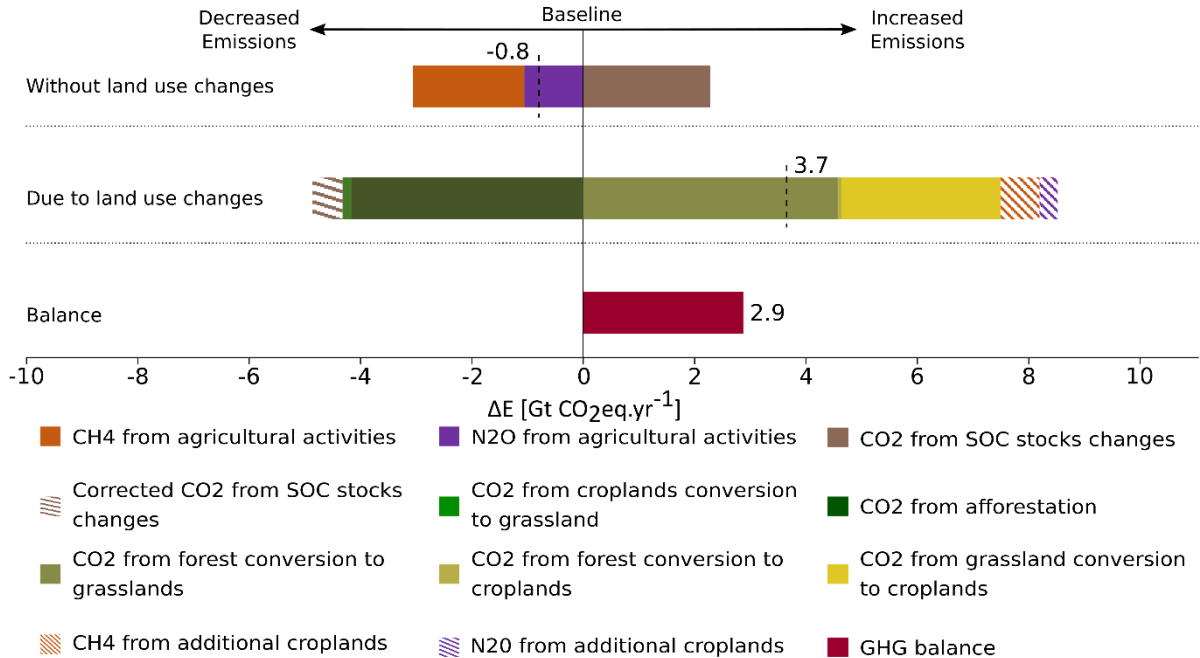


Figure 16: Global changes in the GHG emissions (in Gt CO₂eq.yr⁻¹) of the REF 100% diets adapted organic scenario compared to the baseline. The global change in GHG emissions is decomposed between GHG emissions without and with land-use changes. Full bars represent changes in GHG emissions and striped bars represent corrections due to land-use changes (see Methods).

Intermediate scenarios of organic farming expansion

Because considering a 100% of the global agricultural area under organic farming is a drastic and unrealistic thought experiment, we also explored scenarios with lower extents of organic farming. We found a non-linear response of the global GHG budget with an increase of the global share of organic farming (Figure 17). Such non-linear response of GHG emissions to organic farming expansion was found for each gas considered and was explained by the non-linear emissions due to land-use changes (Figure S22). We found that the response curve of the global GHG budget was mainly driven

by CO₂ emissions or removal (Figure 17) – which are themselves driven by CO₂ emissions or removal from land-use changes (Figure S22).

More specifically, we found reduction of the GHG budget up to 20% of the global agricultural lands occupied by organic farming – with a potential reduction of GHG emissions by 70% compared to the baseline (-3.6 Gt CO₂eq.yr⁻¹, Figure S23). Such reduction of GHG emissions in a scenario with 20% of the global agricultural lands occupied by organic farming (together with a diets adapted to the global food supply – is explained by a negative budget of GHG emissions due to land-use changes (-3.3 Gt CO₂eq.yr⁻¹), alongside a negative balance between N₂O, CH₄ and CO₂ emissions on current agricultural lands (-0.3 Gt CO₂eq.yr⁻¹). Such negative budget is explained by (i) a 28% reduction in grassland requirements – resulting in a removal of -3.7 Gt CO₂eq.yr⁻¹ of atmospheric CO₂ from afforested grasslands – and (ii) a 2% reduction in cropland requirements – resulting in a removal of -0.3 Gt CO₂eq.yr⁻¹ of atmospheric CO₂ from croplands converted to grasslands. Regional specificities (Table S18) lead and to 0.5 Gt CO₂eq.yr⁻¹ emissions from forests converted to grasslands to 0.2 Gt CO₂eq.yr⁻¹ emissions from grasslands converted to croplands. While the decrease in grassland requirements is explained by reduction of livestock products in the estimated organic diets adapted to the food supply (Table S16), the decrease in cropland requirements is explained by a higher share of organic crop produced for food purposes – which compensated the yield reduction induced by the expansion of organic farming.

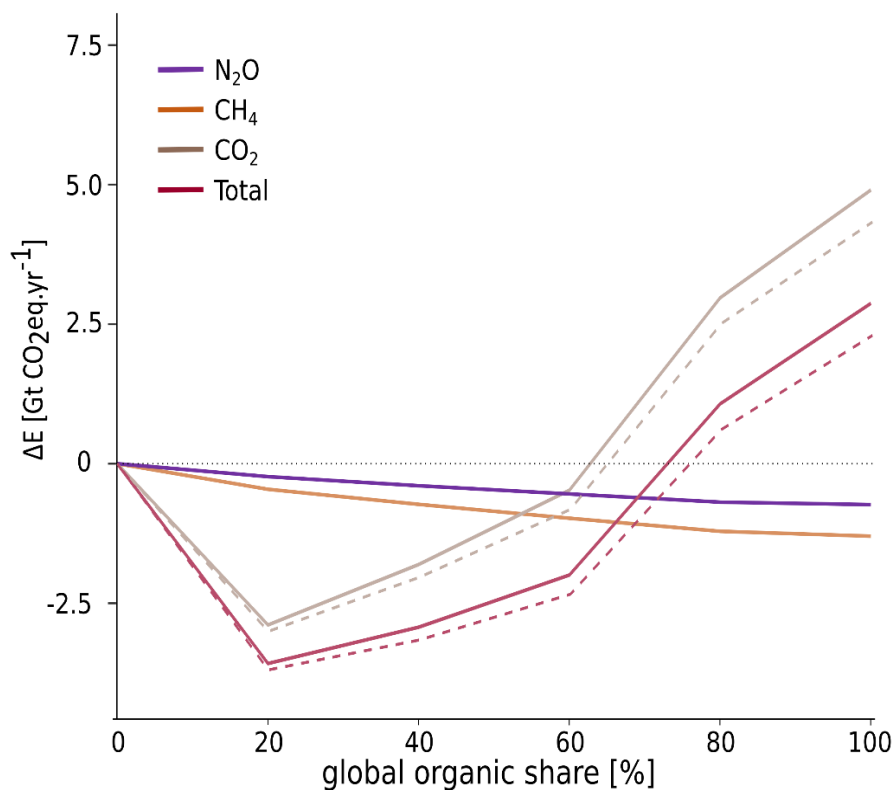


Figure 17: Changes in GHG emissions in intermediate scenarios of diets adapted organic farming expansion compared to the baseline. Full lines represent scenarios without cover crops in organic farming (here called REF diets adapted organic scenario), and dashed lines represent scenarios where cover crop are systematically used on 25% of organically managed croplands (here called diets adapted organic 25% CC, see Chapter II).

Above 20% of the global agricultural lands occupied by organic farming, the yield reduction effect becomes predominant, thus resulting in increased cropland requirements (Figure 18). Up to 60%

of the global agricultural lands occupied by organic farming, CO₂ removal from afforested grasslands – explained by reduced grassland requirements – still overcome CO₂ emissions due to land-use changes – mainly due to increased cropland requirements, resulting in a reduced GHG budget compared to the baseline (Figure 17). Due to an exponential increased cropland requirements (Figure 18) – explained by increased competitions for N fertilizers in organic farming – above 60% of the global agricultural lands occupied by organic farming, the net GHG budget from land-use changes become positive and lead to a global increase of the GHG budget compared to the baseline.

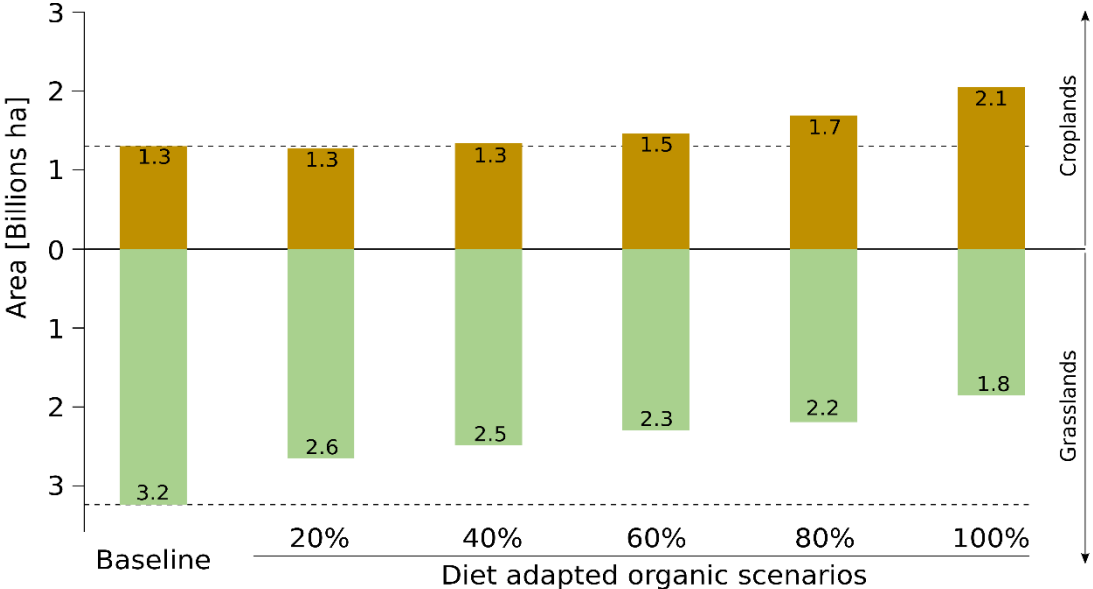


Figure 18: Global croplands and grassland requirements (in billion ha) in the intermediate diets adapted organic farming expansion scenarios and the baseline. The brown bars represent the croplands and the green bars the grasslands for both the diets adapted organic scenarios and the baseline. The black dashed lines represent the croplands and grassland requirements levels in the baseline. Values in each bar show the absolute value of croplands and grassland requirements in each scenarios (in billions ha).

Global options to reduce GHG emissions in organic farming

Covering soils by catch and cover-crops – to protect soils from erosion, to maintain year round carbon inputs to the soil, to recycle nutrients or to control pests and weeds – is common practice that many organic farmers implement (Barbieri et al., 2017). Based on a previous meta-analysis on the extent of cover-crops, we considered that cover cropping could be potentially applied on 25% of global croplands managed organically (Poeplau and Don, 2015) – hereafter called the diets adapted organic 25% CC scenario – and we estimated the global GHG budget of global organic farming expansion scenarios accounting for the effect of cover crops on SOC stocks and the GHG emissions associated to their changes. We found that with the 100% diets adapted organic 25% CC scenario, the discrepancy in GHG net emissions to the baseline is 11% lower than within the REF 100% diets adapted organic scenario (Figure 19).

Food waste reduction has often been suggested as an option to reduce the GHG footprint of organic farming (Muller et al., 2017). We found that with a 50% food waste reduction (or more), A full conversion of organic farming would exhibit lower GHG net emissions than the baseline (Figure 19). In the REF 100% adapted diets organic scenario with 50% food waste reduction, we found a 2% GHG

emission reduction compared to the baseline. In this scenario, we estimated a 0.7 Gt CO₂eq.yr⁻¹ net GHG emissions due to land-use changes – explained by increased cropland requirements of 0.2 billion ha (Figure S24) – combined with a net decreased of GHG emissions (-0.8 Gt CO₂eq.yr⁻¹) from agricultural activities on current agricultural lands. In all scenarios with food waste reduction, we found that net emissions from land-use changes would not compensate the decrease of GHG emissions from agricultural activities on current agricultural lands. However, food waste reduction could also result in a GHG emission reduction in the baseline. We estimated that in a scenario with 50% food waste reduction and 0% of organic farming worldwide (hereafter called the 50% relative baseline), GHG emissions would be reduced by 38%. Compared to 50% relative baseline, the REF 100% adapted diets organic scenario with 50% food waste reduction would exhibit 37% higher GHG net emissions (Figure S25), and the REF 20% adapted diets organic scenario with 50% food waste reduction would have 67% lower GHG emissions.

Diet adapted scenarios		Global organic share	Waste Reduction		
			0%	50%	100%
REF	organic scenario	20%	-70%	-105%	-140%
		40%	-57%	-88%	-133%
		60%	-39%	-69%	-105%
		80%	21%	-23%	-71%
		100%	56%	-2%	-72%
25% C	organic scenario	20%	-72%	-107%	-142%
		40%	-62%	-93%	-137%
		60%	-46%	-76%	-111%
		80%	12%	-32%	-80%
		100%	45%	-13%	-83%
Baseline			0%	-38%	-108%

Figure 19: Changes in global agricultural GHG net emissions (%) between the diets adapted organic scenarios, food waste reduction scenarios and the baseline. In each cell, the value represents the discrepancy in GHG emissions (%) between each scenario and the baseline (bottom left cell with a red frame). The colour indicates GHG increase (red) or GHG decrease (blue) compared to the baseline – the intensity of the colour depends on the distance to the baseline.

Discussion and conclusion

Organic farming is often promoted as a potential option to reduce GHG emissions (Muller et al., 2017; Niggli et al., 2009) at the global scale. However, previous studies did not consider potential systemic feedbacks due to the expansion of organic farming, and especially the severe N fertilisation limitation that might come along (Barbieri et al., 2021; Smith et al., 2018). Here, we provide a first estimate of GHG emissions in scenarios of global organic farming expansion – accounting for possible systemic feedbacks and all emitting sectors affected by the development of organic farming – compared to current emissions.

We found that a fully organically managed world would increase agricultural GHG emissions by 56%. Such result contrasts with previous studies estimating 3-40% GHG emission reduction in global scenarios of organic upscaling (Muller et al., 2017; Niggli et al., 2009). However, a recent study on organic farming expansion at the scale of England and Wales found similar results to ours (Smith et al., 2019) – both studies found a potential 56% GHG budget increased in organic farming compared to the baseline. The increased GHG emissions found in our study is explained by the 57 lower caloric cropland productivity that we found, resulting in large GHG emissions from land-use changes needed to feed the global population. Those results highlight the necessity to consider whole-system effects when estimating the impact of alternative farming systems – such as organic farming – on GHG emissions (Seufert and Ramankutty, 2017), with special attention to the availability of N fertilising resources and their impact on food production (Barbieri et al., 2021).

We also found that a scenario with only 20% of the global agricultural lands under organic management would lead to a 70% reduction in agricultural global GHG emissions compared to the baseline. Additionally, GHG emissions in organic farming expansion scenarios can remain lower relative to the baseline if up to 60% of the global agricultural land is converted to organic management. Those results highlight the large potential for organic farming expansion level to minimizing GHG emissions and suggest an optimal level of organic farming expansion that minimize GHG emissions. To the best of our knowledge, such a concept of optimal level of organic farming expansion has not yet been discussed in the scientific literature. These results are in line with a previous study showing that, without accounting for land-use changes, organic farming can be extended over up to 60% of the global agricultural land while maintaining the global food production (Barbieri et al., 2021). Moreover, in our study, we found an optimum at about 20% of global agricultural land under organic management. We also found that the choice of farming practices possibly implemented in organic farming – such as cover cropping – could reduce GHG emissions in global organic farming expansion scenarios and potentially increase the optimal level of organic farming expansion.

As mentioned above and in **Chapter II**, in this study, we limited the definition of organic farming to the ban of synthetic outputs (fertilizers and pesticides), differences in crop rotations (Barbieri et al., 2017) and differences in livestock management (Gaudaré et al., 2021). This definition occults the diversity of farming practices that are possible under organic farming regulations (Seufert et al., 2017). The exploration of this range of practices could lead to additional GHG emission reduction in organic farming either by improving N availability for cropland soils – resulting in higher cropland productivity in organic farms – or by reducing the emission intensity of agricultural practices (e.g. cover crops could reduce GHG emissions by 11% in a fully organically managed world thanks to additional carbon storage). Special attention must be paid to increasing N availability in organic farming – as we found that its severe limitation is the main explanation of increased GHG emissions in an organic world, because of the induced increased cropland requirements. As mentioned in **Chapter II**, the use of

leguminous (or mixed with non-leguminous) cover crops to increase N availability through biological N fixation or N leaching limitation (Abdalla et al., 2019) would help to close the N fertility gap between organic farming and the baseline (Badgley et al., 2007). Other additional sources of N – such as urban composts, green wastes, food industry by-products or eventually sewage sludges – might also help to close this gap. However, if increasing N availability in organic farming would increase cropland productivity, it might also increase the intensity of agricultural activities, resulting in additional N₂O and CH₄ emissions. Modelling the potential benefits of applying such additional practices in organic farming would require further systemic studies, which were beyond the scope of this study.

The estimation of land-use changes requires accurate data on current land uses and on human food diets. Regarding human diets, while there is evidence of differences between consumers including a high share of organic products in their diet vs. other consumers (Baudry et al., 2019), there is no available estimation of future diets under large-scale organic farming expansion. Therefore, we assumed that food diets would adapt to changes in agricultural production. It is likely that this assumption does not reflect the reality (Le Mouël et al., 2018), though it gives indication on how the diets might evolve when agricultural production systems face strong N fertilization deficiency. However, previous studies concluded that the expansion of organic farming should come with change in the global food demand (Billen et al., 2021; Erb et al., 2016; Morais et al., 2021).

There exists a wide variety of modelling approaches to estimate global agricultural land requirements (Heistermann et al., 2006; Schaldach et al., 2011). In this study, we chose to use GlobAgri-AgT, a mass balance model that estimates agricultural land requirements for different scenarios of crop and livestock productivity and of human food diets. GlobAgri-AgT is based on a simple representation of the equilibrium process between resources (supply) and utilisations (demand) of agri-food products at both the regional and the global scales. Compared to other models – such as Integrated Assessment Models (Bouwman and Kram, 2006) or equilibrium economic models (Corong and Tsigas, 2017; Forslund et al., 2020) – such simple representation of the agri-food market does not encompass potential feedbacks between crop and livestock productivity, output and input prices, trade and land requirements (Forslund et al., 2020; Mazzocchi et al., 2012). However, none of the existing market and trade models considers both conventional and organic markets and trade. Furthermore, introducing organic markets and trade in such models is made difficult by the lack of data on organic agri-food markets at the global scale. Nevertheless, to the best of our knowledge, this study is the first estimation of land requirements in an organic world, using a combination of models where crop yields are endogenous and trade in agri-food products among broad regions may adjust, allowing thus to spatialize, even partially, land-use changes.

Finally, this study provides a methodological approach to estimate GHG emissions in scenarios of organic farming expansion – and more generally in scenarios of alternative farming systems expansion – accounting for systemic feedbacks. Despite the simple representation of organic farming we used, this study could be used to test other forms of organic farming, accounting for additional practices helping to close the gap of food production (especially on N availability and agricultural land areas).

Conflict of interest

The authors declare no competing interests.

Acknowledgment

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Data treatment & code availability

GOANIM was used in its most recent version deposited in a public repository (https://github.com/Pie90/GOANIM_public). All analyses on GOANIM, RothC and the N₂O-CH₄ models were made using R x64 3.5.3. The GlobAgri-AgT model analyses were made using GAMS x64 34.3.0.

Authors' contributions

U.G., S.P. and T.N. designed the overall study; U.G., S.P, T.N and C.LM designed the specific part on agricultural land requirements. U.G. and P.B. performed the modelling work based on the GOANIM model. C.LM and U.G. performed the modelling work based on GlobAgri-AgT. U.G. performed the modelling work on the N₂O-CH₄ model. All authors were involved in the interpretation of results and contributed actively to writing and revising the manuscript.

General discussion and conclusion

Summary and perspectives



Summary of our key results

Livestock as a key component of organic farming systems

The ban of synthetic N fertilizers limits the diversity of N resources in organic farming. Among the available N fertilizing resources, livestock manure is a key resource for organic soil fertilisation (Lampkin, 2000). In addition to the participation in the nutrient recycling process, the livestock sector also plays a key role in the food supply system. On the one hand, livestock production provides rich food commodities with high concentration of amino acids and nutrients (Mottet et al., 2017). On the other hand, livestock production is a major anthropogenic driver of pollution and it challenges food security through strong feed vs food competition (Corong and Tsigas, 2017; Laisse et al., 2018a; Mottet et al., 2017; Wilkinson, 2011). For those reasons, the livestock sector is a key component of organic farming systems. The organic principles as defined by the IFOAM clearly set up a goal of animal welfare in organic livestock management. This principle is implemented into organic regulations (Lampkin et al., 2017) with large effects on the organic livestock production systems— such as length of the grazing period, feed ration composition and diseases management (Van Wagenberg et al., 2017). Most studies on organic farming expansion scenarios did not account for those differences between organic and conventional livestock management (Barbieri et al., 2021; Erb et al., 2016; Morais et al., 2021; Smith et al., 2018) and, when considered, those differences were limited to a productivity gap (Muller et al., 2017). This poor consideration of organic to conventional differences in livestock management efficiency was mainly explained by the lack of synthetic review highlighting such differences.

In **Chapter I**, we carried out a meta-analysis to provide a global comparison of organic vs conventional livestock management based on three topics: (i) animal productivity, (ii) feed ration composition and (iii) feed-use efficiency – meaning the amount of livestock products per unit of feed required. Our results confirmed that feed ration composition differ in organic vs. conventional farming, with higher forage (+16%) share for organic ruminants and the absence of synthetic feed (such as synthetic amino acids) for any organic animal species. Such differences in the feed ration composition is mainly explained by organic regulations that ban synthetic inputs and that aim at a high degree of organic farms' self-sufficiency (Lampkin et al., 2017). These differences between organic and conventional livestock feed ration contributes to the productivity gap (-12% in organic compared to conventional livestock) we found between both husbandry systems. We also found a 14% lower feed-use efficiency in organic compared to conventional livestock farming. More precisely, we found significant lower feed-use efficiency for organic poultry broilers and dairy cattle compared to their conventional counterparts. Due to a 45% longer lifespan, organic poultry broilers show a 47% lower feed-use efficiency that conventional ones. As for organic dairy cattle, we found a 11% lower feed-use efficiency compared to conventional ones. Such lower feed-use efficiency for organic dairy cattle is mainly explained by their lower productivity compared to conventional ones. Though the higher share of forage also explains the lower feed-use efficiency (as it is less digestible) but in a lower extent. However, for organic dairy cattle, we found a higher share of non-competing feed – meaning feed that cannot be used as human food – in their feed ration compared to their conventional counterparts. This result leads to higher non-competing feed-use efficiency (37%) by organic dairy cattle compared to conventional ones. These results suggest that organic dairy cattle – and probably all organic ruminant livestock – could be less in competition with human food than their conventional counterparts.

We then used the estimates from **Chapter I** to provide more precision in the simulation of livestock production in GOANIM – by changing livestock feed ration composition and productivity

levels (see **Annex III**). In addition to those precisions, we also refined the simulation of organic livestock production in GOANIM by (i) simulating non-productive animals for both the feed requirements and N excretion rates, (ii) limiting forage harvest from permanent grasslands to fit sustainable grazing intensities (Erb et al., 2016), (iii) limiting forage harvest from temporary pasture to respect a feasible uptake threshold (Soussana and Lemaire, 2014) and (iv) implementing the 2019 IPCC guidelines on manure management and nitrogen losses towards the environment (N₂O and N₂ emissions, N leaching, and NH₃ volatilization). Accounting for all those precisions brought to the GOANIM V2 (see **Annex III**). Compared to the first GOANIM version (GOANIM V1, Barbieri et al. 2021), we found no differences in the amount of people potentially fed in a fully organic world (**Table 5**). However, we found differences in the energetic sources to feed the world population. Due to (i) a 7% higher cropland energetic productivity – resulting in a 15% higher crop-based food energetic production – and a 60% livestock population reduction (expressed in livestock units) in GOANIM V2 compared to GOANIM V1, we found a higher share of crop products (97% of the total food energy produced) in GOANIM V2 compared to GOANIM V1 (83%). Such differences in the livestock population were also translated in the spatial distribution of livestock populations (**Figure S20**).

Table 5: Comparison of the main results from the two different versions of the GOANIM model and the baseline.

	Croplands			Pasture		Livestock		Total	
	Total Energy	Energy for feed	Energy for food	Energy from temporary pasture	Permanent pasture used as feed	Population	Energy Produced	Food energy	People fed
Unit	[10 ¹² MJ]	[10 ¹² MJ]	[10 ¹² MJ]	[10 ¹² MJ]	[10 ¹² MJ]	[LU]	[10 ¹² MJ]	[10 ¹² MJ]	[Million people]
Baseline	49.8	23.3	26.5	4.1	20	1 089	3.2	29.7	8 847
GOANIM V1	21.3	6.0	15.3	4	44	866	3.2	18.5	5 503
GOANIM V2	22.9	5.3	17.6	3.3	10	345	0.6	18.2	5 434

GHG emissions from agricultural activities and lands

Organic farming is often considered as a potential option to decrease field scaled GHG emissions. Meta-analyses have shown a reduction of N₂O emissions (Skinner et al., 2014) – due to the ban of synthetic N fertilizers – and an increase of soil carbon sequestration – due to a higher amount of soil carbon inputs combined to a different composition (García-Palacios et al., 2018; Gattinger et al., 2012) – in organic farming compared to conventional farming. However, due to 20-30% lower yields in organic farming (Ponisio et al., 2015; Seufert et al., 2012), those meta-analyses also show that GHG emissions might be higher in organics when expressed per unit of crop products (Skinner et al., 2014). However, these estimations are based on meta-analyses of field experiments representative of situations where organic farming occupies less than 2% of global agricultural lands (IFOAM, 2020) and with transfer of fertilizing material from conventional towards organic farms through farmyard manure (Nowak et al., 2013). However, as mentioned above, we found deep changes in the global food production in scenarios of large organic farming expansion, as estimated by GOANIM. Such changes might affect the potential of organic farming to reduce agricultural GHG emissions.

In **Chapter III**, we confirmed that N₂O emissions would be reduced in organic farming compared to the baseline (-60%). We found that this reduction resulted in a mean reduction of -0.7 kg CO₂eq.ha⁻¹.yr⁻¹, a reduction significantly higher than reported in meta-analysis of field experiments (Skinner et al., 2014). In both approaches, the ban of synthetic fertilizers is one of the main reasons of

such reduction in N₂O emissions. Therefore, the main difference between what we modelled and the results provided by (Skinner et al., 2014) is due to the competition for N fertilizers that comes with organic farming expansion. Such competition led to a reduction of organic N fertilizers application on organically farmed lands and especially manure. We found that compared to the baseline, N from manure applied on croplands was reduced by 48% (**Annex IV**) thus resulting in a 0.5 Gt CO₂eq.yr⁻¹ reduction in N₂O emissions at the global scale. In meta-analysis of field experiments, N₂O emissions are higher in organic compared to conventional farming when expressed per unit of food produced. Unexpectedly, we found -35% lower N₂O emissions per unit of kcal produced for food in scenarios of global organic farming expansions compared to the baseline. This result might be explained by the optimized N fertilization in our organic farming scenarios – as defined by the GOANIM model – that tend to minimize the quantity of N fertilizers applied per kcal of food produced in those scenarios (Barbieri et al., 2021).

Indirectly, this reduction of N fertilizers application on organic farmed lands affects the global livestock population by reducing feed availability (Barbieri et al., 2021; Smith et al., 2018). We found a 68% reduction of the global livestock population (expressed in livestock units) – in a fully organically managed world compared to the baseline – resulting in a global 62% reduction of CH₄ emissions from enteric fermentation and manure management. This global drop in livestock population also reduced CH₄ emissions from manure management process. Additionally, the lower presence of primary crops in organic compared to conventional crop rotations (Barbieri et al., 2019) induces lower rice harvested areas globally (31%) resulting in a 37% CH₄ emissions reduction from paddy rice management. More generally, we found a 60% CH₄ emissions reduction in a fully organically managed world compared to the baseline. This reduction was also observed when CH₄ emissions were expressed per kcal of food produced (-35%).

In **Chapter II**, we combined the GOANIM model with the RothC model to estimate changes in soil organic carbon stocks in scenarios of global organic farming expansion. We found that the previously mentioned reductions in yields and livestock populations resulted in an overall 43% reduction of soil carbon inputs in a fully organically managed world compared to the baseline. This soil carbon input reduction resulted in a diminution of soil organic carbon stocks in croplands (-10% at 20 years after a conversion towards organic farming), which represents an annual loss of about 0.23 Mg C.ha⁻¹.yr⁻¹ – a significantly opposite results to what is claimed in meta-analysis of field experiment (+0.45 Mg C.ha⁻¹.yr⁻¹ (Gattinger et al., 2012)). We also found a reduction in grassland soil organic carbon stocks (-5% at 20 years after a conversion towards organic farming), resulting in an overall 6% reduction of soil organic carbon stocks in agricultural lands (croplands and grasslands combined). In **Chapter III** we estimated the annual CO₂ emissions that these soil organic carbon stocks reduction would represent. We found an overall global emissions of 2.3 Gt CO₂eq.yr⁻¹ due to soil organic carbon stocks reduction (in both croplands and grasslands combined) in an organically managed world. Our modelling approach allowed us to estimate the potential of different farming practices application to increase soil organic carbon stocks in organic farming – such as cover crops and conventional manure application. Our results confirmed the potential of cover crops to increase soil organic carbon stocks (Poeplau and Don, 2015). However, such potential would not be enough to fully compensate the soil organic carbon stocks reduction. As conventional manure is no longer available in a fully organically managed world, we can observe an effect of its application only in scenarios of intermediate organic farming expansion. We found that applying conventional manure in organic farms would help to mitigate the reduction in soil organic carbon stocks that comes with organic farming expansion. Applying conventional manure in organic farmed land affects SOC stocks in two ways. *First*, it results

in a transfer of carbon from conventional to organic farms, thus resulting in (i) increased SOC stocks in organically managed croplands and (ii) decreased SOC stocks in conventionally managed croplands. We can expect that both SOC stocks changes (in conventionally and organically farmed land) might compensate themselves. *Second*, applying conventional manure in organic farms, will increase N availability for organic crops. Such increased N availability will lead to increased crop yields in organic farming, thus increasing organic crop residues production and the amount of those residues left on soils. As a consequence, applying conventional manure would indirectly increase soil carbon inputs. We expect this second effect to be the prevailing effect of applying conventional manure in organic farmed land on global SOC stocks.

These results – contrasting with previous meta-analyses of field experiments – highlight that the estimation of the potential of GHG emissions reduction of organic farming offtake cannot be based only on the extrapolation of local field observations without considering whole system effects. Put differently, the contrast between observed or experimental carbon sequestration data vs. our modelling results illustrates that simulating the geographic expansion of organic farming systems needs to consider the systemic feedbacks that go along with organic farming expansion itself (Nesme et al., 2021; Seufert and Ramankutty, 2017). In particular, special attention must be paid to the availability of N fertilising resources and their effects on crop biomass production (Barbieri et al., 2021; Smith et al., 2019).

Global productivity, land requirements and land-use changes.

Systemic feedbacks of organic farming expansion result in competition for N fertilizing resources in organic farming (Barbieri et al., 2021; Smith et al., 2018). Such competition for N fertilizing resources leads to reduced crop yields and as a consequence reduced food production (Barbieri et al., 2021; Smith et al., 2018). Using GOANIM, we found a 57% reduction of the global cropland energetic production in an organic world compared to current cropland productivity, and an overall 49% reduction in the total food production. This reduction of the global cropland energetic production echoes previous analysis showing that 30 to 50% of current crop yields are explained by the use of synthetic fertilizers (Stewart et al., 2005). In **Chapter III**, we found that this global food production reduction results in a 58% increase in the global cropland requirements (+ 0.7 billion ha) in an organic world, mainly resulting in expansion of croplands over grasslands (0.7 billion ha). Such increase of cropland areas has two effects: (i) CO₂ emissions (7.4 Gt CO₂eq.yr⁻¹) due to loss of organic carbon stocks (in both biomass and soils) and (ii) additional N₂O and CH₄ emissions (1 Gt CO₂eq.yr⁻¹) from agricultural activities on newly farmed croplands.

The competition for N fertilizers caused by systemic feedbacks also leads to necessary changes in livestock population (Barbieri et al., 2021; Smith et al., 2018), with important reduction of the livestock population (-68% expressed in livestock units) and transition towards ruminant livestock. Those changes in the global food production are likely to have strong effects on consumers' behaviour. In this study, we assumed that human diets will adapt so that the mean global food demand fits the mean global food production. As changes in human diets is a long process facing several social, political and economic bottlenecks (Mozaffarian et al., 2012; Shepherd, 2002), such assumption might not be fully realistic. However, there is evidence that consumers including organic products in their purchases have different diets than those who do not (Baudry et al., 2019). Additionally, there is evidence that a fully organic world might not be feasible without deep changes in human food diets

(Erb et al., 2016; Morais et al., 2021; Muller et al., 2017). In a scenario where the mean global food demand will adapt to the mean global food production in a fully organically managed world, we found that demand of livestock products (expressed in per capita daily energetic intakes) will be reduced by 78%, while the share of pulses would be increased by 300%. This reduction in the share of livestock products in the human diets results in a global reduction of grassland requirements (-41%), mainly resulting in grassland abandonments – over which half could be potentially left for afforestation. Such afforestation could partially compensate the GHG emissions induced by the increase in global cropland areas.

Changes in the GHG budget with organic farming expansion is not linear.

The systemic feedbacks mentioned above were not considered in previous studies estimating GHG emissions in scenarios of large organic farming expansion (Morais et al., 2021; Muller et al., 2017). In those studies, GHG emissions were estimated by extrapolating results from meta-analyses of field experiments, resulting in a linear response of the GHG agricultural budget to intermediate scenarios of organic farming expansion (Muller et al., 2017) – meaning scenarios where organic farming occupies a limited share of the global agricultural land (i.e. 20%). In our study, we found that the GHG budget response to the share of the global agricultural lands occupied by organic farming – hereafter called %org – is parabolic-like. Such parabolic response of the GHG budget to organic farming expansion is caused by two opposite effects, whose weight depends on the share of the global agricultural lands occupied by organic farming. *First*, changes in human diets and especially the reduced demand of livestock products, results in reduced grassland requirements, and thus in atmospheric CO₂ removal from afforested grasslands. *Second*, global crop yield reduction induced by the competition for N fertilizers coming with organic farming expansion results in increased cropland requirements, and thus GHG emissions from land-use changes and additional agricultural activities. In our study, in situations where organic farming occupies less than 60% of global agricultural lands, the effect of changes in human diets is predominant, resulting in reduced GHG emissions compared to the baseline. Above 60%, the effect of decreased cropland productivity overcome the potential benefits of changes in human diets, thus resulting in increased GHG emissions compared to the baseline. This parabolic response of the GHG budget to organic farming expansion suggests that there might be an optimal share of organic farming (hereafter called %org_{opt}) worldwide that would minimize GHG emissions. In **Chapter III**, we estimated this optimal share of organic farming to be around 20% with a potential 70% reduction of GHG emissions compared to the baseline (**Figure 20a**).

However, the global GHG budget of a fully organically managed world and the shape of the GHG balance response curve to %org also depends on the way organic farming is captured and simulated in our model. We tested the effect of considering a higher share of cover crops in organic compared to conventional farming (Barbieri et al., 2017) on global SOC stocks. We found that using cover crops in organic farming would attenuate the increase of GHG emissions in the REF 100% organic scenario, but also would displace the %org_{opt} towards a higher share of organic farming and lower level of GHG emissions (**Figure 20b**). This result highlights what potential effect of considering a larger diversity of farming practices in organic farming would have on the GHG balance of organic farming expansion scenarios.

As land-use change highly depends on food diets (Alexander et al., 2015), we also tested the effect of changes in food consumption behaviours – and especially reduced food waste and losses - on the overall GHG balance response curve to %org. We found that reducing food waste and losses would

reduce GHG emissions compared to the baseline for all scenarios of organic farming expansion – meaning from 0 to 100% of the global agricultural lands occupied by organic farming (**Figure 20c**).

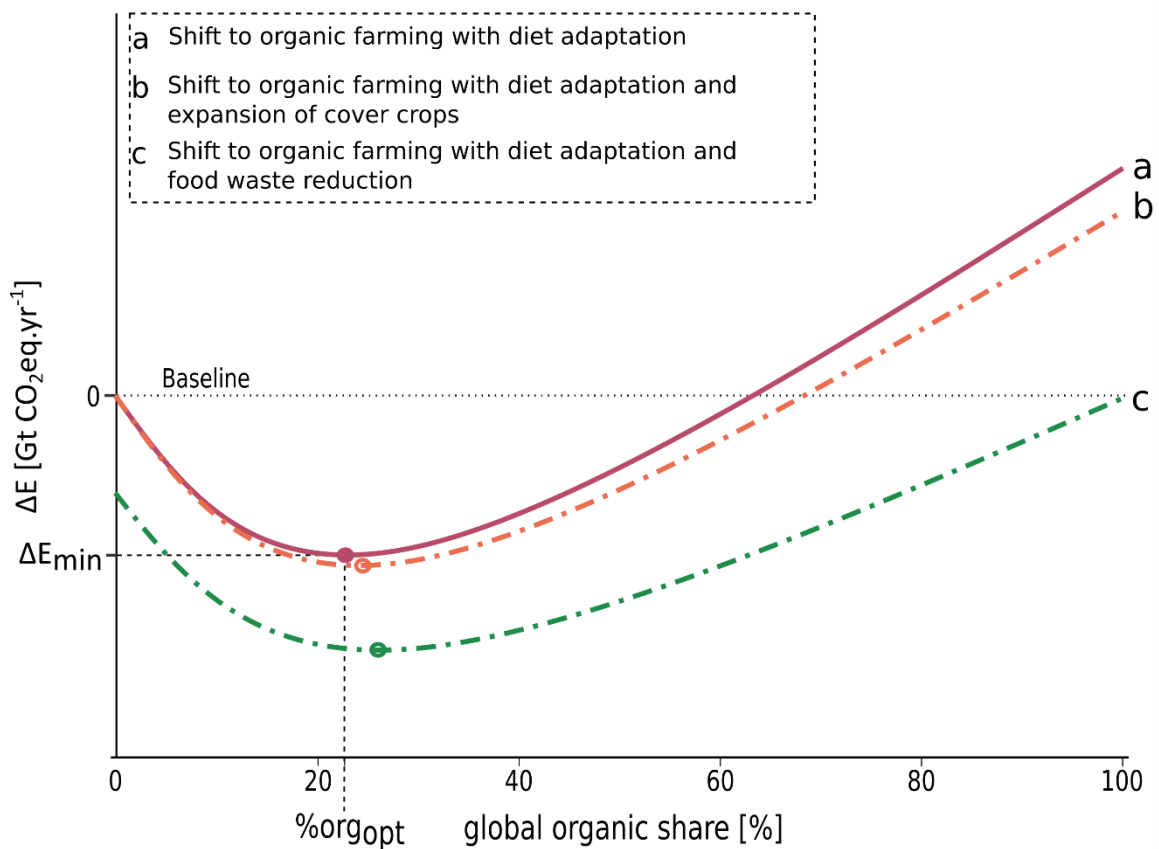


Figure 20: Schematic representation of the changes in GHG emissions with organic farming expansion. ΔE represents the difference in GHG emissions between a given scenario and the baseline. The global organic share represents the variable share of the global agricultural lands occupied by organic farming. Circles represent the lower point of each curves. Dashed-pointed curves represent scenarios simulated in this dissertation.

Comparison with previous studies

In the past decade, only two studies attempted to estimate GHG emissions in scenarios of global organic farming expansion using a modelling approach (**Table 6**, (Morais et al., 2021; Muller et al., 2017)), and another study made the same attempt at the regional scale of England and Wales (Smith et al., 2019). Among those studies, we observed a diversity of approaches and assumptions that led to differences in the results obtained. In this section we compare the methodological approach between this dissertation and those studies, and we explain how the observed differences affect the results.

Crop yield estimation

We observed differences in the way crop yields are estimated. GOANIM, used in this study, estimates (~10x10km) spatially explicit crop yields for 61 crops using crop yield response curves to soil N supply. Such modelling approach is highly similar to the one used by Smith et al., 2019. The main

difference between both studies is the scale considered. Smith et al., 2019 focused on England and Wales while we worked at the global scale (**Table 6**). In his study, Morais et al., 2021 also estimates crop yields based on their response to N availability. However, their crop yields estimation is made at the regional scale, which does not encompass for potential local limitation that would furthermore reduce N availability. Finally, the last study (Muller et al., 2017) had the most distant approach compared to ours. Crop yields were estimated by extrapolating results from meta-analyses of field experiments comparing organic to conventional crop yields (Badgley et al., 2007; Seufert et al., 2012). As mentioned previously, such approach does not encompass for the effect on crop yields of systemic feedback coming with organic farming expansion.

Those different methods explain the differences observed in the crop yield estimates between the four studies. As both methods are highly similar, our estimation of crop yield changes in a fully organically managed world compared to the baseline (-57%) is close to the estimation made by Smith et al., 2019 (-40%). Unfortunately, yields are not reported in Morais et al., 2021 which does not allow the full comparison to our respective approaches. As expected, the most distant approach resulted in a highly different estimation of crop yield changes. They used two scenarios, with 8 and 25% reduced crop yields in organic farming compared to the baseline respectively. Such differences in crop yield estimates might explain many of the observed differences in the estimation of agricultural land requirements.

Agricultural land requirements and land-use change

All studies considered potential changes in agricultural land requirements with the expansion of organic farming. More precisely, they all considered a potential increased cropland requirements induced organic farming expansion. In all studies changes in agricultural land requirements were converted into land-use changes and, GHG emissions from those land-use changes were accounted in the global GHG budget of organic farming expansion scenarios. However, the approaches to estimate agricultural land requirements and land-use changes differed in several aspects between studies.

First, as cropland requirements is partly driven by cropland productivity, the above mentioned differences in crop yield estimations highly affect the land requirements estimations. *Second*, agricultural land requirements and land-use changes are also highly driven by changes in human diets (Alexander et al., 2015; Meyfroidt et al., 2013). Note that two studies did not considered changes in human food diets (Muller et al., 2017; Smith et al., 2019). The study of Morais et al., 2021 particularly well encompasses the potential effect of different diets on land-use changes, by testing several diet options in his scenarios. The approach used in Morais et al., 2021 differs from our approach as they assumed that the food production will adapt to the food demand, and we assumed the contrary. *Thirdly*, we note differences on the land-use change considered. While all studies estimated increased cropland requirements (**Table 6**), (Muller et al., 2017) considered grasslands to remain constant and (Morais et al., 2021) only considered scenarios without deforestation – meaning the total agricultural lands remain constant and only croplands expansion over grasslands is possible. Note also that only one study spatially estimated agricultural land requirements and land-use changes (Morais et al., 2021), thus encompassing regional differences in term of GHG emissions due to land-use changes. *Finally*, while all studies only estimated GHG emissions due to land-use changes, (Smith et al., 2019) accounted for a carbon opportunity cost – meaning the amount of carbon that could have been sequestered in land converted to croplands if they were afforested.

These different approaches in land requirements and land-use changes estimation might result in important differences in GHG emissions due to land-use changes. Regarding land requirements and land-use changes estimation, we found similar increased cropland requirements than Smith et al., 2019: +39% (in our study) vs +40%. Such similarity is mainly due to similar crop yield estimations. Morais et al., 2021 found large variation in cropland requirements changes in organic farming expansion scenarios (+7 to +390% compared to the baseline). Such large variation is explained by the variety of human diets tested in their approach. Note that Morais et al., 2021 is the only study that also spatially estimated cropland requirements and land-use changes. Finally, Muller et al., 2017 estimated increased cropland requirements of only 18 to 33% without changes in human diets. Such low increased cropland requirements compared to our study is mainly explained by the differences in crop yields estimations. As for GHG emissions from land-use changes, note that two studies did not specify the GHG emissions attributed to land-use changes (Morais et al., 2021; Muller et al., 2017), thus making the comparison to our study impossible. The only study that provided such information was Smith et al., 2019, but, due to different scaling of the analysis – England and Wales vs global scale - we could not compare results on GHG emissions from land-use changes.

SOC stock changes

Except for the study of Smith et al., 2019, no previous study considered changes in SOC stocks in the estimations of agricultural GHG emissions within organic farming expansion scenarios (**Table 6**). This is a severe limitation to the previous published studies given the large role that agricultural soils play in the overall GHG budget of organic farming expansion scenarios.

Note also that if they considered changes in SOC stocks in their study, Smith et al., 2019 estimated changes in SOC stocks by extrapolating results from meta-analyses of field experiments (Gattinger et al., 2012; Kirk and Bellamy, 2010). As mentioned in **Chapter II**, such extrapolation cannot capture all systemic effects of large organic farming expansion on SOC stocks. More specifically, such approach does not encompass the reduction in carbon inputs to cropland soils due to crop yield reduction. Additionally, Smith et al., 2019 did not consider possible carbon transfers from grasslands to croplands (through ruminant livestock manure) possibly resulting in grasslands SOC stock depletion. Therefore, in their study, Smith et al., 2019 might have overestimated the potential of organic farming to sequester carbon in agricultural soils, resulting in possible underestimated GHG emissions in scenarios of organic farming expansion in England and Wales.

Table 6: Comparison between studies estimating GHG emissions in scenarios of global organic farming expansion.

Organic scenario			Studies				
			Mueller et al. 2017	Smith et al. 2019	Morais et al. 2021	This study	
Simulation year			2050	current	2050	current	
Spatial scale			Global	England and Wales	Global	Global	
Models used			SOL-Model	OLUM	BioBaM	GOANIM, RothC, GlobAgri-AgT	
Resolution			World	2.7 arc-min	11 world regions	5 arc-min	
Baseline			BAU scenario in 2050	Emissions in the year 2010	Emissions in the year 2000	Emissions estimated in the year 2000	
Agronomic parameters	Organic to conventional yield-gap	Methods	Extrapolation of results from meta-analyses of field experiments	Simulated according to soil N availability	Simulated according to soil N availability	Simulated according to soil N supply	
		Value	-8% or -25% (t DM.ha-1.yr-1)	-40% (ME.ha-1.yr-1)	No values	-56% (ME.ha-1.yr-1)	
Livestock population			No changes	Livestock population is optimized to maximise food production.	Estimated to fit the global food demand.	Livestock population is optimized to maximise food production.	
100% organic world	Diet and land-use changes	Dietary changes	Scenarios Link with production	No changes NS	No changes NS	6 different diet tested Production adapted to diet	Organic diet adapted scenario Diet adapted to production
		Land requirements	Main hypothesis	grasslands = constant	Land expansion only outside England and Wales	No deforestation	See chapter III
	Global average		croplands: +16-33%	agricultural lands : +50%	Croplands: ~7% to 390% higher	croplands: +58% grasslands: -41%	
	GHG emissions	Due to changes in SOC stocks	Methods Values	Not considered	Extrapolation of meta-analysis for croplands +18 to +0.28 Mg C ha ⁻¹ yr ⁻¹	Not considered	Estimated using the RothC model croplands: -0.23 Mg C ha ⁻¹ yr ⁻¹ grasslands: -0.09 Mg C ha ⁻¹ yr ⁻¹
N ₂ O and CH ₄		NS	~-11%	NS	-60%		
Due to land-use change		NS	~0 to 30 Mt CO ₂ eq.yr ⁻¹	NS	3.7 Gt CO ₂ eq.yr ⁻¹		
GHG budget			3-7% lower	+56% with high overseas LUC -5% with low overseas LUC	~57% lower to 29% higher	+56% compared to the baseline	
Intermediate scenarios of organic farming expansion (20-80%)			Linear response of GHG emissions to organic farming expansion	Not simulated	Not simulated	Non-linear response of GHG emissions to organic farming expansion	
Additional farming practices			Not considered	Not considered	3 additional farming practices resulting in higher N availability	Additional soil carbon sequestration from cover crops	

Global GHG budget of an organic world

Finally, those different approaches yielded in different GHG estimates in scenarios of organic farming expansion (**Table 6**). We found similar results than the one obtained in the worst case scenario of Smith et al., 2019 (+56% of annual GHG emissions), due to the many similarities of both approaches – spatially explicit yield estimation and consideration of all potential land-use changes. Again, comparing our results to those from Smith et al., 2019 is limited due the differences in the scaling of each study. We found higher increase of GHG emissions (in scenarios of large organic farming expansions compared to the baseline) compared to the worst case scenario from Morais et al., 2021 (+56% vs +29% of annual GHG emissions). Such difference is mainly due to (i) the absence of deforestation and (ii) SOC stocks changes in the scenarios presented in Morais et al., 2021. Finally, the study from Muller et al., 2017 might be the one presenting the most distant approach compared to ours. The main difference between both approaches is the way organic yields are estimated. As the approach used by Muller et al., 2017 to estimate crop yields does not encompass potential competition for N fertilizing resources, organic yields are probably overestimated. As a consequence, land-use changes and the related GHG emissions in organic farming expansion scenarios might be underestimated. Similarly to our study, Muller et al., 2017 also found reduced N₂O emissions with organic farming expansion but, they found slightly increased CH₄ emissions from livestock's enteric fermentation. Globally, they found that the reduced N₂O emissions were not compensated by increased GHG emissions from land-use changes and livestock. For those reasons, (Muller et al., 2017) find reduced GHG emissions with organic farming expansion (-3 to -7% of annual GHG emissions) where we find an increase (+56% of annual GHG emissions). Additionally, the way GHG emissions are estimated in (Muller et al., 2017) – meaning based on the extrapolation of results from meta-analyses of field experiments – results in linear decrease of GHG emissions with increasing share of the global agricultural lands occupied by organic farming, while our results exhibit a parabolic-like response (see **Chapter III**).

A new approach with potential for improvement

Potential to increase N availability in organic croplands

The GOANIM model has opened opportunities to estimate both the global food production and the related GHG emissions in large organic farming expansion scenarios while considering potential systemic feedbacks relative to this expansion. The use of the GOANIM model allows to test different scenarios – such as intermediate levels of organic farming expansion (20 to 100% of the global agricultural lands under organic farming) or additional N resources in organic farming (such as conventional manure or waste waters) (Barbieri et al., 2021). Additional N resources in organic farming could increase N availability in organically managed croplands with potential effects on GHG emissions by (i) increasing N₂O emissions and (ii) increasing crop productivity, resulting in both increased of soil carbon inputs in organically managed croplands – which would increase SOC stocks in those lands – and decrease in cropland requirements to feed the world – which would reduce GHG emissions from land-use change. In this section we will discuss global options to increase N availability in organically managed croplands their potential effect on GHG estimations.

Simulations presented in this dissertation did not encompass the large diversity of organic farming practices (Seufert et al., 2017), especially practices that might enhance N availability in

croplands. Yet, such practices are often more present in organic farming compared to conventional farming. Indeed, evidences show that organic farming have more complex crop rotations, composed with more leguminous crops and cover crops than their conventional counterparts (Barbieri et al., 2017). In our use of GOANIM, we did consider higher shares of leguminous crops in organic crop rotations using specific harvested areas for organic farming (Barbieri et al., 2019), but we did not consider potential additional N from potential leguminous cover crops. However, other studies estimating food production in scenarios of organic farming estimate (sometimes much) higher frequency of N fixing crops in organic rotations (Badgley et al., 2007; Billen et al., 2021; Morais et al., 2021), resulting in higher level of N supplied to soils from biological N fixation. Such increase in N availability would have two antagonist effects. On the one hand, increased N availability in organic farming would increase organic crop yields with reducing effects on global cropland requirements and land-use changes. On the other hand, additional available N also means additional N₂O emissions from managed soils. Additionally, higher yields in organic farming would mean more feed available for livestock, resulting in potential increase in the livestock population and additional CH₄ emissions in organic scenarios. As land-use changes are the main driver of the global GHG emissions in organic farming scenarios, we would expect a global decrease in GHG emissions in organic farming scenarios. We would also expect that %org_{opt} would be increased – meaning that the optimal share of agricultural lands occupied by organic farming would increase (Figure 21d). We would expect a similar effect for all additional N resources that could be implemented in organic farming scenarios – such as waste water or recycled urban waste.

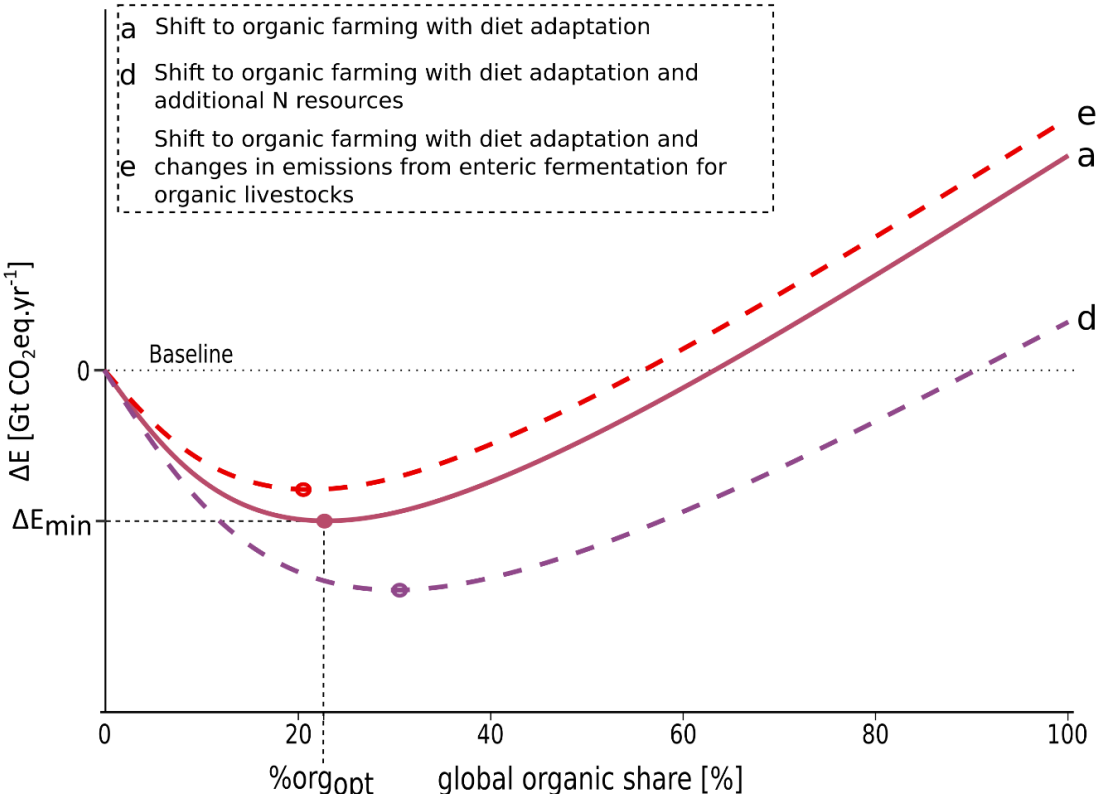


Figure 21: Schematic representation of the changes in GHG emissions with different scenarios of organic farming expansion. ΔE represents the difference in GHG emissions between a given scenario and the baseline. The global organic share represents the variable share of the global agricultural lands occupied by organic farming. Circles represent the lower point of each curves. Dashed curves represent scenarios not simulated in this dissertation.

Potential to improve livestock production simulation

Another point of improvement in our simulation could be on the simulation of livestock production and especially their feeding material. In the GOANIM model, feed rations are defined regionally for each of the nine livestock species considered with default shares of forages, crop residues and grains. However, in a given region, and for a given livestock species, there is large variety of livestock feeding strategies (Herrero et al., 2013). Even though we found that livestock feeding strategies are different in organic compared to conventional livestock management (Gaudaré et al., 2021), those changes might not fully erase the variety of livestock feeding strategies within regions. An improved option would be to give more freedom to GOANIM to define the livestock feed composition regionally – by defining maximum and minimum thresholds for the share of each category (grain, fodder and stovers).

Finally, GOANIM optimization process almost suppresses the monogastric livestock population. Monogastric livestock are highly in competition with human food as their feed ration is mainly based on food-competing feed (Gaudaré et al., 2021). Additionally, they do not participate in the transfer of nutrients from grasslands to croplands. However, the drastic drop of monogastric livestock populations observed in our simulation is not fully realistic. There are probably strong social bottlenecks to such a drop. There are options for future studies to account for such bottlenecks, by either defining minimum thresholds in the locally food produced by monogastric livestock or by providing larger diversity of monogastric feeding strategies – by considering backyard monogastric livestock for instance (Herrero et al., 2013; Mottet et al., 2017).

Changes in livestock production simulation in GOANIM might have several effects on estimations global GHG emissions in organic farming expansion scenarios. *First*, it might increase livestock population in those scenarios and, thus N₂O and CH₄ emissions that come with. *Second*, this potential increased livestock population might result in higher feed vs food competition, potentially leading to higher agricultural land requirements and GHG emissions from land-use changes. *Finally*, changes in livestock production simulation in GOANIM might affect the locals' N budget of croplands. As organically managed cropland fertilization highly depend on nitrogen from manure, changes in livestock population will change the amount of N from manure applied on croplands. Such changes in N availability in organically managed croplands would lead to changes in organic cropland productivity, with potential effects on agricultural lands requirements and GHG emissions from land-use changes.

Potential for more precise N₂O and CH₄ estimations

In this study, we used the latest IPCC tier 1 method to estimate N₂O and CH₄ emissions (IPCC, 2019b, 2019c, 2019e). If a recent study has confirmed the robustness of such approach (Hergoualc'h et al., 2021), in certain cases more precision could be brought by using more detailed information.

First, the IPCC guidelines suggest a linear relation between N fertilizer application and direct N₂O emissions from soils, while recent studies have provided evidence of an exponential relationship (Hoben et al., 2011; Philibert et al., 2012; Shcherbak et al., 2014), which might lead to underestimation of current N₂O emissions (Makowski, 2019). In our study, considering an exponential relationship between N fertilizer application and N₂O soil emissions might not significantly affect N₂O emissions in the organic farming scenarios due to low N fertilization rates in organic vs. conventional farming. However, due to over N fertilization in conventional farming – and especially from synthetic N

fertilization in certain areas – this non-linear relationship between N fertilizer application and N₂O soil emissions might lead to increased N₂O emissions in the baseline (Makowski, 2019). In other words, using a tier 3 approach might increase the organic to conventional gap in N₂O emissions.

Second, we used the Tier 1 approach in our estimation of CH₄ emissions from enteric fermentation, based on default emissions for each livestock species in each region. However, we found that organic ruminants have a more forage-based diet than their conventional counterparts (see **Chapter I**, Gaudaré et al., 2021). The IPCC Tier 1 approach does not account for the diet effect on CH₄ emissions from enteric fermentation – especially the positive effect of forage based diet on CH₄ emissions. Using a Tier 2 approach, as in the GLEAM model (FAO, 2018; Mottet et al., 2017), would better account for this diet effect on CH₄ emissions from enteric fermentation, thereby probably resulting in increased CH₄ emissions in the organic farming expansion scenarios (**Figure 21e**).

Potential for a larger variety of human diets analysed

Several studies have claimed that organic farming expansion might not be feasible without deep changes in consumers' food behaviours (Seconda et al., 2021). Additionally, there is evidence of differences in diets for consumers including large share of organic products in their purchases (Baudry et al., 2019). However, the assumption that diets would change so that the global food demand would fit the food supply might not reflect the reality, especially if we consider social and economic bottlenecks that refrain diets changes (Mozaffarian et al., 2012; Shepherd, 2002). As a comparison, most studies on similar topic considered that the global food demand would orient the global food production, not the contrary (Erb et al., 2016; Morais et al., 2021; Muller et al., 2017).

The main effect of assuming that diets would change so that the global food demand would fit the food supply is minimized GHG emissions from land-use changes in organic farming expansion scenarios. Therefore, moving away from adapted diets would put more pressure on crops with low productivity under organic conditions and would therefore increase the global cropland requirements in scenarios of global organic farming expansion. Such increase of global cropland requirements would lead to global increase in GHG emissions – especially in the 100% organic scenario, with displacement of %org_{opt} farming towards 0% (**Figure 22**).

Additionally, adapting diets so that the global food demand fits the global food production might not be relevant, especially in term of nutritional requirements. In our study, we found an increased demand of plant-based sugar products and a reduced demand of fruits and vegetable consumption. Such results are contradictory compared to the dietary requirement of healthy diets (Willett et al., 2019). Future scenarios should estimate GHG emissions in organic farming expansion scenarios with larger diversity of human diets, and especially diets that fits dietary requirements. Though, as mentioned above, such scenarios will see GHG emissions increase (**Figure 22f**).

Uncertainties brought by coupling GOANIM to GlobAgri-AgT

In our study, we combined different models, which represent a modelling challenge as models often have different objectives, variables and input data. We faced such challenge in our modelling approach, especially in the combination of GOANIM and GlobAgri-AgT. We succeeded to make those two models fit by adapting GOANIM outputs on (i) crop yields and (ii) livestock requirements to the input data requirements of GlobAgri-AgT (see **Chapter III**) and (iii) by defining hypothetical diets

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adapted to the global food production estimated by GOANIM. However, these adaptations of the GOANIM outputs to fit GlobAgri-AgT requirements could not completely offset the differences of the two models, especially in the way they define crop and livestock production. *First*, in GOANIM crop areas are an input data of the model, while those areas are variables in GlobAgri-AgT. *Second*, if in both model the livestock population is a variable, its variations are not driven by the same processes. In GOANIM, livestock population is optimised in order to locally close the N cycle to maximize the food production (Barbieri et al., 2021). In GlobAgri-AgT, the livestock population is estimated in order to meet the food demand regionally (Le Mouël et al., 2018). If those differences do not affect the global land requirements, they lead to differences in regional estimates of food production between the two models, bringing uncertainties in the regional land-use changes estimation and, therefore, in the global estimation of GHG emissions from land-use changes (Figure 22).

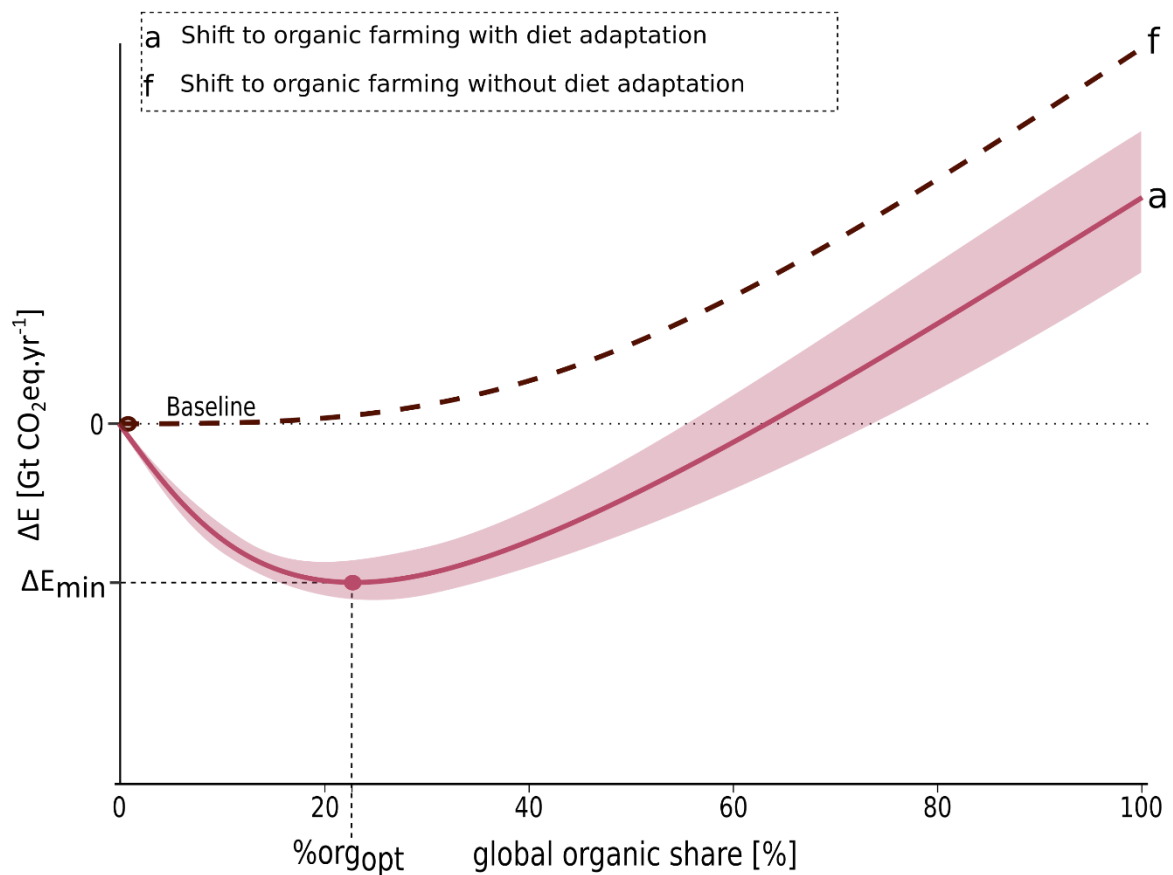


Figure 22: Schematic representation of the changes in GHG emissions with different scenarios of organic farming expansion. ΔE represents the difference in GHG emissions between a given scenario and the baseline. The global organic share represents the variable share of the global agricultural lands occupied by organic farming. Circles represent the lower point of each curves. Dashed curves represent scenarios not simulated in this dissertation. The red shaded area represents the uncertainty due to the estimation of land-use changes.

Potential implications

Further scientific studies.

To the best of our knowledge, this dissertation presents the first estimation of GHG emissions in scenarios of global organic farming expansion by considering potential systemic feedbacks linked to this expansion. In the previous section, we presented several limitations and possible improvements of our approach. In this section, we suggest future scenarios that may be explored to provide more precision in the estimation of the potential of organic farming to reduce agricultural GHG emissions at the global scale.

Scenario including N resources from cover crops. In **Chapter II**, we explored a scenario considering the effect of cover cropping on soil organic carbon stocks through additional soil carbon inputs and soil covering. However, cover crops could also increase N availability to croplands (Badgley et al., 2007; Morais et al., 2021), by either limiting N leaching (Abdalla et al., 2019) or by providing additional N through biological N fixation, if they are based on leguminous crops. Future scenarios might include additional N resources in organic farming from N-fixing cover crops by using a spatially explicit estimation of potential additional N from cover crops in the GOANIM model, as well as a reduced N leaching factor in organic farming. Building such spatially explicit estimation of potential additional N from cover crops would require precise spatial information on (i) period available for cover cropping and (ii) potential cover crops productivity. Period available for cover cropping could potentially be estimated based on spatial information of cropping periods (Kotsuki and Tanaka, 2015; Sacks et al., 2010). However, estimation of the potential cover crops productivity would require a specific meta-analysis on this topic, which might be limited by little data available (especially in developing countries).

Scenario including N-C linked mineralisation. In **Chapter II**, we estimated the potential decrease in soil organic carbon stocks that would be experienced by agricultural lands if managed organically. However, soil organic carbon mineralisation also releases N that is available for plants, and that could boost crop biomass production. A scenario considering such additional N could be explored by developing a feedback loop between GOANIM and the RothC models. *First*, RothC outputs on spatially explicit annual soil organic matter mineralized should be converted in annual soil N mineralised using the C/N ratio of the soil organic matter (Tipping et al., 2016). *Second*, estimated spatially explicit annual soil N mineralized are to be used as additional N resources in GOANIM. *Finally*, the new GOANIM outputs should be adapted again to be used as inputs in RothC. Such feedback loop between GOANIM and RothC should be run until an equilibrium is reached.

Scenario including further precision on livestock production systems. As mentioned previously, the optimisation process of GOANIM yields in drastic change in the global livestock population, namely (i) a 68% reduction of the livestock population (in livestock units) (ii), an almost complete suppression of monogastric livestock and (iii) a drastic spatial redistribution of livestock populations. Three options might be explored to temper the effect of this optimisation process. *First*, considering a larger variety of livestock management systems as presented in previous studies (Herrero et al., 2013; Mottet et al., 2017). *Second*, considering additional feed resources – such as crop by-products, grass from road sides or cover-crops residues. *Third*, GOANIM offers the possibility to impose a minimum share of

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monogastric animals in the simulated livestock populations. This third option, however, might result in lower N recycling and higher feed vs. food competition in global organic farming expansion scenarios, thus potentially resulting in even higher GHG emissions from agriculture.

Scenario including spatial estimation of land-use changes. In **Chapter III**, we combined the GOANIM model to the GlobAgri-AgT model. As mentioned above, improvements can be made for a better combination of those two models. One option would be to spatialize land-use changes (as estimated based on GlobAgri-AgT outputs) in order to estimate new spatially explicit (5 arc-min) cropland and grassland areas. Those new spatially explicit cropland and grassland areas would then be used in GOANIM in order to estimate global food production on those lands. This feedback loop between GOANIM and GlobAgri-AgT should be done until the energetic food production estimated by GOANIM fits the global energetic food demand (expressed in kcal). The modelling of such approach and, especially the step that spatialize land-use changes, would require strong assumption on how and where hypothetical land-use changes might occur, thus probably facing a lack of global data.

Scenario including a global uneven expansion organic farming. Finally, the current use of GOANIM to estimate the global food supply in scenarios of intermediate expansion of organic farming is based on a spatially uniform expansion of organic farming – for instance 20% of all grid cells are converted to organic farming. However, as the amount of N fertilizing resources varies among regions, organic farming expansion might not be similarly limited in all regions. Therefore, one organic farming expansion might aim at estimating local maximum feasible organic farming expansion – meaning the share of local agricultural lands occupied by organic farming under which organic farming does not face nitrogen limitation. This scenario could be tested by using GOANIM in a feedback loop where the share of organic farming in each grid cell increases as long as N availability remain above a certain threshold.

Implications for policy makers, consumers and farmers

In our simulations, we found that a fully organically managed world might increase GHG emissions compared to the baseline – meaning current GHG emissions. However, this result must be use cautiously as it is highly dependent on all assumptions – mostly conservative – made on farming practices implemented in organic farming. Based on the assumption that human diets will change, we also found that an intermediate transition towards a 20% organically farmed world, might reduce GHG emission by 70% compared to the baseline. Note that such a world consist in multiplying by approximately ten times the current agricultural areas under organic farming (~1.5 % of the global agricultural lands (IFOAM, 2020)). Therefore, this dissertation highlight that there is space for organic farming expansion while reducing GHG emissions, provided that deep systemic changes are applied to the agri-food system.

First, our work suggests that a deep redesign of the livestock production sector is needed with the expansion of organic farming. A previous work based on GOANIM has shown that the current spatial segregation between crop and livestock production is a key obstacle for organic farming expansion (Barbieri et al., 2021), as it limits nutrient availability for organically grown crops (Nesme et al., 2015). This previous work also suggests that, in order to reach a feasible organic farming expansion globally, the livestock population should be (i) decreased and (ii) more composed of ruminant livestock. Ruminants are key components of organic farming systems as they allow to transfer nutrients from

grasslands to croplands. Such results have also been discussed on studies at the European and country scales (Billen et al., 2021; Poux and Aubert, 2018; Smith et al., 2018). This redesign of the livestock population is also meant to reduce the feed vs. food competition by favouring ruminant livestock – that are less in competition with human food, especially when managed organically (Gaudaré et al., 2021). Most policies aiming at increasing organic farming regionally, such as the European Green Deal – that aim at converting 25% of agricultural lands to organic farming in the EU by 2030 (European Council, 2020) – often don't consider such changes in livestock populations. Therefore, we suggest that such policies should include tools aiming at reshaping livestock population by favouring local recoupling of crop and livestock production. In Europe, the common agricultural policy (CAP) might use economic incentive towards this goal. A redefinition of organic regulation could also be considered a tool to reach this same objective. For instance, the new French organic regulation bans conventional manure application on organically farmed lands, given the current importance of such fertilizing resource in organic farming, this change in organic regulations might lead to a transition of organic farming towards mixed-farming system at the farm or territorial scale.

Second, our work and other studies show that deep changes in human food consumption patterns are needed along with the expansion of organic farming (Barbieri et al., 2019; Erb et al., 2016; Morais et al., 2021; Poux and Aubert, 2018; Smith et al., 2018). Without such changes in human food consumption behaviours, organic farming expansion will probably lead to increased GHG emissions (**Figure 23.1**). Two options are often considered in that perspective: (i) changes in human diets (**Figure 23.2**) and (ii) reducing food waste and losses (**Figure 23.3**). Our results – which is in line with other recent studies (Erb et al., 2016; Morais et al., 2021) – show that reducing the livestock products' share in human diets is a key target. However, such changes in diets faces strong social bottlenecks that can be overpass by political and economic measures, such as taxes, school programs and changes in dietary guidelines (Mozaffarian et al., 2012; Ritchie et al., 2018; Shepherd, 2002). As food wastes occur on several steps along the food chain, reducing those wastes should come with global coordination of all sectors – food production, transport, retailing and consumption (Dorward, 2012) – based on raising awareness and appropriate political measures. A first step to reduce food waste would be to better identify food waste sources in the food chain (Xue et al., 2017) in order to identify proper paths of action.

Finally, this work, supported by other recent studies (Billen et al., 2021; Morais et al., 2021), shows that a fully organically managed world would lead to increased GHG emissions without strong changes in farming practices – especially by implementing practices that would increase nutrient availability in croplands (**Figure 23.5**) or increase SOC stocks in agricultural lands (**Figure 23.4**). So far, the large diversity of international organic farming regulations is mostly gathered under the ban of synthetic fertilizers (Seufert et al., 2017). Making organic farming more sustainable might require the redefinition of organic regulations to encourage farming practices improving N availability in organic croplands – such as improved crop rotations, enhanced share of leguminous crops in those rotations, the use of cover crops (and especially leguminous cover crops) and potentially allowing external N resource such as waste waters. Note that such farming practices could also be implemented in non-organic farming systems, thus reducing GHG emissions in such farming systems (Arbenz et al., 2016). In the European Green Deal, the lack of a proper definition of organic farming is problematic in this perspective. We strongly suggest that the goal of 25% of organic farming in the EU by 2030 should come with proper definition of farming practices to be implemented within organic farms. More locally, NGOs and public administration should aim at help farmers implement such practices in organic farming by proper farming advisory.

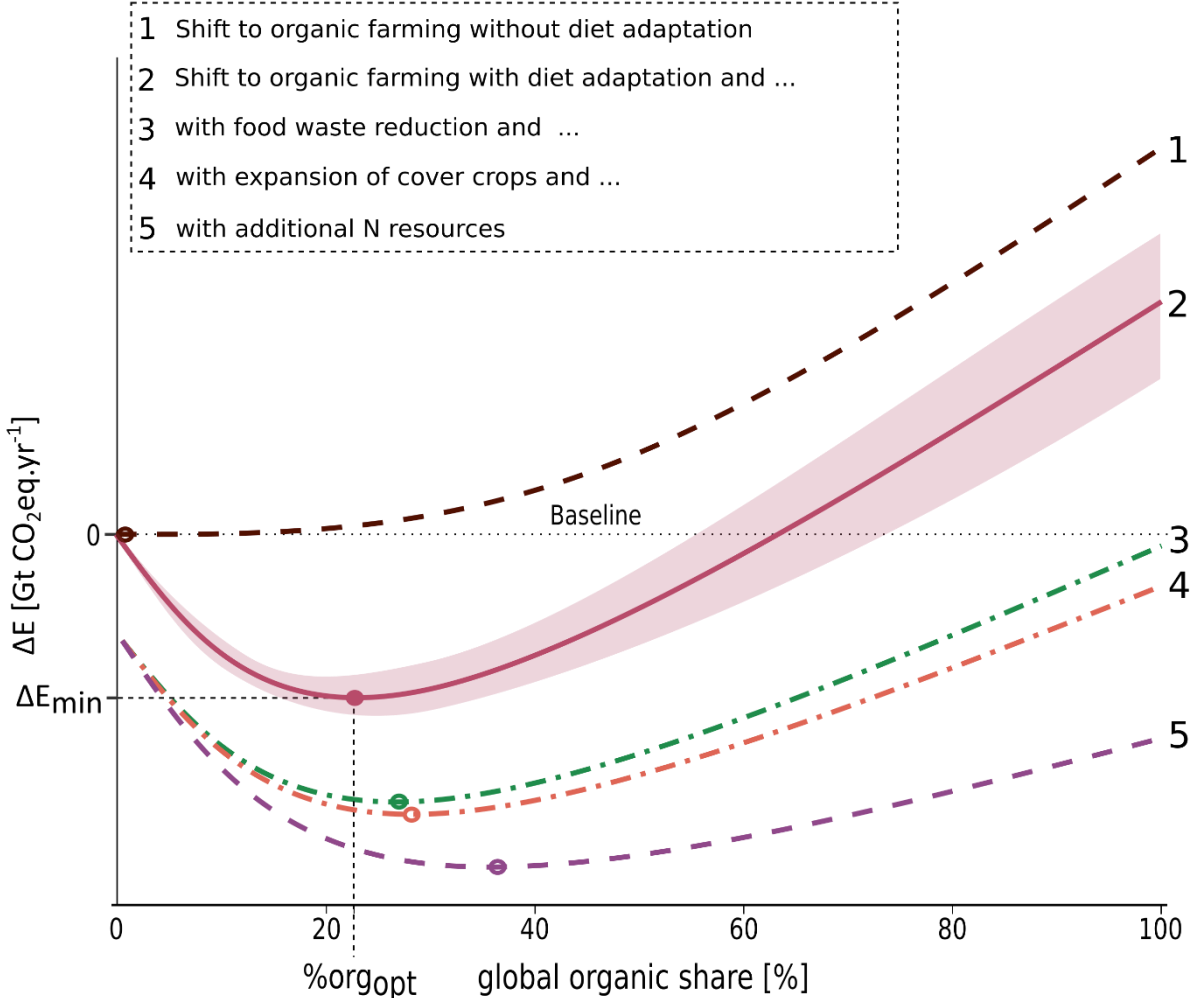


Figure 23: Schematic representation of the changes in GHG emissions with different scenarios of organic farming expansion. ΔE represents the difference in GHG emissions between a given scenario and the baseline. The global organic share represents the variable share of the global agricultural lands occupied by organic farming. Circles represent the lower point of each curves. Dashed-pointed curves represent scenarios simulated in this dissertation. Dashed curves represent scenarios not simulated in this dissertation. The red shaded area represents the uncertainty due to the estimation of land-use changes.

To conclude, this dissertation, by using a new methodological approach, brings an additional vision on the potential of organic farming to reduce GHG emissions from the agricultural sector. This new approach confirmed several results highlighted by previous studies, such as the need of deep changes in (i) livestock production, (ii) food consumption behaviours and (iii) organic farming practices.

Annex I: Supplementary information for chapter I

Supplementary methods

Estimation of milk productivity

We quantified milk production by using the energy corrected milk (ECM) corresponding to a milk standardised at 3.5% fat and 3.2% protein, according to the following formula in **Equation S1** (Tyrrell and Reid, 1965):

$$\text{Equation S1 } ECM = Milk (kg) * (0.327 + 12.95 * [Fat] + 7.65 * [Protein])$$

Where *Milk*, *[Fat]* and *[Protein]* stand for the kg of milk produced, the fat concentration (kg of fat.kg of milk⁻¹) and the protein concentration in the milk (kg of protein.kg of milk⁻¹). Corrected milk productivity was expressed as kg of ECM/unit of time. Milk productivity was also expressed in Mega Joules (2.9 MJ.kg of ECM⁻¹) and kg of Crude Protein (3.2 g CP.kg of ECM⁻¹).

Estimation of feed ration energy content

We calculated the feed ration energy content using the values provided by the Feedipedia (feedipedia.org) and Feedtables (feedtables.com) databases. However, our database did not allow to account for digestive interactions between forage and concentrate intake when expressed in energy. Although those digestive interactions are negligible when feed rations are expressed in dry matter or in proteins, they may be important for energy estimate when feed rations contain more than 40% concentrates. Note, however, that not considering those interactions may lead to small (~5%) overestimate of energy available in feed rations, especially for conventional, concentrate-rich feed rations.

Estimation of the replacement rate

The replacement rate was extracted for studies on dairy cattle herds. It is defined as the ratio of the number of cows entering the herd (heifer and purchased cows) on the total herd population (in %). When only the number of lactations during the animal life span was available, the replacement rate was estimated as the inverse of the number of lactation (Tatar et al., 2017).

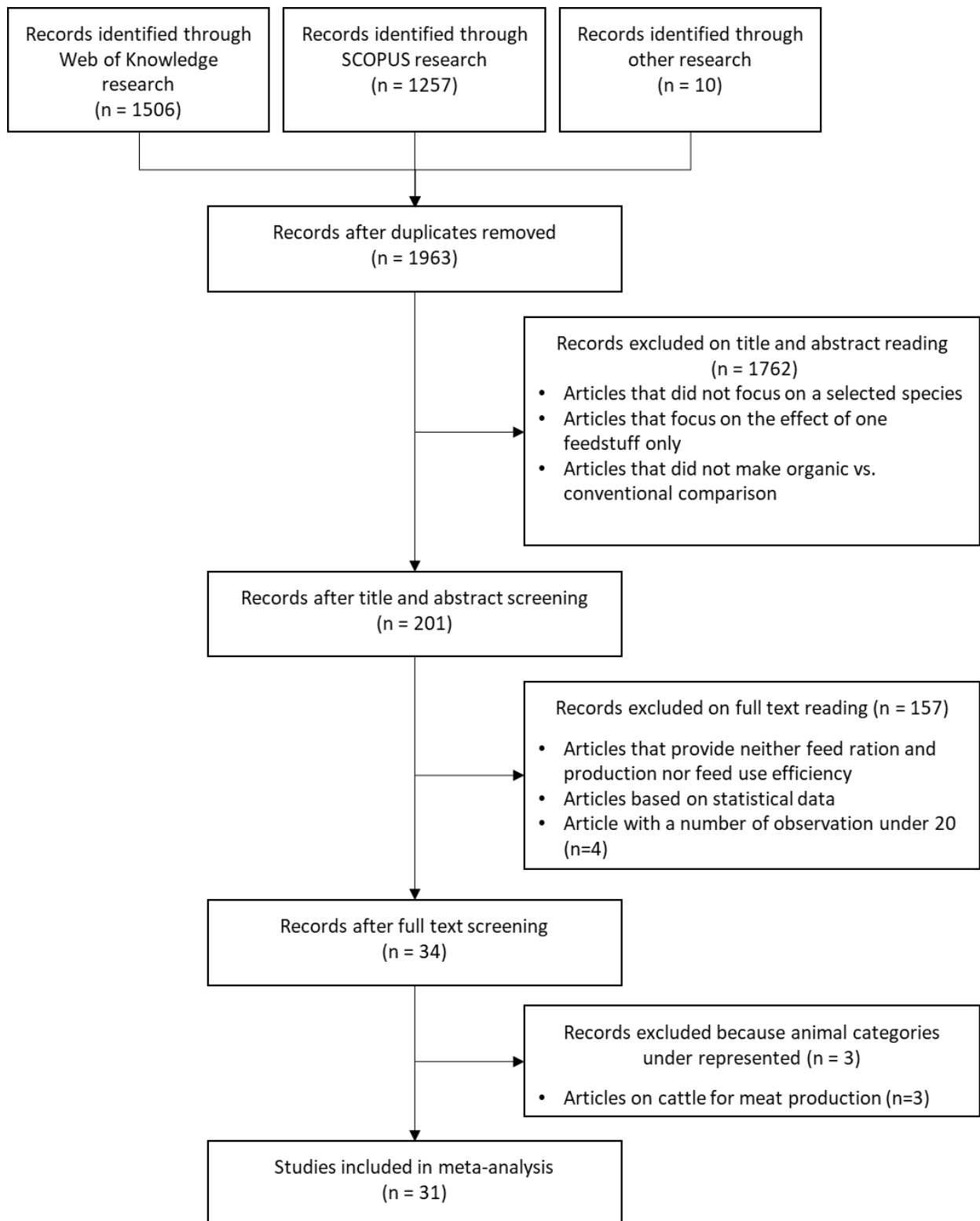


Figure S1 : PRISMA Flowchart representing the procedure used to build up the dataset.

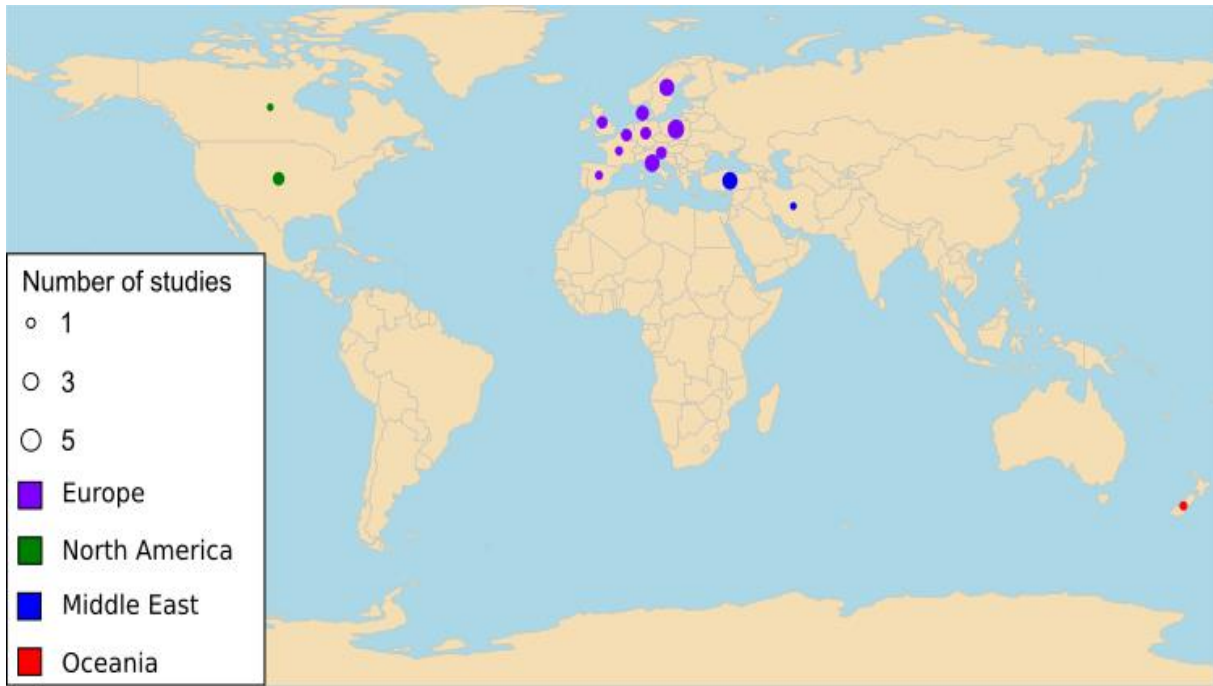


Figure S2: Geographical distribution of the selected articles

Table S1: List of selected articles

Title	Country	First Author	Journal	Year of publication	Nb of observation
Life-cycle impact assessment of organic and non-organic grass-fed beef production in Japan	Japan	Tsutsumi. M	J. Cleaner Production	2018	500
Effect of Organic Production system on the performance and meat quality of two purebred slow-growing chicken breeds	Poland	Sosnowka-Czajka. E	Annals of Animal Science	2017	123
Pasture feeding conventional cows removes differences between organic and conventionally produced milk	New Zealand	Schwendel	Food Chemistry	2017	95
Life Cycle Assessment of Canadian egg products, with differentiation by hen housing system type	Canada	Pelletier	J. Cleaner Production	2017	2137862
Carbon Footprint of conventional and organic beef production systems : An Italian case study	Italy	Burrati. C	Science of the Total Environment	2017	416
Environmental Assessment of Small-scale dairy farms with multifunctionality in Mountain areas	Italy	Salvador. S	J. Cleaner Production	2016	896
Comparison of growth performance and carcass traits of Japanese quails reared in conventional, pasture and organic conditions	Turkey	Inci. H	Revista Brasileira de Zootecnia	2016	90
Fatty acid profiles and antioxidants of organic and conventional milk from low and high-input systems during outdoor period	Germany	Kusche. D	Science of Food and Agriculture	2014	1224
Feeding strategies and manure management for cost-effective mitigation of greenhouse gas emissions from dairy farms in Wisconsin	USA	Dutreuil. M	Journal of Dairy Science	2014	13260
Methods for assessing phosphorus overfeeding on organic and conventional dairy farms	Sweden	Nordqvist. M	Animal	2013	2005
Effects of rearing systems on performance, Egg Characteristics and immune response in two layer hen genotype	Turkey	Kucukyilmaz. K.	Asian-Australasian Journal of Animal Sciences	2012	416
Feeding management and milk production in organic and conventional buffalo farms.	Italy	Di Francia. A.	Italian Journal of Animal Science	2007	534
Performance, meat and carcass traits of with organic versus conventional housing and nutrition	Belgium	Millet. S.	Livestock Production Science	2004	32

Comparison of Carcass Characteristics, Meat Quality, and Blood Parameters of Slow and Fast Grown Female Broiler Chickens, Raised in Organic or Conventional Production System	Turkey	Cömert. M.	Asian-Australas Journal of Animal Sciences	2016	20
Dairy cow nutrition in organic farming system. Comparison with the conventional system	Spain	Orjales. L.	Animal	2018	1559
Economic characteristics and produced milk quality in Holstein lactating cows in organic and conventional systems	Iran	Sharifi. M.	Iranian Journal of Applied Animal Science	2016	30
Effect of on-farm diets for organic pig production on performance and carcass quality	Germany	Sundrum. A.	Journal of Animal Science	2000	100
Organic versus Conventional dairy farming- studies from öjebyn Project	Sweden	Byström. S.	Agricultural Sciences	2002	145
Parameters affecting the environmental impact of a range of dairy farming systems in Denmark, Germany and Italy.	Denmark	Guerci. M.	J. Cleaner Production	2013	656
Differences in whey protein content between cow's milk collected in late pasture and early indoor feeding season from conventional and organic farms in Poland	Poland	Kuczynska. B.	Journal of cleaner Production	2013	85
A comparison of egg quality from hens reared under organic and commercial systems	USA	Taha. Y.S.	IFOAM Conference	2012	240
Effect of production system and farming strategy on greenhouse gas emissions from commercial dairy farms in a life cycle approach	Denmark	Kristensen. T.	Livestock Science	2011	7950
Growth, Carcass and Meat Quality traits of pigs raised under organic or conventional rearing systems using commercially available feed mixtures	Slovenia	Prevolnik. M.	Slovenian Veterinary research	2011	75
Cadmium in organic and conventional pig production	Sweden	Linden. A.	Archives of Environmental Contamination and Toxicology	2001	78
Analysis and simulation modelling of the production in Danish organic and conventional dairy herds	Denmark	Kristensen. T.	Livestock Production Science	1998	1821
Environmental impact evaluation of conventional, organic and	Italy	Boggia. A.	World's Poultry Science Journal	2010	64534

organic-plus poultry production systems using life cycle assessment					
An assessment of the energy footprint of dairy farms in Missouri and Emilia-Romagna	USA	Pagani. M.	Agricultural System	2016	1237
An assessment of the energy footprint of dairy farms in Missouri and Emilia-Romagna	Italy	Pagani. M.	Agricultural system	2016	3038
Conversion to organic farming decreases the vulnerability of dairy farms	France	Bouttes. M.	Agronomy for Sustainable Development	2019	1126
Environmental Impacts of the Beef Production Chain in The Northeast of Portugal Using Life Cycle Assessment	Portugal	Presumido. P.H.	Agriculture	2018	289
Basic chemical composition and mineral content of the milk of cows of various breeds raised on organic and on traditional farms using intensive and traditional feeding systems	Poland	Litwinczuk. Z.	Medycyna Weterynaryjna-Veterinary Medicine-Science and Practice	2018	16388
The status of essential elements and associations with milk yield and the occurrence of mastitis in organic and conventional dairy herds	Swenden	Blanco-penedo. I.	Livestock science	2014	289
Fatty acid and fat-soluble antioxidant concentrations in milk from high- and low-input conventional and organic systems: seasonal variation	United Kingdom	Butler. G	Journal of the Science of Food and Agriculture	2008	5730
Meat and fat quality of Krskopolje pigs reared in conventional and organic production systems	Poland	Tomazin. U	Animal	2018	24
Differing responses n milk composition from introducing rapeseed and naked oats to conventional and organic dairy diets	United Kingdom	Butler. G	Scientific Reports	2019	150
Does rearing system (conventional vs organic) affect ammonia emissions during the growing and fattening periods of pigs?	Slovenia	Ocepek.M	Biosystems Engineering	2016	60

Supplementary results

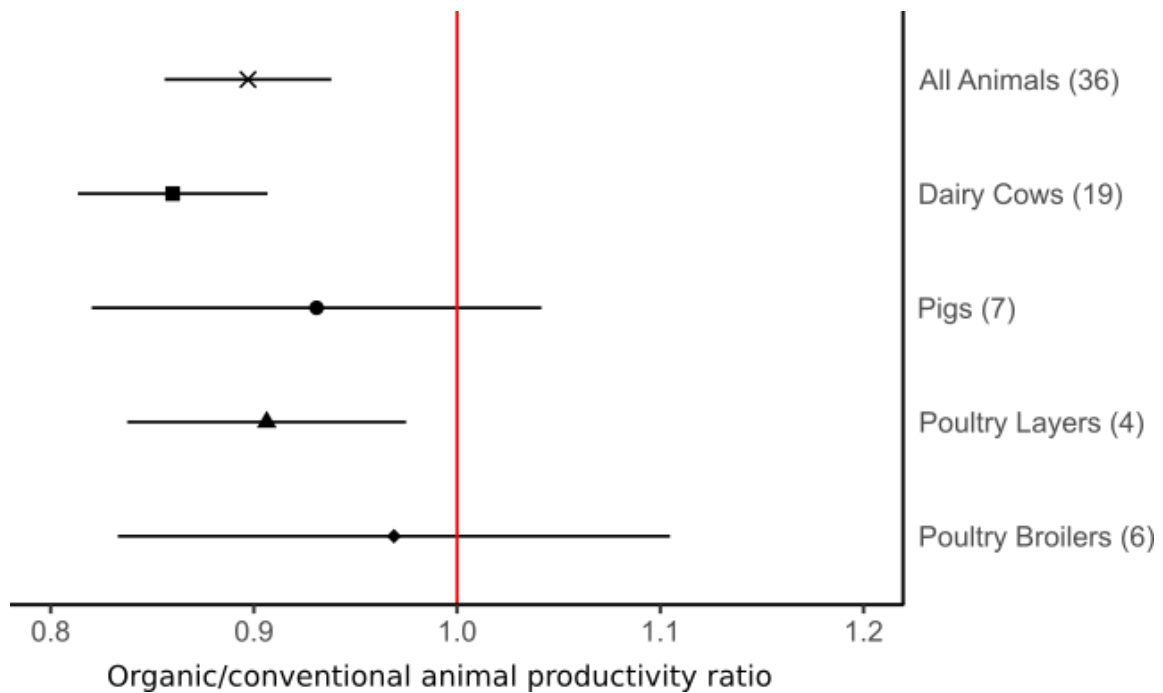


Figure S3: Non-weighted organic-to-conventional animal productivity ratios. Values are the non-weighted means (i.e. not accounting for number of monitored animals) of organic-to-conventional ratios with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one (meaning no differences between organic and conventional animal productivity). A ratio higher than one represents cases where organic farming has a higher productivity than conventional farming.

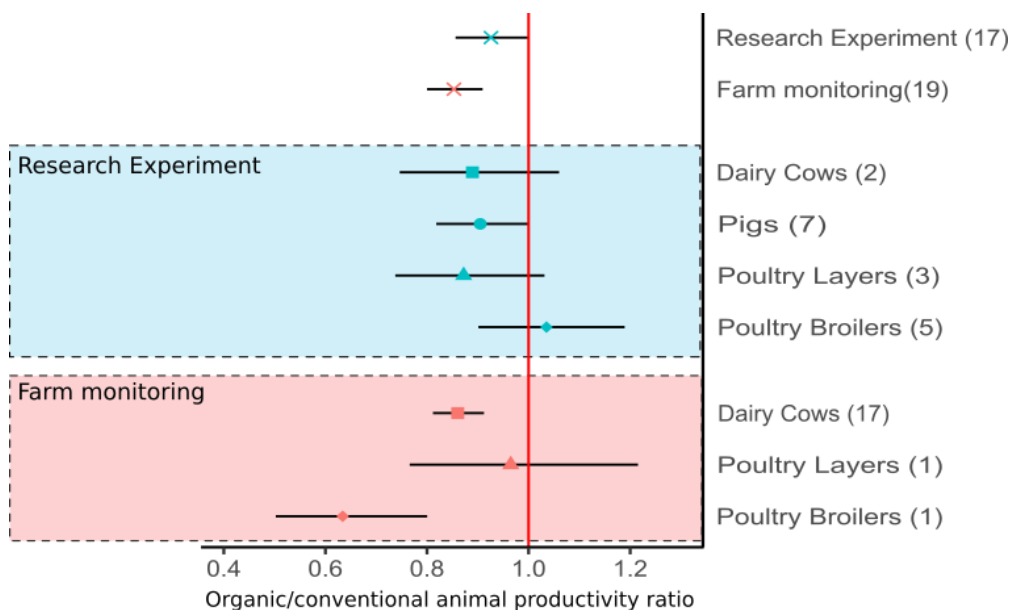


Figure S4: Influence of the type of data collection (experiment vs. farm monitoring) on the organic-to-conventional animal productivity ratios. Values are the weighted means of organic-to-conventional ratios with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one (meaning no differences between organic and conventional animal productivity). A ratio higher than one represents cases where organic farming has a higher productivity than conventional farming. The blue and red zones represent results based on research experiment and on farm monitoring, respectively.

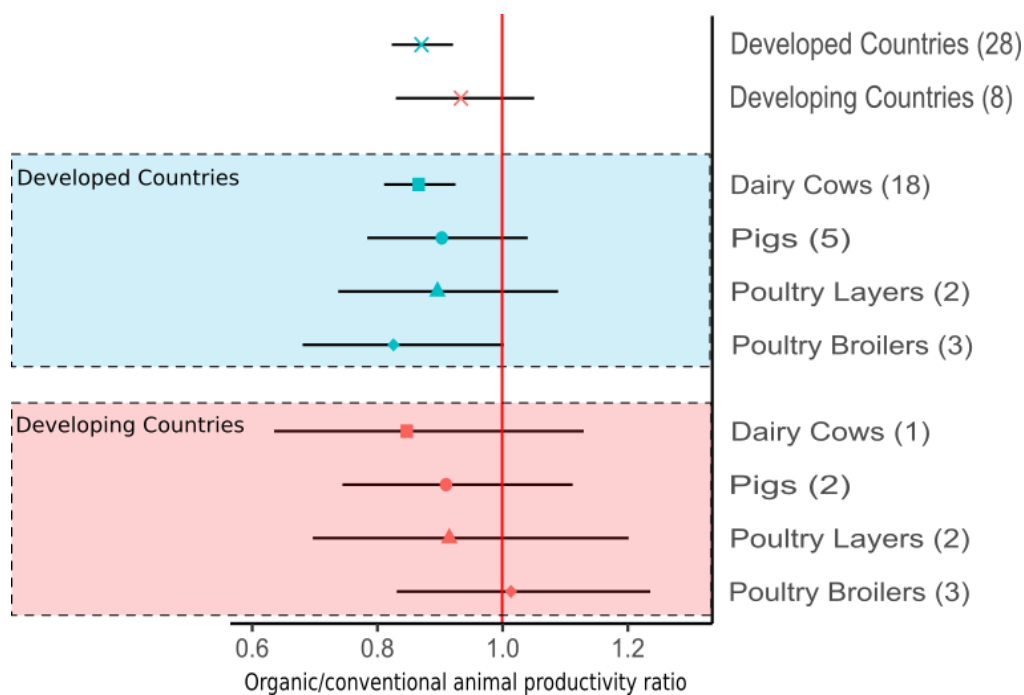


Figure S5: Influence of the origin of the data (developed vs. developing country) on the organic-to-conventional animal productivity ratios. Values are the weighted means of organic-to-conventional ratios with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one (meaning no differences between organic and conventional animal productivity). A ratio higher than one represents cases where organic farming has a higher productivity than conventional farming. The blue and red zones represent results from developed and developing countries, respectively.

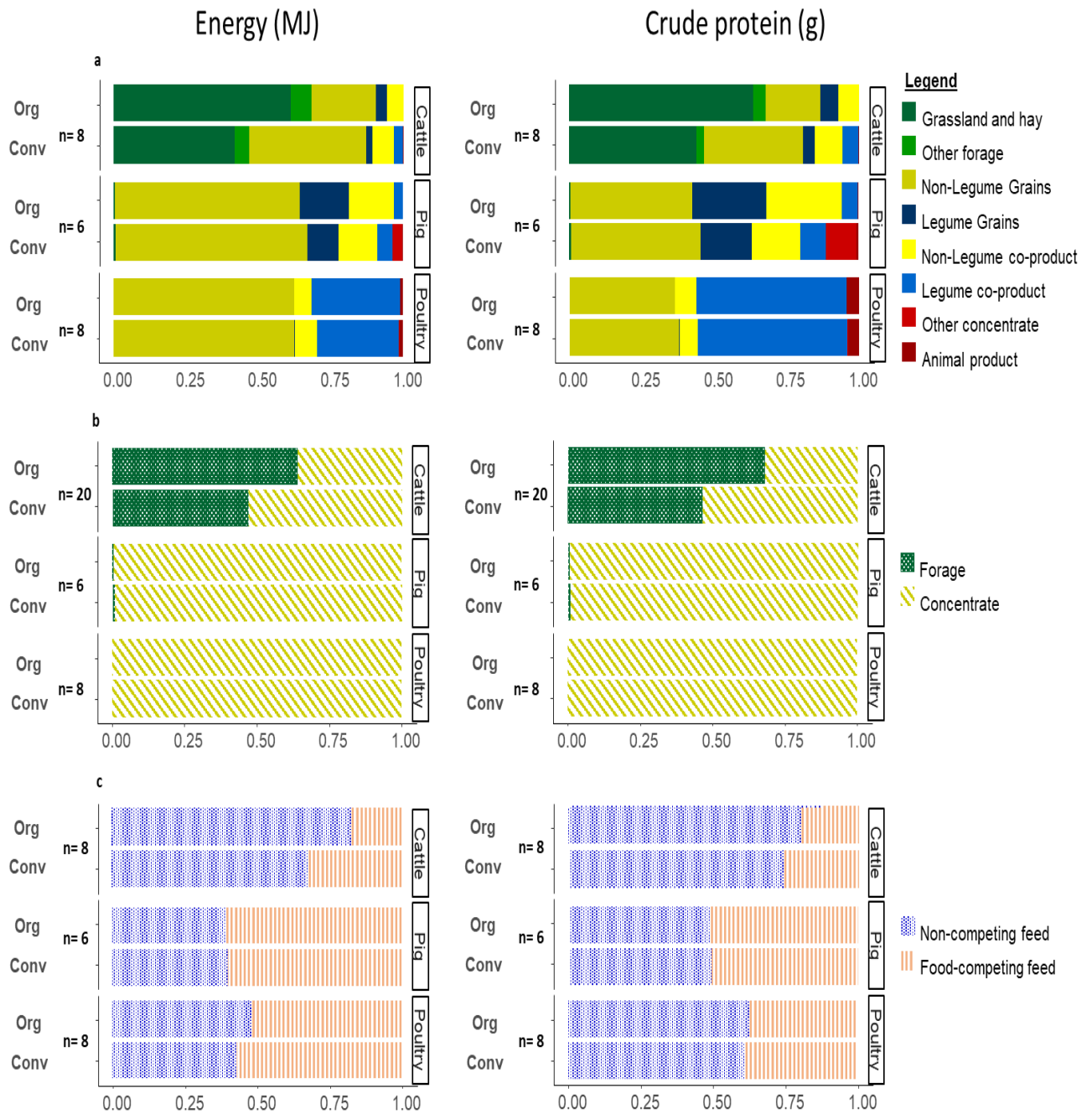


Figure S6: Animal feed rations composition in organic and conventional farming systems for three livestock species. Horizontal bars represent the share of each feed category as a fraction of the total feed ration (expressed in MJ and in crude protein). The composition of the feed ration is expressed based on eight detailed feed categories (a) or clustered as forage vs. concentrate feed (b), or as food-competing vs. non-competing feed (c). Org and Conv refer to organic and conventional farming, respectively. The number of studies supporting each comparison is also given at the left of the horizontal bars.

Table S2: Mean and standard error of each feed category share in the feed ration expressed in mass (kg of DM) for organic and conventional animal systems. Differences between organic and conventional systems were tested using a Kruskal-Wallis test whose results are represented by the p-value.

			Grassland and hay	Other forage	Non- legume grains	Legume grains	Non- legume by- product	Legume by- product	Other concentrate	Animal product	Concentrate	Food- competing feed
Dairy cattle	Org	Mean	63.2%	7.2%	20.9%	3.2%	5.6%	0.0%	0.0%	0.0%	23.8%	24.9%
		S.E.	15.4%	8.2%	7.6%	4.4%	11.0%	0.0%	0.0%	0.0%	11.0%	5.3%
	Conv	Mean	43.6%	5.0%	38.5%	2.0%	7.8%	3.1%	0.0%	0.1%	39.7%	45.8%
		S.E.	10.6%	6.9%	20.0%	2.7%	13.0%	3.0%	0.0%	0.1%	13.7%	11.3%
Kruskal- Wallis test	p_value		0.0758	0.7382	0.206	0.9142	0.4354	0.05391	0.3173	0.3173	0.02828	0.01629
Pig	Org	Mean	0.6%	0.0%	65.0%	16.4%	15.2%	2.8%	0.0%	0.1%	99.4%	91.0%
		S.E.	0.9%	0.0%	8.9%	11.4%	10.4%	4.3%	0.0%	0.2%	0.9%	5.7%
	Conv	Mean	0.6%	0.0%	68.6%	9.1%	13.7%	4.8%	3.0%	0.2%	99.4%	94.1%
		S.E.	0.7%	0.0%	13.8%	10.7%	12.3%	7.0%	4.9%	0.6%	0.7%	6.1%
Kruskal- Wallis test	p_value		0.721	NA	0.5218	0.1659	0.631	0.3191	0.007397	0.902	0.721	0.4233
Poultry	Org	Mean	0.0%	0.0%	64.9%	0.0%	5.3%	28.8%	0.0%	1.0%	100.0%	92.8%
		S.E.	0.0%	0.0%	4.2%	0.0%	5.6%	3.8%	0.0%	1.5%	0.0%	13.1%
	Conv	Mean	0.0%	0.0%	65.3%	0.1%	6.6%	26.6%	0.3%	1.1%	100.0%	93.0%
		S.E.	0.0%	0.0%	4.9%	0.2%	8.4%	7.2%	0.6%	1.7%	0.0%	11.9%
Kruskal- Wallis test	p_value		NA	NA	0.9162	0.3173	0.6358	0.8334	0.02728	0.9079	NA	0.4616

Table S3: Mean and standard error of each feed category share in the feed ration expressed in energy (MJ) for organic and conventional animal systems. Differences between organic and conventional systems were tested using a Kruskal-Wallis test whose results are represented by the p-value.

			Grassland and hay	Other forage	Non- legume grains	Legume grains	Non- legume by- product	Legume by- product	Other concentrate	Animal product	Concentrate	Food- competing feed	
Dairy cattle	Org	Mean	61.1%	7.1%	22.5%	3.6%	5.8%	0.0%	0.0%	0.0%	36.1%	17.3%	
		S.E.	15.7%	8.0%	8.9%	4.6%	11.6%	0.0%	0.0%	0.0%	15.2%	3.9%	
	Conv	Mean	41.7%	5.0%	40.5%	2.2%	7.2%	3.3%	0.0%	0.1%	53.3%	31.7%	
		S.E.	11.2%	7.0%	21.2%	2.7%	13.6%	3.2%	0.1%	0.3%	11.3%	10.0%	
	p_value			0.1172	0.7382	0.2506	0.7465	0.5775	0.05391	0.3173	0.3173	0.02828	0.02828
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Pig	Org	Mean	0.6%	0.0%	63.7%	17.0%	15.6%	3.0%	0.0%	0.1%	99.5%	61.0%	
		S.E.	0.9%	0.0%	9.1%	11.6%	10.1%	4.6%	0.0%	0.2%	0.9%	6.4%	
	Conv	Mean	0.6%	0.0%	66.6%	10.7%	13.4%	5.1%	3.3%	0.3%	99.4%	59.8%	
		S.E.	0.7%	0.0%	13.8%	13.0%	12.7%	7.3%	5.7%	0.7%	0.7%	5.4%	
	p_value			0.721	NA	0.5218	0.4632	0.5218	0.3191	0.007397	0.902	0.721	0.7488
	<hr/>												
Poultry	Org	Mean	0.0%	0.0%	62.5%	0.0%	6.0%	30.5%	0.0%	1.1%	100.0%	51.8%	
		S.E.	0.0%	0.0%	4.7%	0.0%	5.3%	3.4%	0.0%	1.5%	0.0%	6.7%	
	Conv	Mean	0.0%	0.0%	62.5%	0.1%	7.8%	28.1%	0.3%	1.2%	100.0%	57.0%	
		S.E.	0.0%	0.0%	5.0%	0.2%	6.8%	7.2%	0.6%	2.0%	0.0%	5.4%	
	p_value			NA	NA	1	0.3173	0.3174	0.7524	0.02728	0.9079	NA	0.0116

Table S4: Mean and standard error of each feed category share in the feed ration expressed in crude protein (g) for organic and conventional animal systems. Differences between organic and conventional systems were tested using a Kruskal-Wallis test whose results are represented by the p-value.

			Grassland and hay	Other forage	Non- legume grains	Legume grains	Non- legume by- product	Legume by- product	Other concentrate	Animal product	Concentrate	Food- competing feed
Dairy cattle	Org	Mean	63.2%	7.2%	20.9%	3.2%	5.6%	0.0%	0.0%	0.0%	23.8%	24.9%
		S.E.	15.4%	8.2%	7.6%	4.4%	11.0%	0.0%	0.0%	0.0%	11.0%	5.3%
	Conv	Mean	43.6%	5.0%	38.5%	2.0%	7.8%	3.1%	0.0%	0.1%	39.7%	45.8%
		S.E.	10.6%	6.9%	20.0%	2.7%	13.0%	3.0%	0.0%	0.1%	13.7%	11.3%
p_value			0.1745	0.7382	0.3472	0.7465	0.5775	0.05391	NA	0.3173	0.1172	0.1745
Pig	Org	Mean	0.6%	0.0%	65.0%	16.4%	15.2%	2.8%	0.0%	0.1%	99.4%	91.0%
		S.E.	0.9%	0.0%	8.9%	11.4%	10.4%	4.3%	0.0%	0.2%	0.9%	5.7%
	Conv	Mean	0.6%	0.0%	68.6%	9.1%	13.7%	4.8%	3.0%	0.2%	99.4%	94.1%
		S.E.	0.7%	0.0%	13.8%	10.7%	12.3%	7.0%	4.9%	0.6%	0.7%	6.1%
p_value			0.721	NA	0.4233	0.37	0.2002	0.3191	0.007397	0.902	0.721	1
Poultry	Org	Mean	0.0%	0.0%	64.9%	0.0%	5.3%	28.8%	0.0%	1.0%	100.0%	92.8%
		S.E.	0.0%	0.0%	4.2%	0.0%	5.6%	3.8%	0.0%	1.5%	0.0%	13.1%
	Conv	Mean	0.0%	0.0%	65.3%	0.1%	6.6%	26.6%	0.3%	1.1%	100.0%	93.0%
		S.E.	0.0%	0.0%	4.9%	0.2%	8.4%	7.2%	0.6%	1.7%	0.0%	11.9%
p_value			NA	NA	0.9162	0.3173	0.9105	0.9162	0.02728	1	NA	0.3439

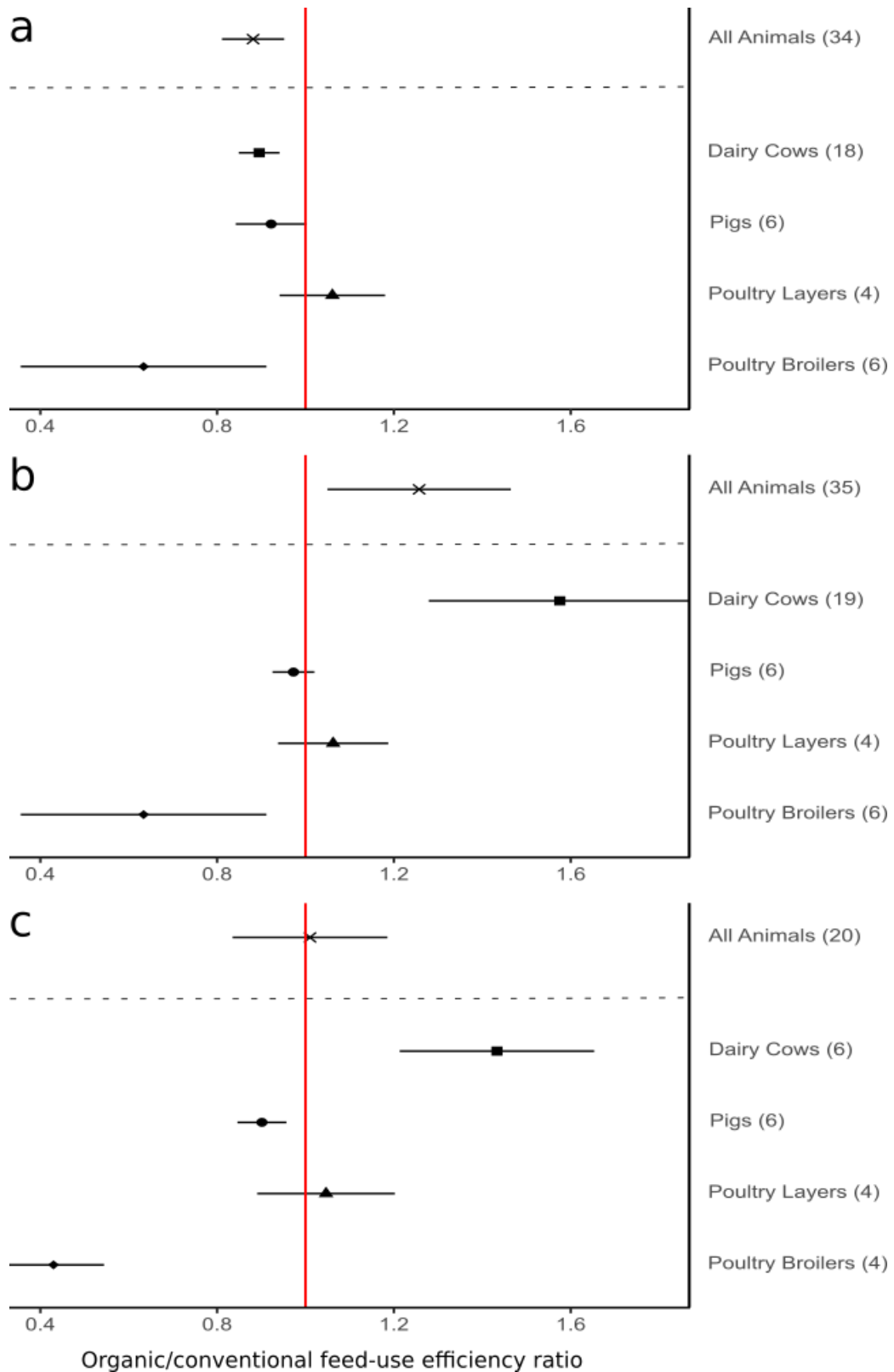


Figure S7: Non-weighted organic-to-conventional feed-use efficiency. Values are non-weighted means (i.e. not accounting for number of monitored animals) of organic-to-conventional ratio with 95% confidence intervals. Feed-use efficiency is calculated based on the entire feed ration (a), on concentrate feed (b), and on food-competing feed (c). The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming.

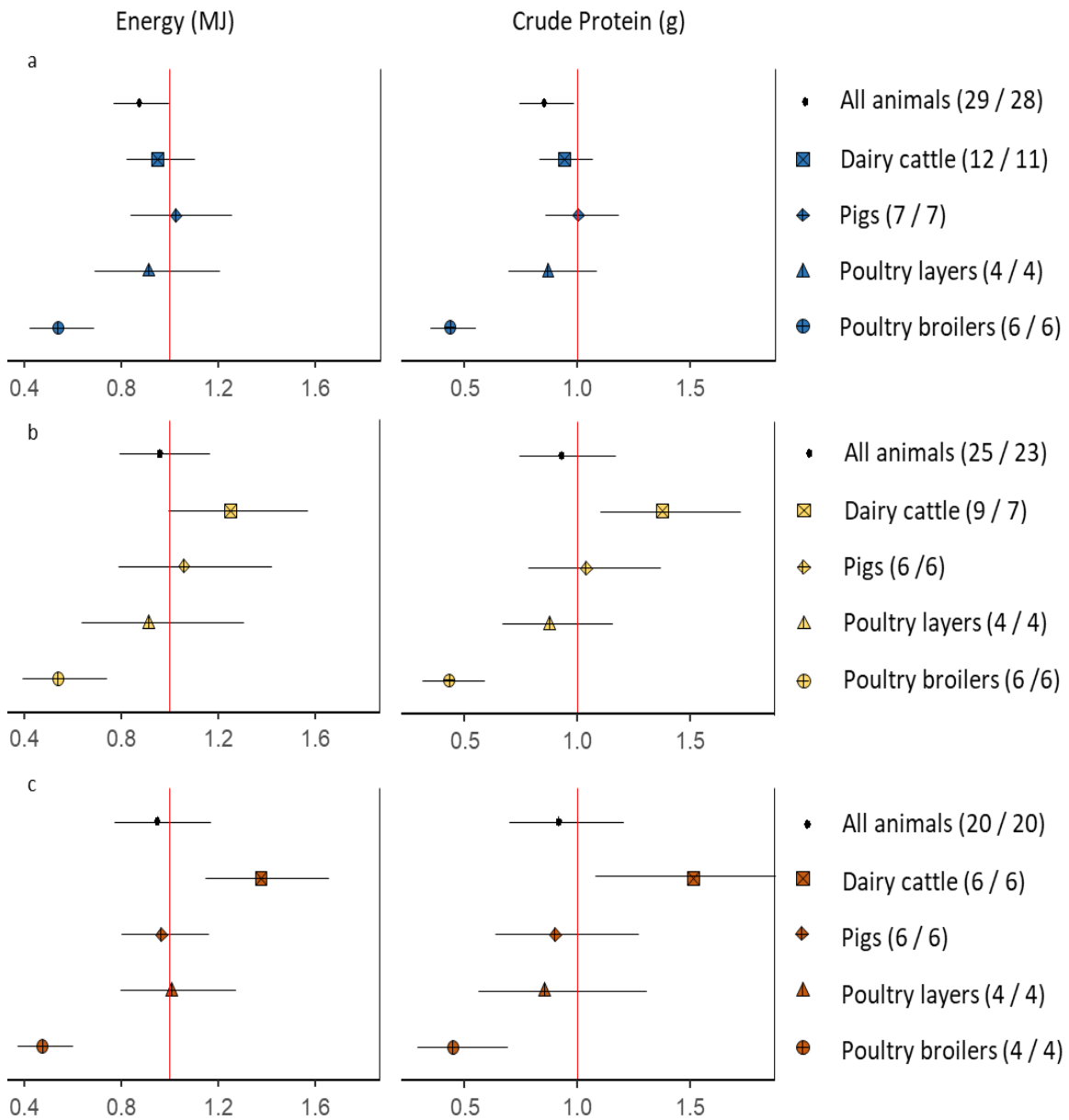


Figure S8: Organic-to-conventional animal energy (left) and crude protein (right) feed-use efficiency. Feed-use efficiency is calculated based on the entire feed ration (a), on concentrate feed (b), and on food-competing feed (c). Values are the weighted means of organic-to-conventional ratio with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ration of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming.

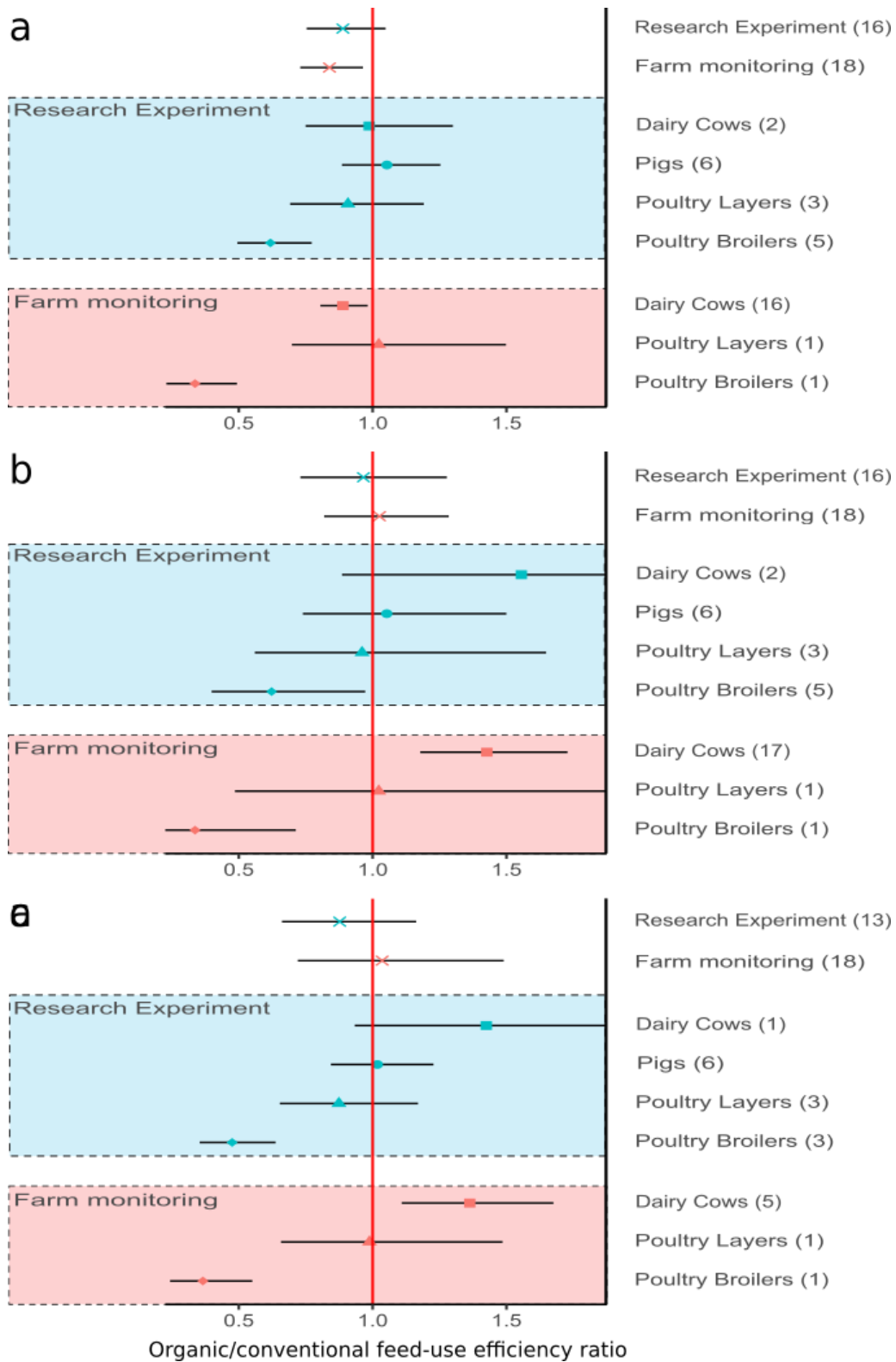


Figure S9: Influence of the type of data collection (experiment vs. farm monitoring) on the organic-to-conventional animal feed-use efficiency. Feed-use efficiency is calculated based on the entire feed ration (a), on concentrate feed (b), and on food-competing feed (c). Values are the weighted means of organic-to-conventional ratio with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming. The blue and red zones represent results from experiment vs. farm monitoring, respectively.

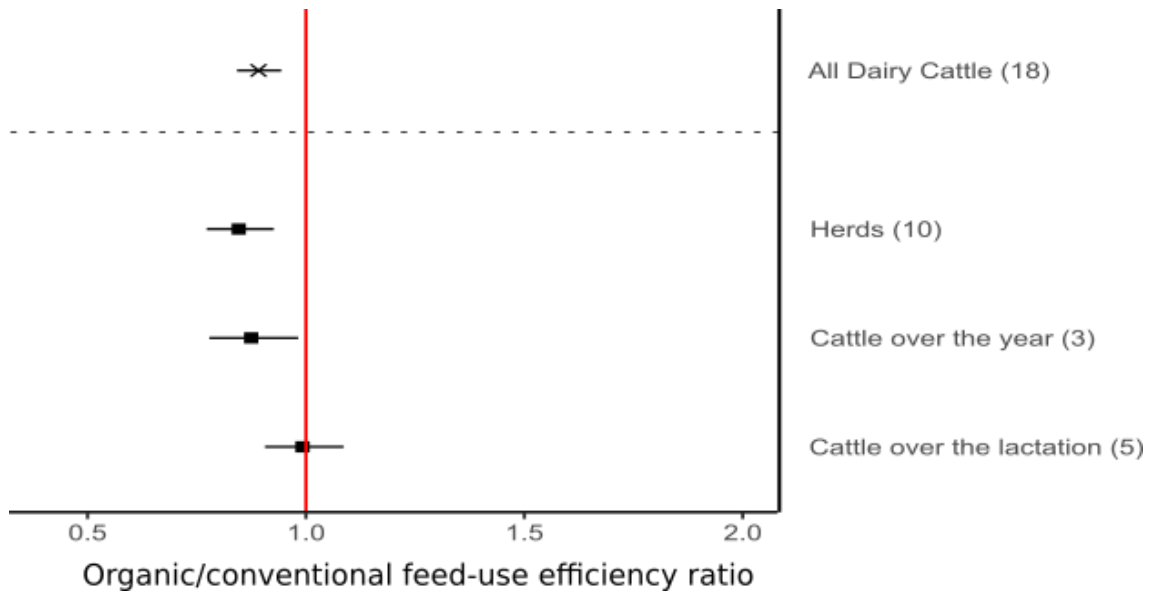


Figure S10: Organic-to-conventional dairy cattle feed-use efficiency calculated at the herd scale, the animal scale over the whole year and the animal scale over its lactation period. Feed-use efficiency is calculated based on the entire feed ration. Values are the weighted means of organic-to-conventional ratio with 95% confidence intervals. The numbers in brackets provide the number of observations for each entity observed. The vertical red line indicates a ration of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming.

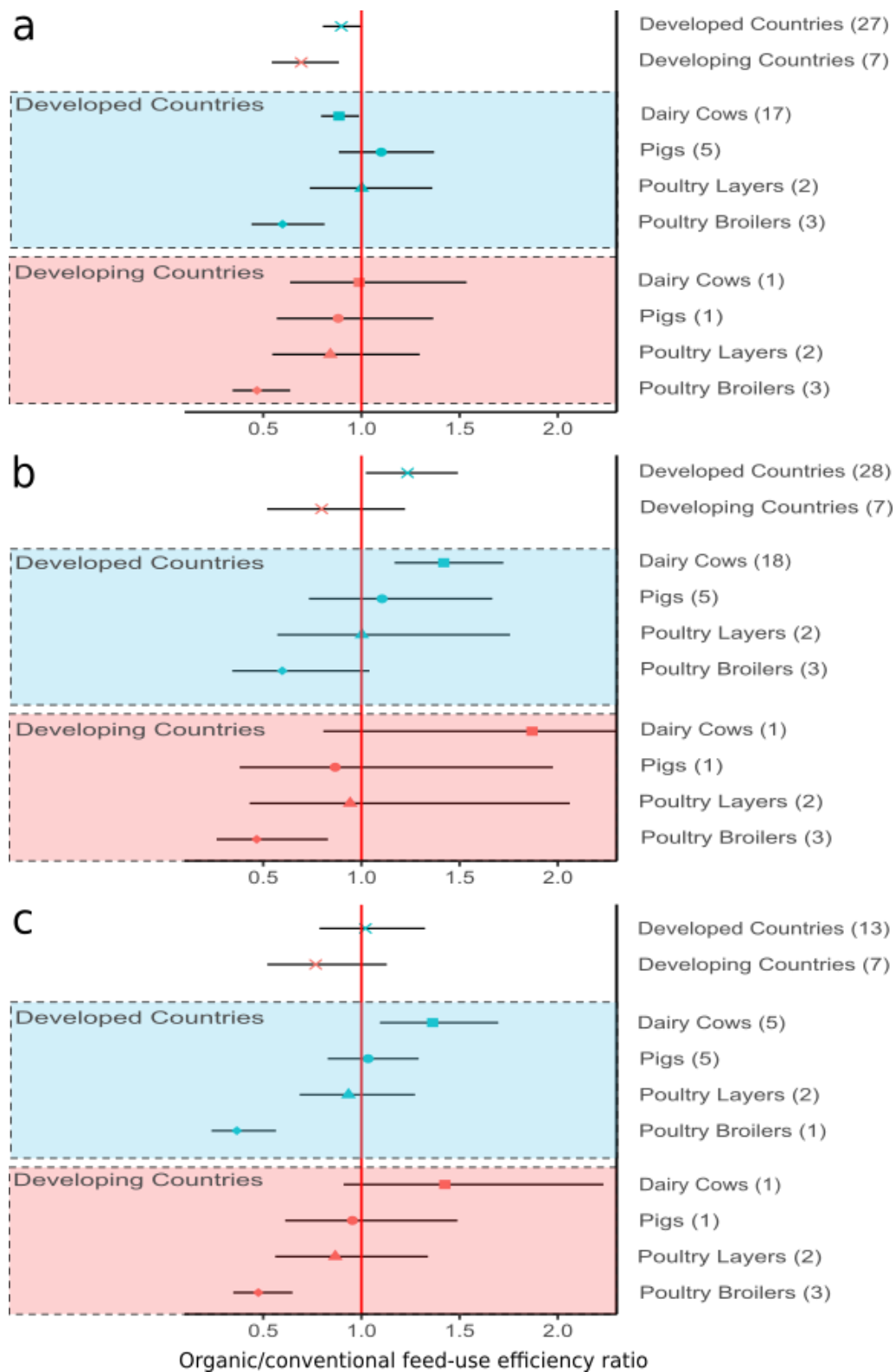


Figure S11: Influence of the origin of the data (developed vs. developing country) on the organic-to-conventional animal feed-use efficiency. Feed-use efficiency is calculated based on the entire feed ration (a), on concentrate feed (b), and on food-competing feed (c). Values are the weighted means of organic-to-conventional ratio with 95% confidence intervals. The numbers in brackets provide the number of observations for each livestock type. The vertical red line indicates a ratio of value one - i.e., no differences between organic and conventional feed-use efficiency. A ratio higher than one represents cases where feed-use efficiency is higher in organic than in conventional farming. The blue and red zones represent results from developed vs. developing countries, respectively.

Table S5: Classification of the feed products in the eight feed categories

Grassland product	Other forage	Non-legume grains	Legume grains	Non-legume by-product		Legume by-product	Other concentrate	Animal product
Alfalfa Hay	Corn Silage	Barley	Faba Bean	Brewers	Molasses	Alfalfa Meal	Amino Acids	Animal Meal
Alfalfa Silage	Oat Hay	Carob	Flaked	Grains	Oil	Alfalfa Meal 18%	Bakery Meal	Blood Meal
Alphalpha	Rice Straw	Grain Mixture	Soybean	Brewes grain	Palm Kernel	Beet Pulp	DL-Methionine	Fat choice
Forage 1	Sorghum	Maize	Lupine	Cane	Expeler	Extruded	Energy booster	white grease
Grass	Silage	Oat	Peas	Molasses	Potato	Soybean	L-Lysine	Fish Meal
Hay	Straws	Oat Flakes	Soybean	Canola Meal	Protein	Full Fat Soybean	L-Threonine	Meat Meal
Italian Ryegrass	Wheat Straw	Rapeseed		Canola Oil	Rapeseed	Solvent	Meal Mixture	Milk Powder
Hay	Wheat silage	Sorghum		Citrus Pulp	Cake	Extracted	Protein	Poultry Fat
Timothy Hay		Sunflower		Corn-Dried	Sorghum	Soybean	concentrate	Poultry
Wild Grass Hay		Triticale		Distillers	Meal	Soybean Hulls		Feather Meal
		Wheat		Grain	Sunflower	Soybean Meal		Poultry Meal
		White Maize		DDGS	Cake	Soybean Meal		Ruminant Fat
		Turnips		Maize Gluten	Sunflower	48%		Swine Fat
				Maize Meal	meal	Soybean Oil		
				Malt Sprout	Sunflower			
				Molasses	Seed Oil			
				Oil	Wheat Bran			
					Wheat			
					Middlings			
					Wheat			
					Shorts			

Annex II: Supplementary information for chapter II

Supplementary methods

Sensitivity estimation

To test the sensitivity of the RothC outputs to variations of SCI values, we considered a combination of two possible sources of uncertainty in SCI values: (i) $\pm 20\%$ uncertainties in the carbon biomass production of both croplands and grasslands and (ii) uncertainties in the repartition of the crop carbon biomass between AgC and BgC , i.e. in root-shoot ratio (RS). The estimation of the minimum and maximum values of AgC and BgC were made following **Equation S2** and **Equation S3**.

$$\text{Equation S2} \begin{cases} AgC_{min} = Yield * 0.5 * 0.8 / HI \\ BgC_{min} = AgC_{min} * RS \end{cases}$$

$$\text{Equation S3} \begin{cases} Total_{max} = Yield * 0.5 * 1.2 * (1 + RS) / HI \\ AgC_{max} = \frac{Total_{max}}{(1 + RS')} \\ BgC_{max} = AgC_{max} * RS' \end{cases}$$

Where AgC_{min} , and AgC_{max} are the minimum values of the aboveground carbon biomass respectively (in $tC \cdot ha^{-1} \cdot yr^{-1}$). BgC_{min} , and BgC_{max} are the maximum values of the belowground carbon biomass respectively (in $tC \cdot ha^{-1} \cdot yr^{-1}$). Where HI and RS represent the crop-specific harvest index (unit-less) and the root-shoot ratio (unit-less), respectively, for each of the considered 45 crop species. $Yield$ refers to the crop yields (in $tons \ DM \cdot ha^{-1}$) as retrieved from Monfreda et al. 2008 (Monfreda et al., 2008) (for the baseline) or from the GOANIM model (for the organic scenarios, Barbieri et al., 2017b). To convert the estimated dry matter production in C, we used a 0.5 coefficient value (in $t \ C \cdot t \ DM^{-1}$). 0.8 is the coefficient used to represent the situation where the carbon biomass production is considered overestimated (-20%). 1.2 is the coefficient used to represent the situation where the carbon biomass production is considered underestimated (+20%), and $Total_{max}$ represents the total plant carbon biomass (in $tC \cdot ha^{-1}$) in this situation. Evidences show that the root-shoot ratio (RS) is higher (up to twice higher) in conditions of low N availability compared to conditions of high N availability (Marschner and Marschner, 2012). We estimated a root-shoot ratio adapted to level of N availability in organically managed croplands (RS') using **Equation S4**:

$$\text{Equation S4} \begin{cases} \text{if } Yield < Yield_{max} \text{ then } RS' = \left(2 - \frac{Yield}{Yield_{max}}\right) * RS \\ \text{if } Yield = Yield_{max} \text{ then } RS' = RS \end{cases}$$

Where $Yield$ is the crop specific yield (in $tons \ C \cdot ha^{-1}$) retrieved from the GOANIM model outputs. $Yield_{max}$ is the crop specific maximum attainable yield for organic farming (in $tons \ C \cdot ha^{-1}$) as defined in the GOANIM model (Barbieri et al., 2021).

Livestock carbon excretion

To estimate the VS (volatile solid, tC.head⁻¹.yr⁻¹) excretion rate from livestock, we used the equation 10.24 of 2019 refinement of IPCC guidelines represented in **Equation S5**.

$$\text{Equation S5 } VS = \left[GE * \left(1 - \frac{DE}{100} \right) + (UE * GE) \right] * \left[\left(\frac{1-ASH}{18.45} \right) \right]$$

Where, *GE* is the gross energy intake (MJ.day⁻¹), *DE* is the feed digestibility (%), *UE* is the urinary energy (% of *GE*) and *ASH* is the ash content of the feed (% of DM). *UE* had a value of 0.02 for pigs and 0.04 for all other animals. In the organic scenario, the estimation of *GE*, *DE* and *ASH* were made using the feed nutritional composition from feedipedia (feedipedia.org). In the baseline, we used data from Herrero et al. 2013 (Herrero et al., 2013) to estimate *DE* and *ASH* and used **Equation S6** (Weiss and Tebbe, 2019) to estimate *GE*.

$$\text{Equation S6 } GE = CP * 0.056 + Fat * 0.096 + (100 - CP - Fat - ASH) * 0.042$$

Where, *CP* is the crude protein content of the ration (%), *Fat* is the fat content of the ration (%) and *ASH* is the mean ash content of the ration (%). *CP*, *Fat* and *Ash* were retrieved from Herrero et al. 2013 (Herrero et al., 2013).

SOC stock estimation using *SCI_{org}* and *SCI_{conv}*

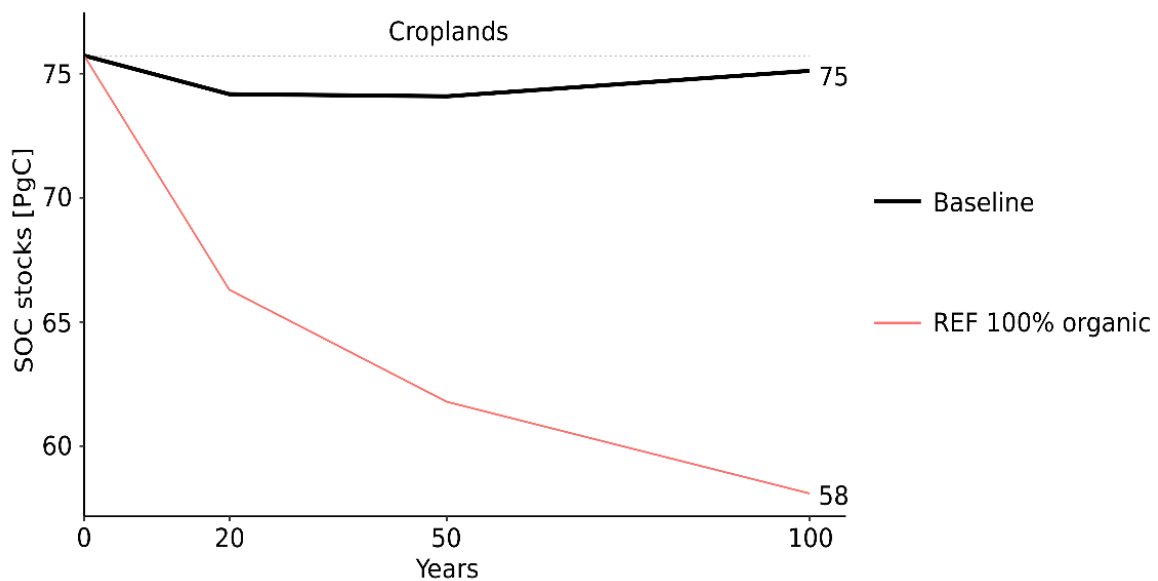


Figure S12: Changes in global SOC stocks (PgC) over time using directly *SCI_{baseline}* and *SCI_{org}* as inputs to the RothC model. Changes in global cropland SOC stocks are reported for the baseline (black line) and the REF 100% organic scenario (red line). Values at the right end of each curve represent the SOC stocks after 100 years. The black dashed lines represent the current global SOC stock for croplands.

Supplementary results

Carbon flows to agricultural soils in an organic world

Table S6: Main outputs from the latest version of GOANIM.

	Energetic yield	Yield			Livestock Population		
		Temporary pastures	Annual crops	Total	Ruminants	Monogastric	Total
<i>Units</i>	<i>Gcal.ha⁻¹</i>	<i>t DM.ha⁻¹</i>			<i>Livestock units</i>		
Baseline	9.4	2.4	2.8	2.8	552	220	772
REF 100% organic	4.5	1.8	1.4	1.5	249	15	264
Ratio organic/baseline	0.48	0.74	0.49	0.53	0.45	0.07	0.34

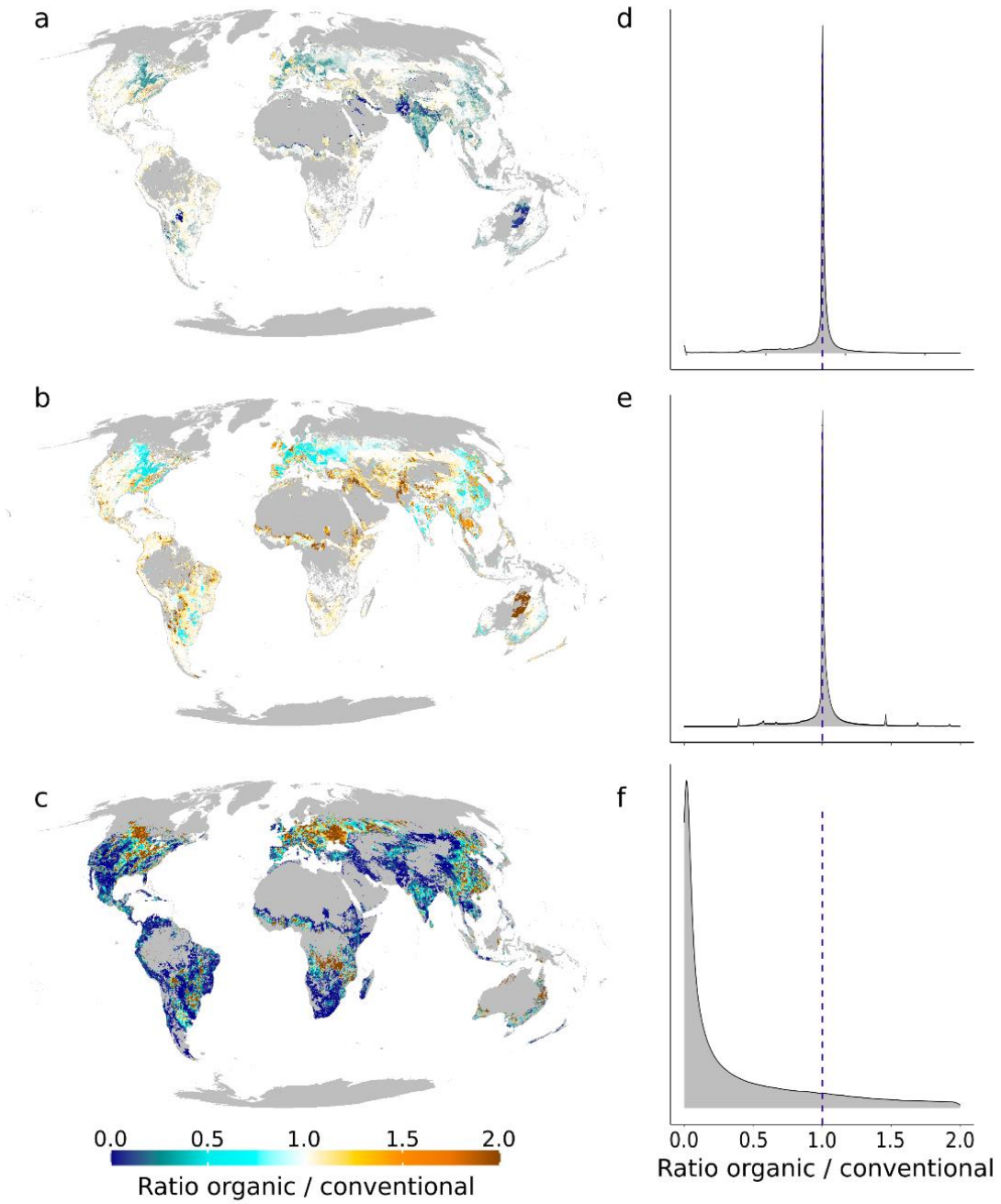


Figure S13: Annual organic to baseline ratios of soil carbon inputs and farmyard manure application for grassland soils. Organic to baseline ratios of soil carbon inputs (panels a and d), of farmyard manure application (panels b and e) and of grass residues (panels c and f) are reported as global maps (a, b & c) and density curve (d, e & f). In the density curves the blue dashed lines indicate the value 1.

SOC stock changes in an organically farmed world

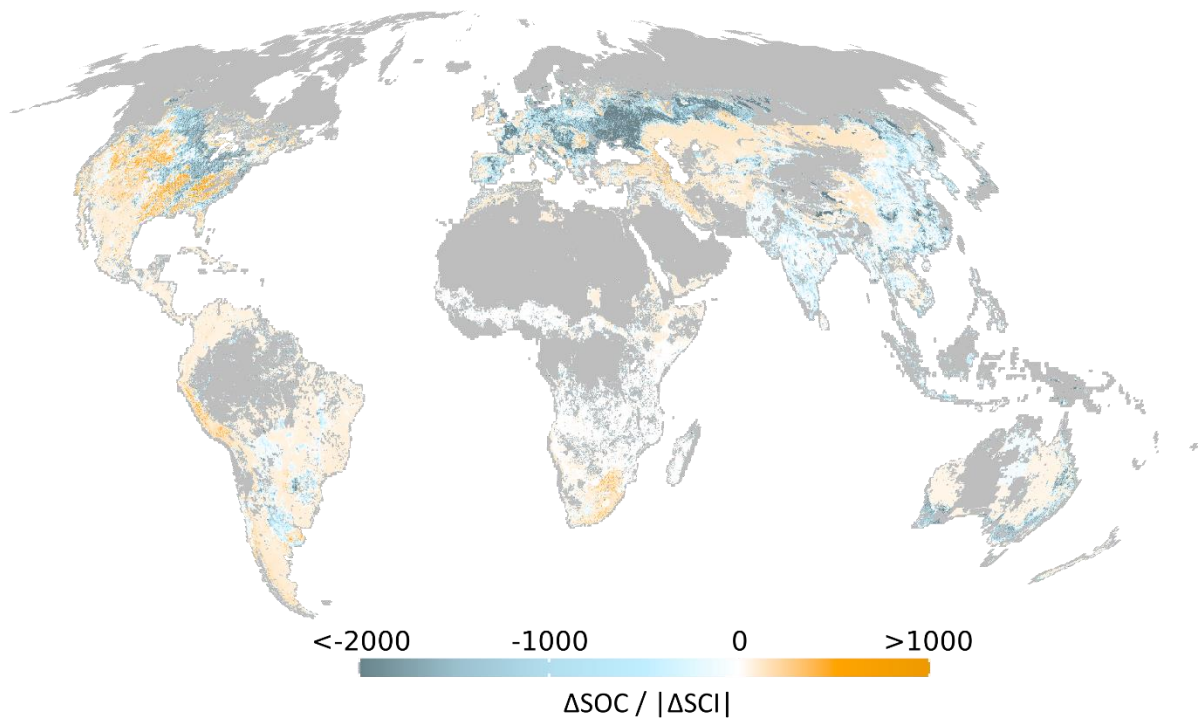


Figure S14: SOC stocks ($t\ C.\text{gridcell}^{-1}$) response to SCI ($t\ C.\text{gridcell}^{-1}$) absolute variations

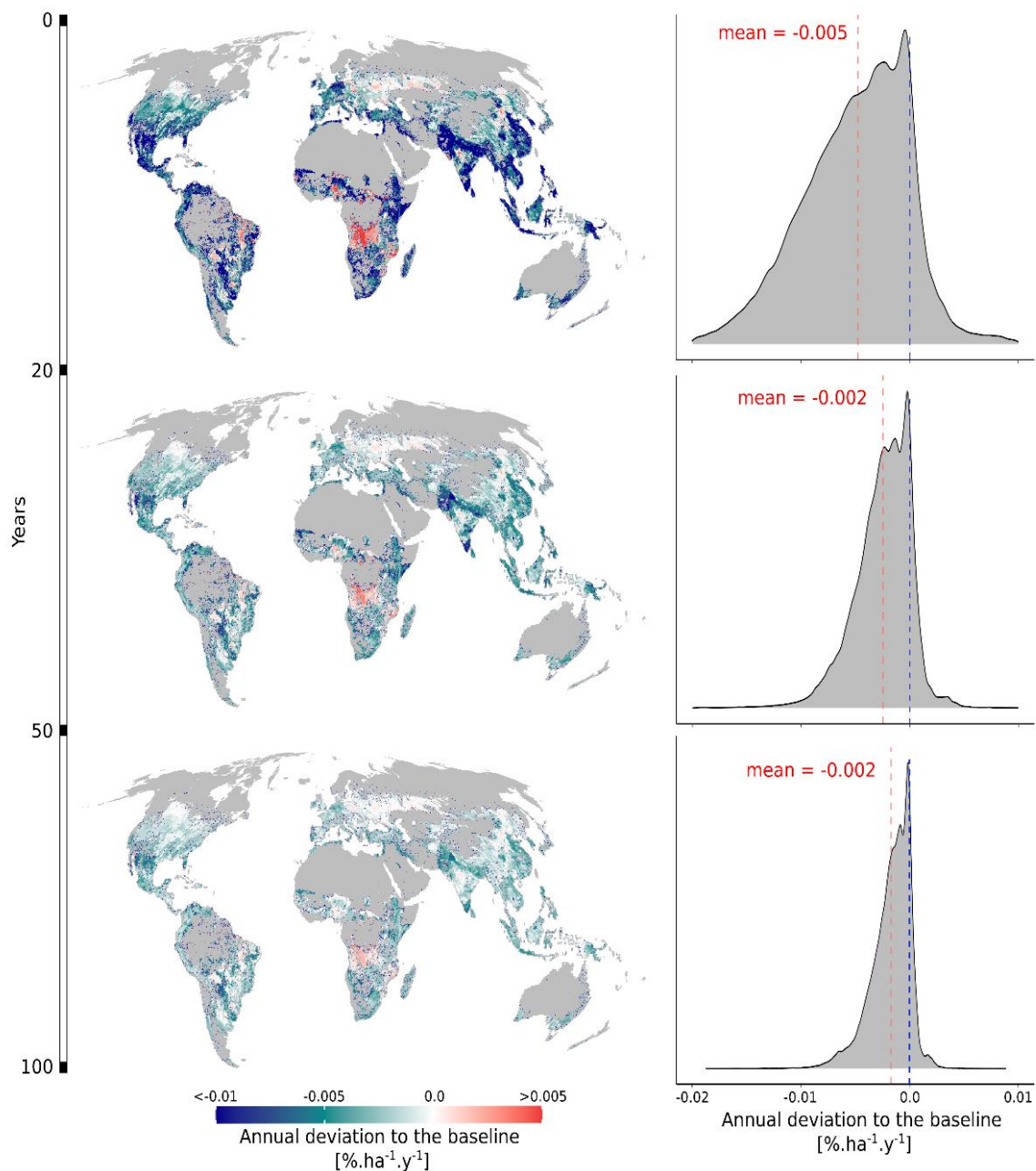


Figure S15: Organic to baseline annual SOC stock change ($\%.ha^{-1}.y^{-1}$). Annual SOC stock change is reported as a map and a density curve for each period after global transition to organic farming (0-20 years, 20-50 years, 50-100 years). In the density curves, the red dashed lines indicate the estimated global mean of organic to baseline ratio of annual SOC stock change per ha, and the blue dashed lines indicate the value 1.

Cover crops potential to improve SOC stocks

Table S7: Global changes in SOC stocks (PgC) for grasslands, croplands and total agricultural land (i.e. grasslands and croplands combined) after 20, 50, and 100 years in a scenario with systematic use of cover crops in organic farming (organic 25% CC). Ratios between the organic and the baseline are indicated.

		<i>Soil organic carbon stocks (PgC)</i>		
		20 years	50 years	100 years
Croplands	<i>Baseline</i>		76	
	<i>Organic 25% CC</i>	72.5	70.5	69
	<i>Ratio organic/baseline</i>	0.95	0.93	0.91
	<i>Difference organic - baseline</i>	-3.5	-5.5	-7
Grasslands	<i>Baseline</i>		121	
	<i>Organic 25% CC</i>	115	115	116
	<i>Ratio organic/baseline</i>	0.95	0.95	0.96
	<i>Difference organic - baseline</i>	-6	-6	-5
Total agricultural lands	<i>Baseline</i>		197	
	<i>Organic 25% CC</i>	187.5	185.5	184
	<i>Ratio organic/baseline</i>	0.95	0.94	0.93
	<i>Difference organic - baseline</i>	-9.5	-11.5	-13

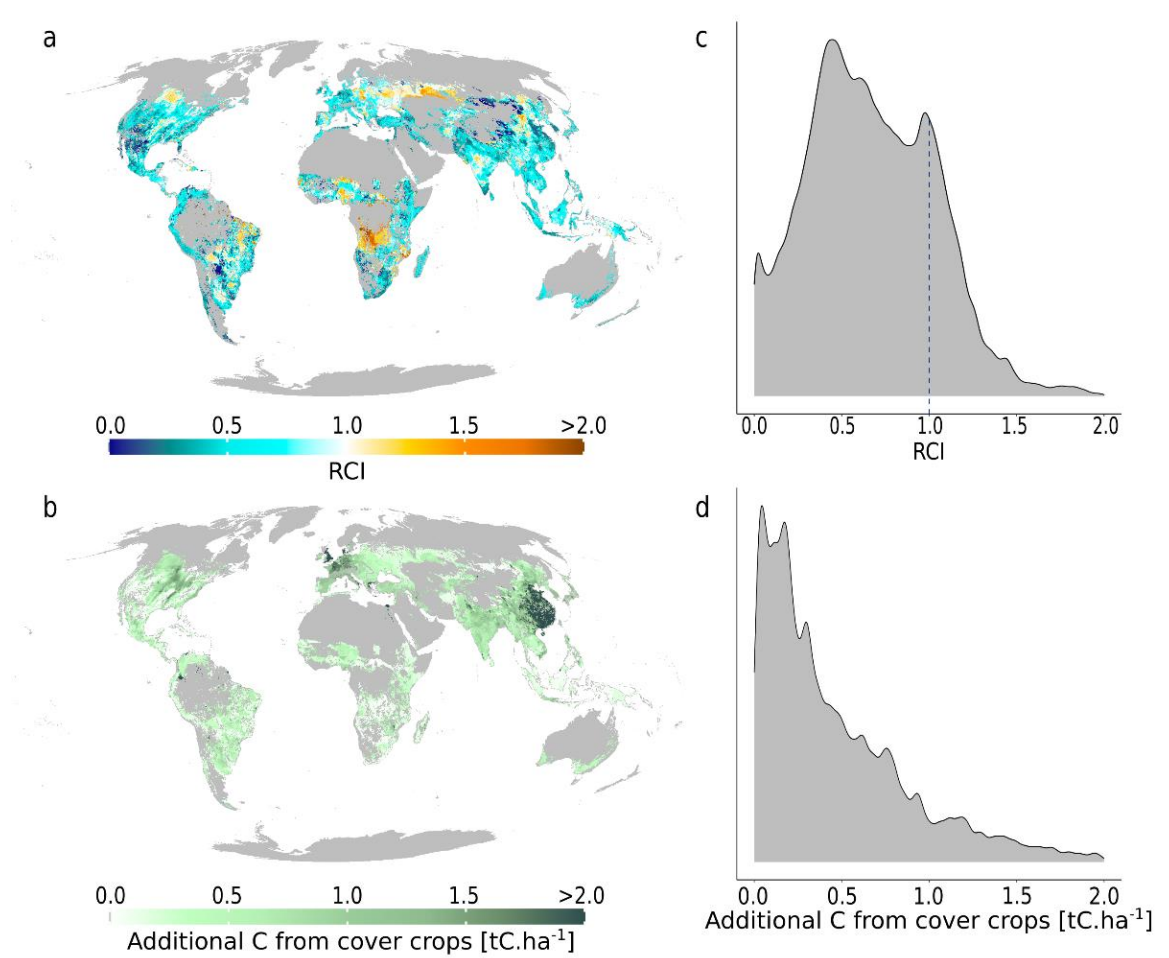


Figure S16: Annual ratios of organic to baseline soil carbon inputs for cropland soils, and annual additional C from cover crops (tC.ha⁻¹). The ratio of organic to baseline soil carbon inputs (RCI) and additional C from cover crops are reported as global maps (a & b) and density curves (c & d). In the density curve representing the organic to baseline ratio of SCI, the blue dashed line indicates the value 1.

Intermediate scenarios of organic farming expansion

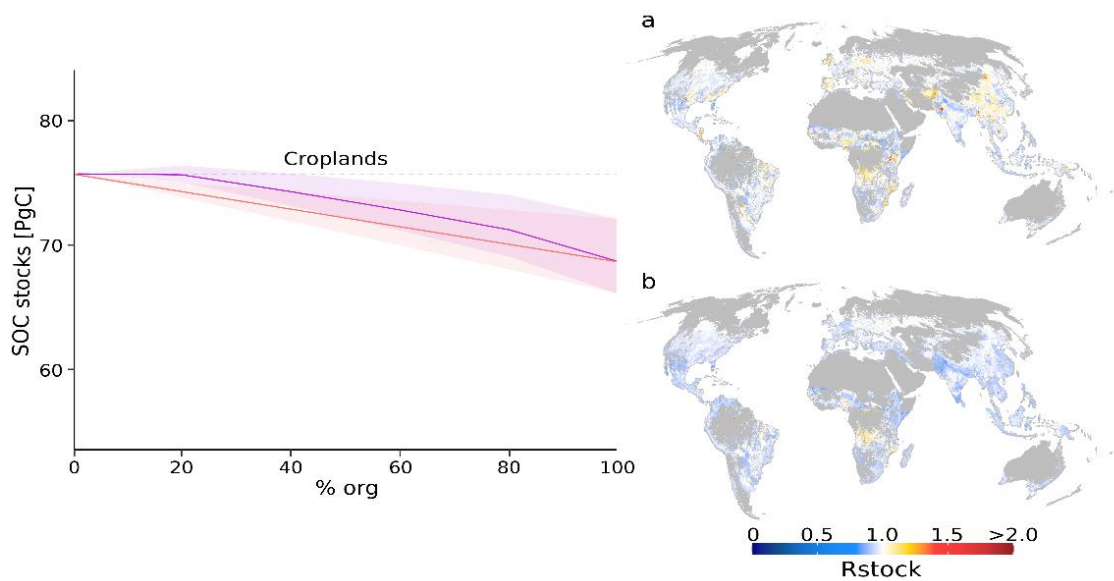


Figure S17: Global changes in soil organic carbon (SOC) stocks in croplands (PgC) with various shares of UAA converted to organic farming, 20 years after conversion to organic farming. The red line represents the situation where conventional manure surplus is not applied on organic croplands; the purple line represents the situation where conventional manure surplus is applied on organic croplands; the dotted black line represents current global stocks. The shaded area around each curve represent the model response to the variation of soil carbon input values (see Methods). Maps represent the ratios of SOC stocks between the 20% of global UAA under organic farming scenario and the baseline, 20 years after conversion to organic farming in the situation where conventional manure surplus is applied on croplands (a) and where it is not applied (b).

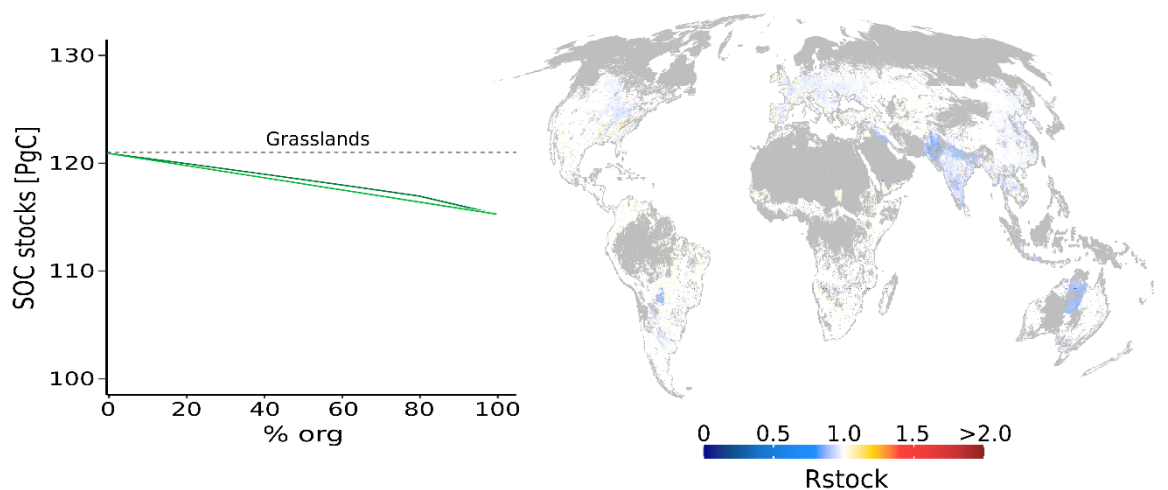


Figure S18: Global changes in soil organic carbon (SOC) stocks in grasslands (PgC) with various shares of UAA converted to organic farming, 20 years after conversion to organic farming. The light green line represents the situation where conventional manure surplus is not applied on organic croplands; the dark green line represents the situation where conventional manure surplus is applied on organic croplands; the dotted black line represents current global stocks. The shaded area around each curve represent the model response to the variation of soil carbon input values (see Methods). The map represents the ratios of SOC stocks between the 20% of global UAA under organic farming scenario and the baseline, 20 years after conversion to organic farming in the situation where conventional manure surplus is applied on croplands.

Table S8: Soil carbon inputs (PgC) for croplands and grasslands for different levels of organic farming expansion. Ratios between the organic and the baseline are indicated.

		Soil C inputs to croplands			Soil C inputs to grasslands		
		Total	Crop residues	Manure	Total	Grass residues	Manure
	<i>Baseline</i>	2.5	0.34	2.8	17.1	0.33	17.4
20%	<i>REF organic scenario</i>	2.3	0.3	2.6	17.1	0.28	17.4
	<i>Ratio organic/baseline</i>	0.92	0.86	0.92	1	0.86	1
40%	<i>REF organic scenario</i>	2.1	0.25	2.4	17.1	0.24	17.4
	<i>Ratio organic/baseline</i>	0.84	0.72	0.83	1	0.72	1
60%	<i>REF organic scenario</i>	1.9	0.2	2.1	17.1	0.19	17.4
	<i>Ratio organic/baseline</i>	0.77	0.58	0.75	1.01	0.57	1
80%	<i>REF organic scenario</i>	1.7	0.15	1.9	17.1	0.14	17.4
	<i>Ratio organic/baseline</i>	0.69	0.44	0.66	1.01	0.43	1

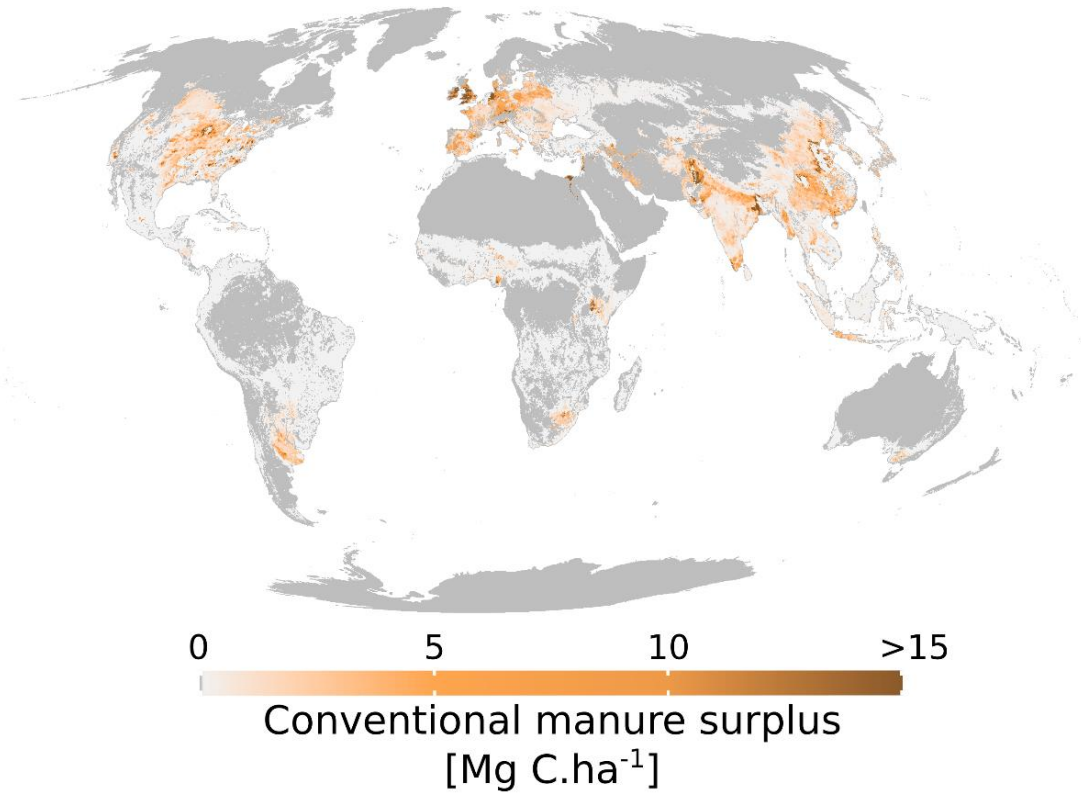


Figure S19: Conventional manure surpluses available for organic croplands (Mg C.ha⁻¹)

Annex III: Changes in GOANIM

Crop and livestock species in GOANIM

Table S9: Different crop and livestock species considered in GOANIM (Barbieri et al., 2021).

Crop species	Livestock species
Alfalfa, Apple, Banana, Barley, Bean, Broadbean, Buckwheat, Cabbage, Cashew, Cassava, Chickpea, Clover, Cocoa, Coconut, Coffee, Cotton, Cowpea, Forages n.e.s., Fruit n.e.s., Grape, Grass n.e.s., Groundnut, Legume n.e.s., Lentil, Linseed, Maize, Maize forage, Mango, Millet, Mixed grass, Oats, Oil palm, Oilseed forage, Olive, Onion, Orange, Pea, Pigeonpea, Plantain, Potato, Pulse n.e.s., Rapeseed, Rice, Rubber, Rye, Sesame, Sorghum, Soybean, Sugar beet, Sugarcane, Sunflower, Sweet potato, Tea, Tobacco, Tomato, Triticale, Vegetable n.e.s., Vetch, Watermelon, Wheat, Yam	Dairy cattle, Meat cattle, Dairy goats, Meat goats, Dairy sheep, Meat sheep, Pigs, Poultry broilers, Poultry layers,

Nitrogen fluxes update

The estimation of N fluxes in the first version of GOANIM (GOANIM V1, (Barbieri et al., 2021)) was based on the 2006 IPCC guidelines. The latest GOANIM version (GOANIM V2) has been updated to the latest IPCC guidelines (2019) by modifying the default values as follows. *First*, we changed all default direct N₂O emission factors from N application on croplands. We also changed the fraction of this N applied on cropland that volatilise and leach by using the updated coefficient (Table S10).

Table S10: Comparison of default values for direct N₂O emissions, N volatilisation and N leaching coefficient between the 2006 and 2019 IPCC guidelines (IPCC, 2019c).

	Unit	IPCC 2006	IPCC2019
Direct N ₂ O emissions factor EF ₁	Synthetic fertilisers in wet climates		0.016
	Organic fertilisers in wet climates	kg N ₂ O-N.kg N ⁻¹	0.006
Direct N ₂ O emissions factor EF ₁ (flooded rice)	All fertilisers Dry climate		0.005
	Continuous flooding		0.003
Fraction that volatilises	Single and multiple drainage	kg N ₂ O-N.kg N ⁻¹	0.003
	Synthetic fertilisers	(kg NH ₃ -N + NO _x -N). kg N ⁻¹	0.1
Fraction that leaches	Organic fertilisers		0.2
		kg N.kg N ⁻¹	0.3

Second, we updated the default values of manure repartition between management systems using the table 10A.6 of the 2019 IPCC guidelines (IPCC, 2019b). *Finally*, we update the amount of N lost according to each management systems using updated direct N₂O default emissions factors from N managed. We also changed the fraction of this N applied on cropland that volatilise and leach by

using coefficient retrieved from table 10.21 and table 10.22 of the 2019 IPCC guidelines (IPCC, 2019b), respectively. We also accounted for direct N₂ emissions using emission factors retrieved from table 10.23 of the 2019 IPCC guidelines (IPCC, 2019b).

Changes in livestock feeding rations, productivity and nitrogen excretion.

In **Chapter I** (Gaudaré et al., 2021), we found that organic feed ration for dairy cattle was composed 40% less concentrate compared to conventional farming (**table S2**). We also assumed that this difference observed for dairy cattle production could be applied for all ruminant species. To account for this difference, we used the following equations (**Equation S7** to **Equation S10**).

$$\text{Equation S7 } \%G_{org} = \%G_{conv} * 0.6$$

$$\text{Equation S8 } \%F_{org} + \%S_{org} = \%F_{conv} + \%S_{conv} + \%G_{conv} * 0.4$$

$$\text{Equation S9 } \%F_{org} = (\%F_{org} + \%S_{org}) * \frac{\%F_{conv}}{\%F_{conv} + \%S_{conv}}$$

$$\text{Equation S10 } \%S_{org} = (\%F_{org} + \%S_{org}) * \frac{\%S_{conv}}{\%F_{conv} + \%S_{conv}}$$

Where $\%G_{org}$ and $\%G_{conv}$ represents the share of grains (i.e. concentrates, as defined in GOANIM) in the total feed ration, $\%F_{org}$ and $\%F_{conv}$ represents the share of forages in the total feed ration and $\%S_{org}$ and $\%S_{conv}$ represents the share of stovers in the total feed ration of organic and conventional ruminant livestock, respectively.

In **Chapter I**, we also found a 5% lower productivity for organic livestock compared to conventional livestock. To account for this difference we used **Equation S11** for all livestock species (with the exception on of poultry broilers).

$$\text{Equation S11 } Prod_{org} = Prod_{conv} * 0.95$$

Due to a longer lifespan, we also found that organic poultry broilers have a lower feed use efficiency. To account for this results, we increased their energetic requirement using **Equation S12**

$$\text{Equation S12 } E_{req,org} = E_{req,conv} * 1.85$$

Similarly to the yield max definition in the first GOANIM version (Barbieri et al., 2021), we assumed that the changes mentioned above were only applicable for countries with high agricultural performances – meaning where current agricultural yields were at least 75% of the potential yield (**Table S11**).

Table S11: List of developed and developing countries considered in the modifications relative to the livestock production.

Countries where modifications were applied	Other countries
Afghanistan, Argentina, Australia, Austria, Bangladesh, Belgium, Belize, Benin, Bhutan, Bolivia, Brazil, Brunei Darussalam, Burkina Faso, Cambodia, Cameroon, Canada, Chad, Chile, China, Colombia, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Democratic People's Republic of Korea, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, French Guiana, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea Bissau, Guyana, Honduras, Hungary, Iceland, India, Indonesia, Iran (Islamic Republic of), Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Lebanon, Liberia, Libya, Macedonia, Madagascar, Malaysia, Mali, Mauritania, Mexico, Montenegro, Morocco, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Republic of, Korea, Russian Federation, Saudi Arabia, Senegal, Serbia, Sierra Leone, Slovakia, Slovenia, Somalia, South Africa, Spain, Sri Lanka, Sudan, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Thailand, Timor-Leste, Trinidad and Tobago, Turkey, Uganda, United Arab Emirates, United Kingdom, United Republic of Tanzania, United States of America, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zimbabwe	Albania, Algeria, Angola, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Bulgaria, Burundi, Central African Republic, Congo, Cote d'Ivoire, Democratic Republic of the Congo, Equatorial Guinea, Eritrea, Estonia, Gabon, Guinea, Haiti, Kazakhstan, Latvia, Lesotho, Lithuania, Luxembourg, Malawi, Mongolia, Mozambique, Nigeria, Puerto Rico, Qatar, Republic of Moldova, Romania, Rwanda, South Sudan, Suriname, Togo, Tunisia, Turkmenistan, Ukraine, Western Sahara, Zambia

Non-productive animals also consume feed and produce manure and, thus participate to both the feed-food competition and cropland fertilization. Therefore, in this latest version of GOANIM, we also accounted for non-productive animals (hereafter called young animals) in livestock energetic requirements (for the 9 livestock species considered in GOANIM). To estimate the livestock energetic requirement, we used **Equation S13** and **Equation S14**.

$$\text{Equation S13 } E_{req} = E_{req,adults} * W_{adults} * (1 + C_{young/adults}) + E_{req,production}$$

$$\text{Equation S14 } C_{young/adults} = Ratio_{young/adults} * \frac{LU_{young}}{LU_{adults}}$$

Where E_{req} ($\text{kcal.heads}^{-1}.\text{yr}^{-1}$) is the annual livestock energetic requirement, $E_{req,adults}$ ($\text{kcal.kg}^{-1}.\text{yr}^{-1}$) is the annual livestock energetic requirement for an adult to maintain its weight, W_{adults} is the weight of an adult (kg.heads^{-1}) and $C_{young/adults}$ is the weight ration of young and adult animals (**Table S12**). $E_{req,adults}$ ($\text{kcal.heads}^{-1}.\text{yr}^{-1}$) is the annual livestock energetic requirement for an adult production. In **Equation S14**, $Ratio_{young/adults}$ is the number of young animals per adult animals and was estimated based on FAOSTAT³ data on total livestock and productive animals populations.

³ <https://www.fao.org/faostat/>

Table S12: Regional values of $C_{young/adults}$.

Region	Cattle		Goats		Sheep		Pigs	Poultry
	Dairy	Meat	Dairy	Meat	Dairy	Meat		
CIS	7%	9%	15%	24%	9%	16%	4%	0%
EAS	22%	27%	17%	19%	5%	8%	4%	0%
EUR	12%	15%	5%	5%	3%	7%	2%	0%
LAM	27%	34%	22%	22%	10%	20%	8%	0%
MNA	6%	7%	8%	8%	4%	6%	8%	0%
NAM	23%	29%	33%	33%	3%	7%	2%	0%
OCE	25%	32%	16%	16%	3%	7%	2%	0%
SAS	22%	28%	13%	13%	8%	13%	12%	0%
SEA	28%	35%	25%	25%	2%	3%	3%	0%
SSA	28%	35%	5%	5%	10%	16%	11%	0%

CIS : Commonwealth of Independent State (Central Asia)
EAS: East Asia
EUR: Europe
LAM: Latin America
MNA: Middle East North Africa
NAM: North America
OCE: Oceania
SAS: South Asian Sub-continent
SEA: South-East Asia
SSA: Sub-Saharan Africa

We also included young animals in the estimation of the livestock N excretion rate using equation **Equation S15**.

$$\text{Equation S15 } N_{excreted} = N_{req,adults} * W_{adults} * (1 + C_{young/adults}) - N_{production}$$

Where $E_{excreted}$ (kg N.heads⁻¹.yr⁻¹) is the annual livestock N excretion rate, $N_{req,adults}$ (kg N.kg⁻¹.yr⁻¹) is the annual livestock N requirement for an adult to maintain is weight, W_{adults} is the weight of an adults (kg.heads⁻¹) and $C_{young/adults}$ is the weight ration of young and adults animals (**Table S12**). $N_{production}$ (kg N.heads⁻¹.yr⁻¹) is the annual livestock N requirement for an adults production.

Fodder availability

In the latest version of GOANIM we also provide more precision on fodder availability, as follows. *First*, there is a maximum grazing intensity – meaning the annual amount of grass removed from grassland by livestock animals – above which permanent grassland exploitation is not sustainable – meaning that there productivity might be reduced (Erb et al., 2016). Therefore, we made the assumption that the grazing intensity of permanent grasslands under organic management would respect a sustainable limit. This limit was set-up using a grazing intensity threshold as defined in (Erb et al., 2016). *Second*, the above-ground biomass of temporary pastures is not entirely cut or grazed by livestock animals and part of this above-ground biomass remain on field (Soussana and Lemaire, 2014). Therefore, we made the assumption that the above-ground biomass of temporary pastures cannot be fully sustainably used as fodder. Based on (Soussana and Lemaire, 2014), we assumed that only 80% of the above-ground biomass produced by temporary pastures was available for livestock feeding. We also assumed that the N in the non-harvested above-ground biomass is in a closed loop – is returned directly to the soil as crop residues, thus reducing the total net N demand of temporary pastures. This assumption was translated in GOANIM by a change in the maximum attainable yield of temporary pastures in organic farming following **Equation S16**.

$$\text{Equation S16 } Yield_{max,update} = Yield_{max} * 0.8$$

Annex IV: Supplementary information for chapter III

Supplementary material

IPCC guidelines

Table S13: Enteric fermentation's emission factors (kg.CH₄.head.yr⁻¹).

Region	Cattle		Sheeps	Goats	Pigs	Poultry
	Dairy	Meat				
Africa	76	52	5	5	1	0
Asia	78	54	5	5	1	0
Eastern Europe	93	58	9	9	2	0
Russia	93	58	9	9	2	0
India	73	46	5	5	1	0
Latin America and Caribbean	87	56	5	5	1	0
North Africa	76	52	5	5	1	0
Middle East	76	60	5	5	1	0
North America	138	64	9	9	2	0
Oceania	93	63	9	9	2	0
Western Europe	126	52	9	9	2	0

GlobAgri-AgT set up.

Table S14: Main categories considered in GlobAgriAgT

Geographic regions	Crop category	Livestock products
Brazil/Argentina	Fibres etc.	Bovine meat
Canada/USA	Fruit and vegetables	Dairy
China	Pulses	Eggs
North Africa	Roots and tubers	Pork meat
Rest of America	Maize	Poultry meat
EU-27	Other cereals	Small ruminant meat
India	Rice	
West Africa	Wheat	
Oceania	Sugar plants and products	
Rest of Asia	Other plant products	
East, Central and Southern Africa	Other products	
Rest of the world	Grass-like forages	
Former Soviet Union	Other forages	
Near and Middel East	Grass	

Intermediate scenarios of organic farming expansions

As mentioned in **Chapter II**, we also explored more realistic scenarios of intermediate conversion to organic farming by redefining $Yield_{i,r}$, $\beta_{l,i,r}$ and $Diet_{f,r}$ using **Equation S17**, **Equation S18** and **Equation S19**, respectively.

$$\text{Equation S17: } Yield_{i,r} = \frac{Yield_{o,i,r} * HA_{o,i,r} * \%org + Yield_{b,i,r} * HA_{b,i,r} * (1 - \%org)}{HA_{o,i,r} + HA_{b,i,r}}$$

Where $Yield_{o,i,r}$ and $Yield_{b,i,r}$ are the yield of crop category i in region r in the REF 100% organic scenario and the baseline, respectively. $HA_{o,i,r}$ and $HA_{b,i,r}$ are the harvested area of crop category i in region r in the REF 100% organic scenario and the baseline respectively. $\%org$ represent the share of the global agricultural lands occupied by organic farming.

$$\text{Equation S18: } \beta_{l,i,r} = \frac{\beta_{o,l,i,r} * Pop_{o,l,r} + \beta_{b,l,i,r} * Pop_{b,l,r} * (1 - \%org)}{Pop_{o,l,r} + Pop_{b,l,r}}$$

Where $\beta_{o,l,i,r}$ and $\beta_{b,l,i,r}$ are the annual input to output ratio for livestock production l , crop category i and region r in the REF 100% organic scenario and the baseline, respectively. $Pop_{o,l,r}$ and $Pop_{b,l,r}$ are the livestock population of livestock production l in region r in the REF 100% organic scenario and the baseline respectively.

$$\text{Equation S19: } Diet_{f,r} = Diet_{o,f,r} * \%org + Diet_{b,f,r} * (1 - \%org)$$

Where $Diet_{o,f,r}$ and $Diet_{b,f,r}$ represents the food demand for each agri-food product f in each region r in the REF 100% organic scenario and the baseline, respectively.

Scenarios of food waste reduction

As reducing food waste in retailing systems and households represent a key lever to improve the global food availability, we explored two scenarios representing a reduction of 50% and 100% of food waste using **Equation S20**.

$$\text{Equation S20: } Diet_waste_reduction_{f,r} = Diet_{f,r} * (1 - \%lost_{retailing,f,r} * \%reduced) * (1 - \%lost_{households,f,r} * \%reduced)$$

Where $Diet_waste_reduction_{f,r}$ represents the food demand for each agri-food product f in each region r with a certain level of food waste reduction. $Diet_{f,r}$ represents the food demand for each agri-food product f in each region r without food waste reduction. $\%lost_{retailing,f,r}$ and $\%lost_{households,f,r}$ represent the share of agri-food product f in each region r lost in retailing and households respectively. $\%lost_{retailing,f,r}$ and $\%lost_{households,f,r}$ were retrieved from (Gustavsson et al., 2013). $\%reduced$ represent the level of food waste reduction – meaning either 50% or 100%.

Supplementary results

Conversion of agricultural lands to organic farming and related GHG emissions

Table S15: Main results of the latest GOANIM version on cropland production, Livestock population and N in farmyard manure.

	Cropland production			Livestock Population			N in farmyard manure		Grasslands used as feed [% of the global NPP]
	Total energy [e+15 kcal]	Food energy [%]	Feed energy [%]	Total population [LU]	Ruminant [%]	Monogastric [%]	Excreted [e+9 kg N]	Applied on croplands [e+9 kg N]	
Baseline	10.9	68%	42%	1089	72%	28%	146	27	10%
REF 100% organic	4.7	90%	10%	346	94%	6%	82	14	5%
Ratio organic/baseline	0.43			0.32			0.56	0.52	

	Total production			Total food production		
	Total energy [e+15 kcal]	Crop based products [%]	Livestock products [%]	Total energy [e+15 kcal]	Crop based products [%]	Livestock products [%]
Baseline	12.7	94%	6%	7.1	89%	11%
REF 100% organic	5.6	97%	3%	4.4	96%	4%
Ratio organic/baseline	0.44			0.61		

	Number of people fed [billions]
Baseline	8.8
REF 100% organic	5.4

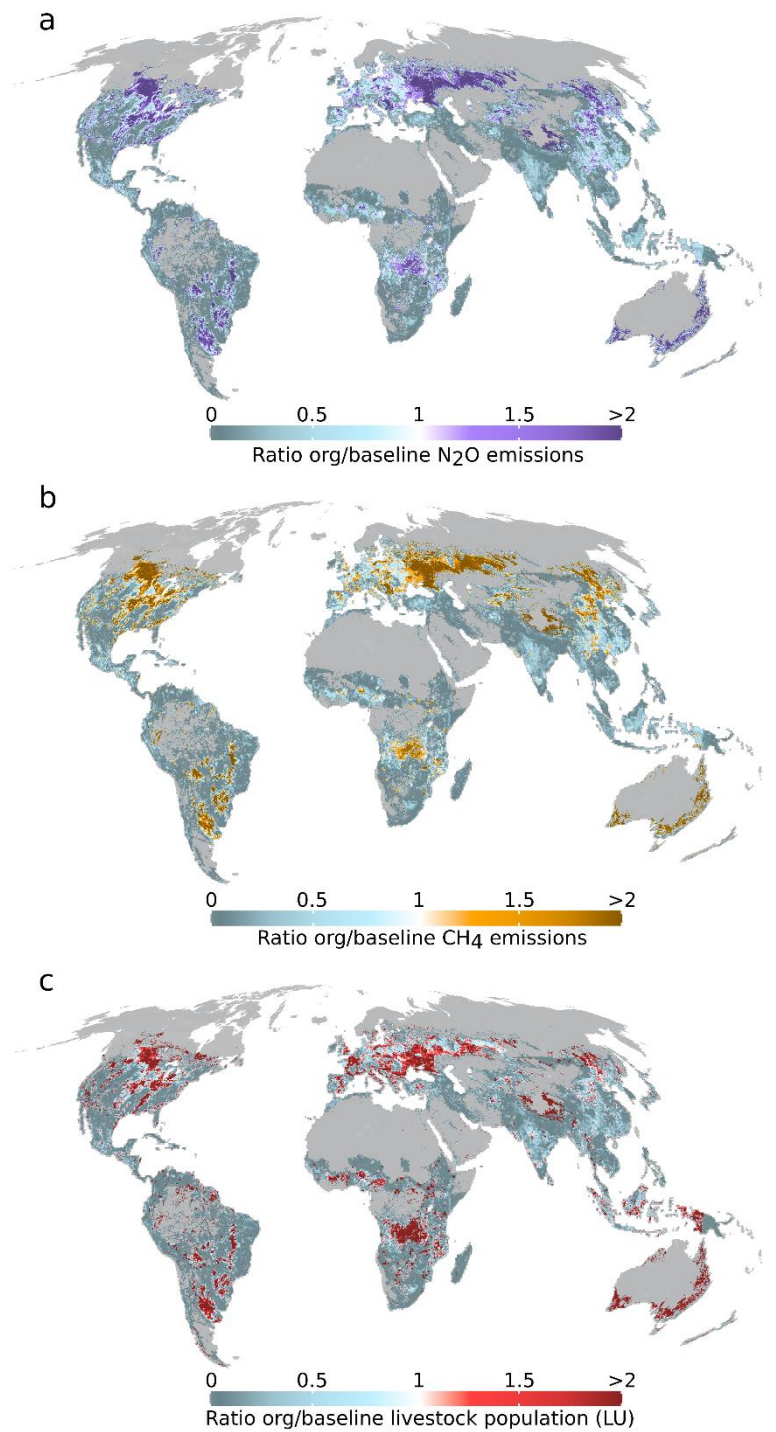


Figure S20: REF 100% organic scenario to baseline ratio of N₂O emissions (a), CH₄ emissions (b) and livestock population (c). N₂O and CH₄ emissions correspond to the sum of the emissions (Gt CO₂eq.ha⁻¹.yr⁻¹) for each of their respective emitting sector. Livestock population corresponds to the sum of the population (expressed in livestock units) of the 9 livestock species considered in the GOANIM model.

Table S16: Composition of the global mean human diet in % of the kcal.cap⁻¹.day⁻¹.

For the 21 food categories in GlobAgriAgT				For 8 categories			
	Baseline	REF 100% organic	Ratio		Baseline	REF 100% organic	Ratio
Bovine meat	1%	1%	0.73	Livestock products	13%	3%	0.22
Poultry meat	2%	0%	0.03	Cereals	53%	52%	0.98
Pork meat	2%	0%	0.02				
Small ruminant meat	0%	1%	1.59	Pulses	4%	14%	4.09
Dairy products	6%	1%	0.20	Fruits and vegetables	8%	3%	0.38
Eggs	1%	0%	0.02	Oilcrops	6%	6%	0.90
Maize	7%	17%	2.53	Sugar plants and products	10%	14%	1.34
Rice	25%	15%	0.59				
Wheat	18%	10%	0.54	Roots and Tuber	5%	5%	0.93
Other cereals	3%	10%	3.21	Others	1%	3%	3.01
Soyabeans products	2%	10%	6.43				
Other pulses	2%	4%	2.18				
Fruits and vegetables	8%	3%	0.38				
Oilpalm products	0%	1%	3.00				
Rape and Mustardseed products	1%	1%	1.05				
Sunflowerseed products	1%	1%	1.07				
Other Oilcrops products	4%	2%	0.62				
Sugar plants and products	10%	14%	1.34				
Roots and Tuber	5%	5%	0.93				
Fibers	0%	0%	0.00				
Other plant products	1%	3%	3.73				

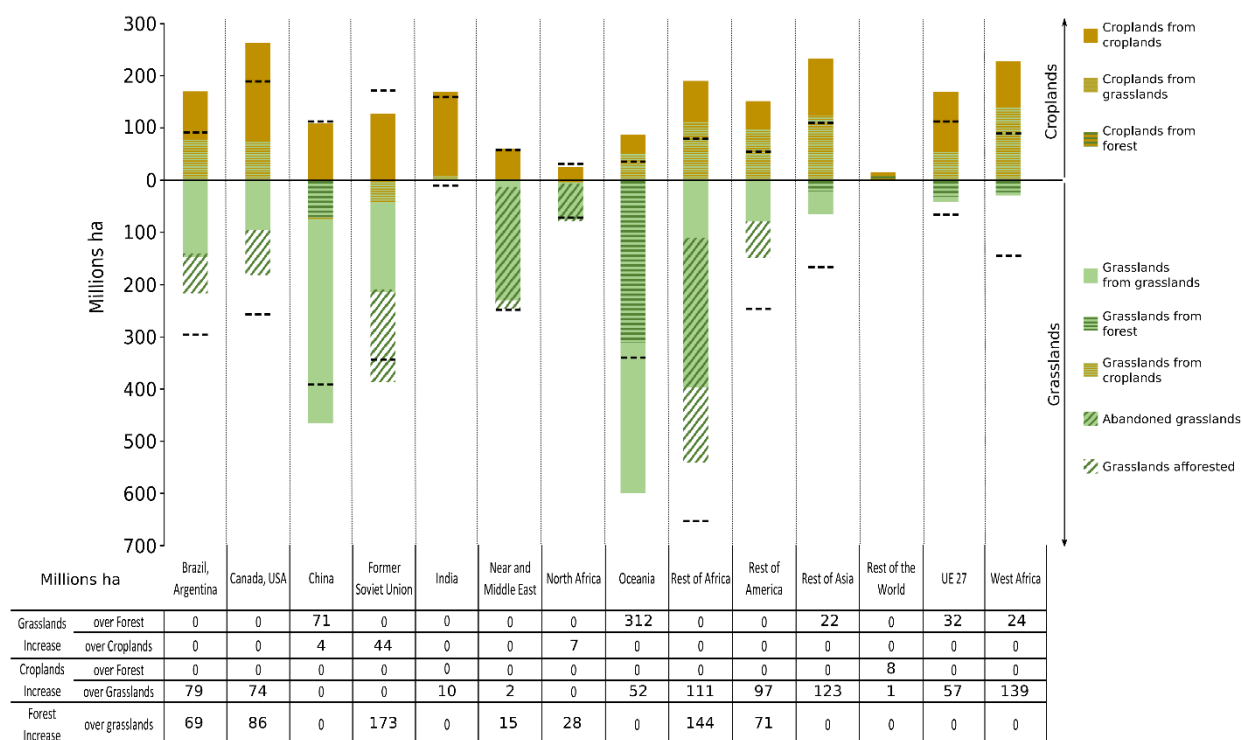


Figure S21: Regional cropland and grassland requirements and land-use changes in the REF 100% diet adapted organic scenario and the baseline. The brown bars represent the cropland requirements (in billion ha) and the green bars the grassland requirements (in billions ha) for both the organic scenario and the baseline. The black dashed lines represent the croplands and grasslands used in the baseline for each region.

Table S17: Regional GHG budget (Gt CO₂eq.yr⁻¹) in the baseline and the REF 100% organic scenario.

Regions	Baseline	REF 100% organic scenario	Ratio	ΔEmissions
Brazil, Argentina	0.6	-0.1	-11%	-0.7
Canada, USA	0.4	0.1	20%	-0.4
China	0.9	1.4	166%	0.6
Former Soviet Union	0.2	-0.9	-523%	-1.1
India	0.7	0.2	31%	-0.5
Near and Middle East	0.1	0.0	-35%	-0.2
North Africa	0.1	0.0	-14%	-0.1
Oceania	0.1	3.4	2507%	3.3
Rest of Africa	0.5	-0.8	-177%	-1.3
Rest of America	0.3	0.1	17%	-0.3
Rest of Asia	0.7	0.9	140%	0.3
Rest of the World	0.0	0.1	537%	0.1
UE 27	0.4	0.9	208%	0.5
West Africa	0.1	0.5	443%	0.4

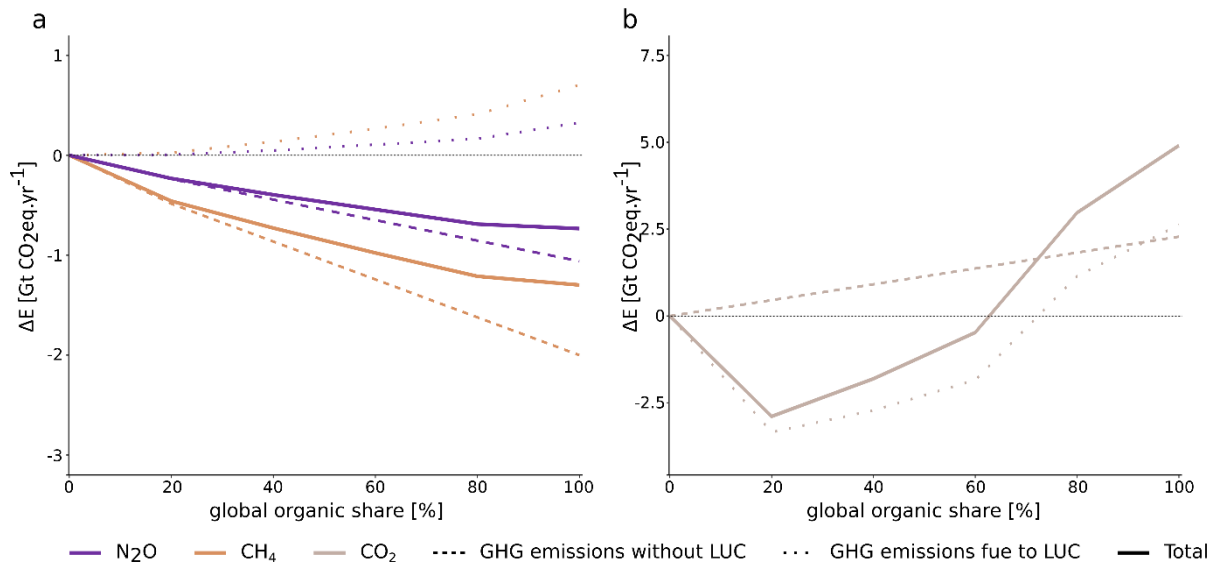


Figure S22: Changes in N₂O, CH₄ (a) and CO₂ (b) emissions between different diet adapted scenarios of organic farming development and the baseline. Purple lines represent N₂O emissions, orange lines represent CH₄ emissions and brown lines represent CO₂ emissions. Dashed lines represent the emissions without land use changes, pointed lines represent the emissions due to land use changes and the full line represent the sum of both.

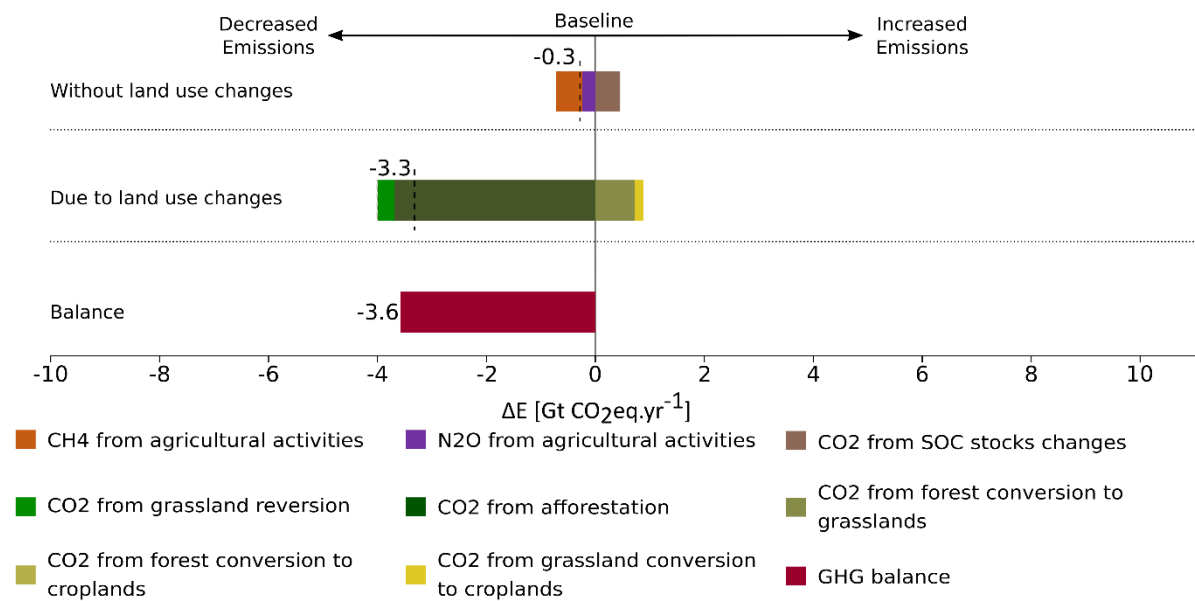


Figure S23: Global changes in the GHG emissions (in Gt CO₂eq.yr⁻¹) of the REF 20% diet adapted organic scenario compared to the baseline. The global change in GHG emissions is decomposed between GHG emissions without and with land-use changes. Full bars represent changes in GHG emissions and striped bars represent corrections due to land-use changes (see Methods).

Table S18: Regional GHG budget (Gt CO₂eq.yr⁻¹) in the baseline and the REF 20% organic scenario.

Regions	Baseline	REF 20% organic scenario	Ratio	ΔEmissions
Brazil, Argentina	0.6	-0.3	-52%	-0.9
Canada, USA	0.4	-0.2	-44%	-0.6
China	0.9	1.3	152%	0.4
Former Soviet Union	0.2	-0.4	-249%	-0.6
India	0.7	0.6	95%	0.0
Near and Middle East	0.1	0.0	13%	-0.1
North Africa	0.1	0.0	35%	0.0
Oceania	0.1	-0.3	-232%	-0.4
Rest of Africa	0.5	-0.5	-114%	-1.0
Rest of America	0.3	-0.2	-65%	-0.6
Rest of Asia	0.7	0.6	85%	-0.1
Rest of the World	0.0	0.0	52%	0.0
UE 27	0.4	0.2	50%	-0.2
West Africa	0.1	0.1	121%	0.0

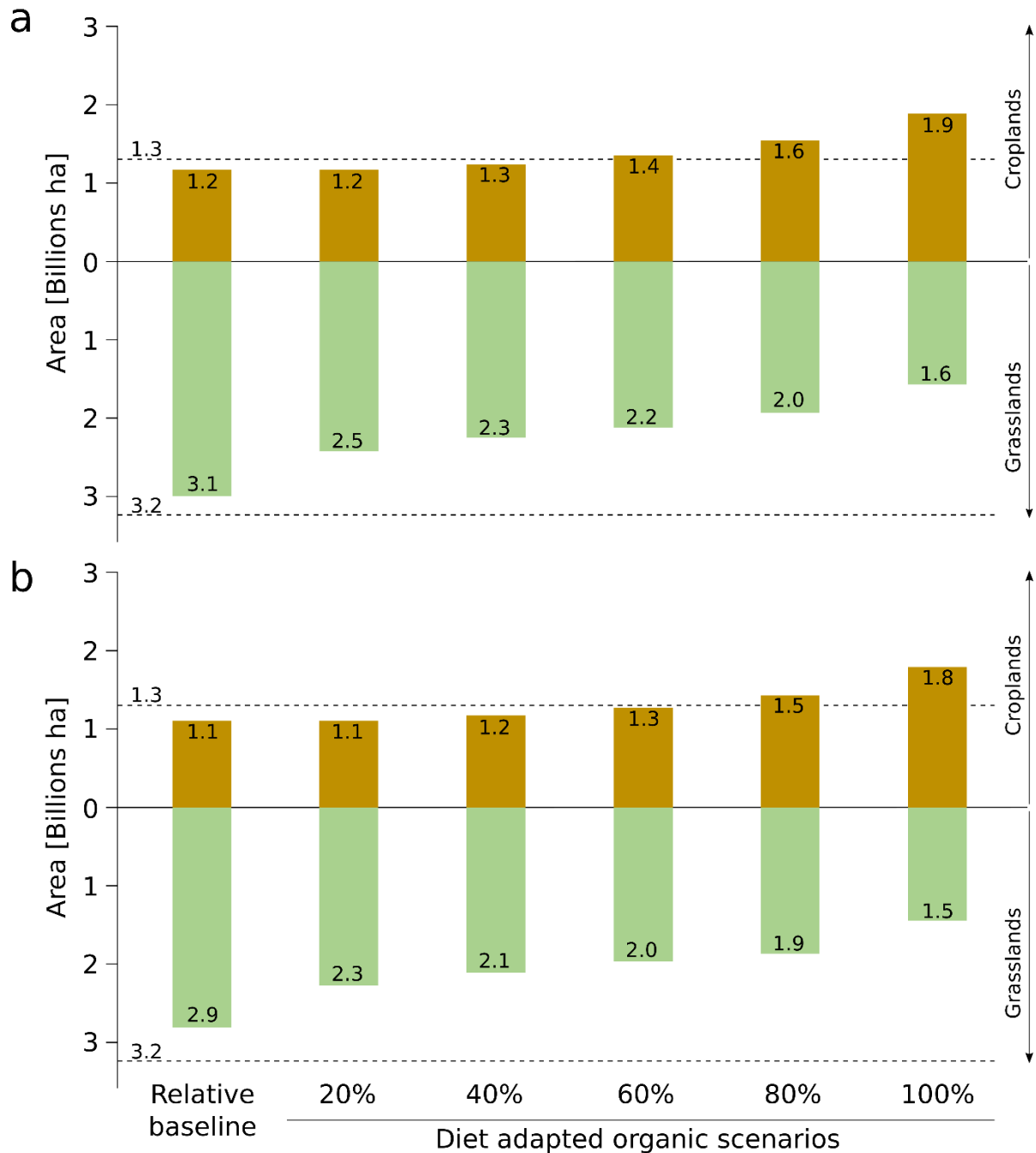


Figure S24: Global cropland and grassland requirements (in billion ha) in the intermediate diet adapted organic farming expansion scenarios and the baseline with 50% (a) and 100% (b) food waste reduction. The brown bars represent the croplands and the green bars the grasslands for both the diet adapted organic scenarios and the baseline. The black dashed lines represent the croplands and grassland used in the baseline. Values in each bar show the absolute value of cropland and grassland requirements in each scenarios (in billions ha).

		Waste Reduction			
		0%	50%	100%	
Diet adapted scenarios	REF organic scenario	20%	-70%	-67%	-32%
		40%	-57%	-50%	-25%
		60%	-39%	-31%	3%
		80%	21%	15%	37%
		100%	56%	37%	36%
25% C organic scenario	20%	-72%	-69%	-34%	
	40%	-62%	-54%	-29%	
	60%	-46%	-37%	-4%	
	80%	12%	6%	28%	
	100%	45%	25%	25%	

Figure S25: Changes in global agricultural GHG net emissions (%) between the diet adapted organic scenarios, food waste reduction scenarios and the relative baselines. In each cell, the value represents the discrepancy in GHG emissions (%) between each scenario and the baseline (bottom left cell with a red frame). The colour indicates GHG increase (red) or GHG decrease (blue) compared to the baseline – the intensity of the colour depends on the distance to the baseline.

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