



Remote sensing-based assessment of the role of climate change, land use and land cover on drought in Nigeria

Pius Nmamdi Nwachukwu

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Pius Nmamdi Nwachukwu. Remote sensing-based assessment of the role of climate change, land use and land cover on drought in Nigeria. Signal and Image processing. Université de Perpignan, 2022. English. NNT : 2022PERP0035 . tel-04032405

HAL Id: tel-04032405

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THÈSE

Pour obtenir le grade de
Docteur

Délivrée par
UNIVERSITE DE PERPIGNAN VIA DOMITIA

Préparée au sein de l'école doctorale

« Énergie Environnement » ED 305

Et de l'unité de recherche

ESPACE DEV

Spécialité : **Sciences Pour l'Ingénieur**

(Applied Remote Sensing)

Présentée par : **Pius Nnamdi NWACHUKWU**

Remote sensing-based assessment of the role of climate change, land use and land cover on drought in Nigeria

Soutenue le 13 décembre 2022, devant le jury composé de

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Declaration

I hereby declare that, except where specifically cited, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification at this or any other university. Parts of this thesis have been published in journals as a pre-requisite for my graduation as a first author. This dissertation is entirely my work and contains nothing that is the result of previous work by any other person(s). This dissertation contains equations, figures and tables. All figures that I do not exclusively develop have been referenced, and sources declared.

Pius Nnamdi Nwachukwu

Dedication

This thesis is dedicated to the following people;

-To the late Prince Pius Nwachukwu Anaba, who saw the vision and laid the foundation for this achievement but unfortunately could not witness the end. As the saying goes, what the trunk could not do, let the branches do.

-To Joy (2nd in Command) for standing by and witnessing the whole troubles and struggles.

-To Eze, who made the beginning a possibility

-To Nolan, Ian and Coral for their inspiration

-To Caroline, who supported me with prayers

Acknowledgments

This thesis is a result of research carried out at the Laboratory of ESPACE-DEV, University of Perpignan Via Domitia, with full support and funding from the Petroleum Technology Development Fund, through the Federal government of Nigeria.

First, my sincere gratitude goes to my supervisor Professor Samira El Yacoubi, and my co-supervisors, Dr Marie-Paul Bonnet and Dr Frederic Sàtge, for their support, constructive criticisms and for always compelling me to seek more knowledge.

I appreciate my wife, who has been my closest friend, and who took care of our children alone while I was away. On numerous occasions, you adjusted to sleeping with pieces of paper on our bed and always reminded me of how far I could go, you are always in my heart.

I must appreciate my brother Eze Nwachukwu who set the standard that I am striving to reach. You will forever be in my mind. My heartfelt gratitude goes to the Director of the National Centre for Remote Sensing (NCRS) Jos, Dr E.N Gajere, for not having any doubt in me and facilitating my approval to embark on a staff development leave.

Accepting that no piece of this work is produced in isolation, I must appreciate the staff and students at the ESPACE-DEV, University of Perpignan, who provided all sorts of support. On a special note, I express my profound gratitude to the staff members of the doctoral school (Energy and Environment) who always provided answers to my numerous challenges.

My family members helped in countless ways. The support from my sisters – Adaku Anaba, Josephine Orji, Uchenna Nwogu, Edith Anaba, and Odinakachi Anaba.

And finally, to those who do not believe in me, your doubts helped me attain this level.

Table of Contents

1	Résumé	1
1.1	Aperçu de la télédétection pour l'évaluation hydrologique	1
1.2	Variabilité climatique végétation et stress hydrique	3
1.3	Le contexte de l'impact du changement climatique sur l'hydrologie évaluation du système	6
1.4	Évaluation hydrologique et du changement climatique dans cette thèse . .	8
2	Abstract in English	11
2.1	Overview of Remote Sensing for Hydrologic Assessment	11
2.2	Climate Variability Vegetation & Water Stress	13
2.3	The context of Climate Change Impact on Hydrologic System Assessment .	16
2.4	Hydrologic & Climate change Assessment in this thesis	17
3	Introduction	23
3.1	Overview	23
3.2	Remote Sensing (RS) capabilities	23
3.3	Climate Change Impact on Hydrology & Water Resources	27
3.4	Land Use / Land Cover & Drought from Climate Change Perspective . . .	29
3.5	Statement of the problems	31
3.6	Scope of this thesis	33
3.7	Aim & Objectives of the study;	34
3.8	Study Area	35
3.9	Dissertation structure	39
4	State of the Art	49
4.1	Overview	49
4.2	Hydrological Systems & Climate Drivers	49
4.2.1	Atmosphere	52
4.2.2	Land surfaces	53
4.2.3	Oceans	55

4.3	The climate change	56
4.4	Evapotranspiration	59
4.4.1	Methods for Estimating Evapotranspiration	61
4.4.2	Energy Balance Bowen Ratio (EBBR)	63
4.4.2.1	Eddy covariance (EC)	66
4.4.2.2	Lysimetry	67
4.4.2.3	Scintillometer	67
4.5	Remote Sensing-Based Drought Monitoring	69
4.5.1	Active microwave observations	70
4.5.2	Passive microwave observations	72
4.5.3	Land Uuse & Land Cover in Climate Change & Drought	74
4.6	Current Trends on Hydrological Assessment for Drought Identification . . .	76
4.6.1	Assessing Climate Change Impact on Hydro-ecology	79
4.6.2	Assessing Anthropogenic Impacts	83
4.6.3	Earth Observation in Hydro-ecologic Studies	84
4.6.4	Process Based Hydrological in Assessment	85
4.6.5	Artificial Intelligence Hydrological Studies	86
4.7	Drought Impacts in Sub-Saharan Africa	86
4.7.1	Conclusion	88
5	Validation of Satellite Precipitation Products for Rainfall Analysis in Nigeria	113
5.1	Overview	113
5.2	Introduction	114
5.2.1	Precipitation Monitoring across Remote Regions	114
5.2.2	Satellite-Based Precipitation Estimate Prospect	114
5.2.3	Toward a Broad Overview of Satellite-Based Precipitation Reliability across Nigeria	116
5.2.4	Study Objectives	117
5.3	Materials	117
5.3.1	Rain Gauge Observations	117
5.3.2	Brief Descriptions of the Satellite-Based Precipitation -Products . .	118

5.4	Methods	122
5.4.1	Database Pre-Processing	122
5.4.2	SPP Assessment	122
5.5	Results	123
5.5.1	SPP Reliability on the National Scale	123
5.5.2	SPP Reliability for Different Climatic Regions	126
5.6	Discussion	132
5.6.1	Long-Term SPPs for Precipitation Trend Analysis	132
5.6.2	Enhancement from TRMM to GPM SPPs	133
5.6.3	Towards an Enhanced Precipitation Dataset over Nigeria	135
6	Time Series Drought Assessment Across Nigeria	145
6.1	Overview	145
6.2	Introduction	146
6.3	Materials & Methods	149
6.3.1	Dataset	149
6.3.2	Detecting Precipitation Trend	151
6.3.3	SPI and SPEI drought indices	152
6.3.3.1	Standardised Precipitation Index (SPI)	152
6.3.4	Standardised precipitation evaporation index (SPEI)	154
6.3.4.1	Drought Identification	155
6.4	Results	157
6.4.1	MK Trend	157
6.4.2	Temporal Variation Between the SPI and SPEI	157
6.4.3	Monthly Variations in the SPI and SPEI	162
6.4.4	Extreme Droughts at Point Locations	163
6.4.5	Spatial Distribution of the SPI and SPEI Trends	166
6.4.5.1	SPI	166
6.4.5.2	SPEI	171
6.5	Discussion	171
6.5.1	Characterisation of Drought severity	171
6.5.2	SPI and SPEI distribution cross the ecological zones	173

6.6	Conclusion	175
7	Sensitivity of Evapotranspiration Across Nigeria	187
7.1	Overview	187
7.2	Introduction	188
7.3	Study Area, Materials & Methods	191
7.3.1	Data Description & Methodology	191
7.3.1.1	Climate dataset	191
7.3.2	Data Processing	195
7.3.3	Trends Analysis & Statistical Test	196
7.3.3.1	Theil-Sen Formula Slope	197
7.4	Results and Discussion	197
7.4.1	(Overview of Nigerian Climate Pattern	197
7.4.2	Climatic Trend on the National Scale	198
7.4.3	Climate Trend at the Pixel Level	200
7.4.4	ET sensitivity to other climate variables	204
7.4.5	Mann-Kendall Trend Severity on Land Use Classes	205
7.4.6	ET Pattern with Major Influencing Variables	205
7.5	Conclusion	208
8	General Conclusions	217
8.1	Overviews	217
8.1.1	Remote Sensing Capabilities	218
8.1.2	From Climate Change Perspective	220
8.1.3	Drought Propagation	222
8.2	Challenges, Future Work & Perspectives	223
A	List of Abbreviations	I

List of Figures

1	A schematic diagram showing the ability of remote sensing to monitor climate from space. Adapted from Yang et al. (2013)	24
2	Illustration of passive vs active remote sensing with different platforms. Adapted from Thenkabail (2018)	25
3	A location map of Nigeria showing the ecological zones. Precipitation amount varies from the Guinea Savannah/Rain forest region with a high volume of precipitation most part of the year to the Sahel region with scanty precipitation; source: The author.	35
4	Map of Nigeria showing the digital elevation model; source: The author.	36
5	Map of Nigerian showing precipitation distribution; source: The author.	37
6	Map of Nigeria showing temperature distribution; source: The author.	38
7	Water cycle showing the hydrologic cycle components. Adapted from https://water.ca.gov/library/modeling-and-analysis/	51
8	Electromagnetic spectrum (EMS) showing the different sections of the spectrum. The microwave region is from 0.1cm to 1m. Adapted from; https://geolearn.in/microwave-remote-sensing/	71
9	A map of Nigeria showing the locations reference meteorological stations	118
10	Mean yearly precipitation	120
11	Box plot of KGE and statistical summary	125
12	KGE values obtained at the grid cell level of all the SPPs	126
13	R scores obtained at the grid cell level of all the SPPs	128
14	The β values obtained at the grid cell level for all SPPs	129
15	The Vr values obtained at the grid cell level for all SPPs	130
16	Median KGE values obtained from all the grid cells	133
17	Comparative display of TRMM and GPM product performance at the gauge locations	134
18	Output of the best product in each location	134
19	Annual average precipitation of 9 stations in annual spread across the ecological zones (Sahel, Sudan and Guinea/Rainforest) of the study area within the period 1981–2020.	158
20	SPI plots showing the duration and magnitude of drought across Nigeria	159

21	SPEI plots showing the duration and magnitude of drought across Nigeria	160
22	Statistical description of SPEI and SPI distribution. σ =standard deviation; μ = mean	161
23	Forty-year SPEI & SPI analysis from 9 locations selected according to different latitudes and longitudes, as well as the ecological zones covering Nigeria.	165
24	Nigeria's SPI distribution on 3-, 6-and 12-months timescale in 1982	167
25	Nigeria's SPI distribution on 3-, 6-and 12-months timescale in 1983	168
26	Nigeria's SPEI distribution on 3-, 6-and 12-months timescale in 1982	169
27	Nigeria's SPEI distribution on 3-, 6-and 12-months timescale in 1983	170
28	Heat map showing the concentration and severity of extreme drought events	172
29	Spatial pattern of the mean monthly and seasonal ET, temperature, precipitation, solar radiation and wind speed during the period (1981-2020).	194
30	Monthly and seasonal hydroclimatic variability. (a) Temperature (b) Evapotranspiration; (c) Precipitation (d) Solar radiation & (e) Wind speed. The blue trend lines and confidence interval represents the monthly trend, while the green and purple indicates Dry and Wet season, respectively	200
31	Mann-Kendall Trend result showing the magnitude of positive trends in slope. Row (a) is the interannual magnitude of the variables; (b) is the magnitude of positive trends in the dry season; (c) is the magnitude of the trends in the wet season	202
32	Percentage of the positive trends from the climatic variables on different land use classes	206

List of Tables

4.1	Global Water Resources Allocation. Source: Gleick (1996)	52
5.1	Summary of main characteristics and references of the SPPs	121
6.1	SPI and SPEI classification and categories	156
6.2	Extreme droughts events	163
6.3	Means of extreme and severe droughts from the indices at the point locations	163
7.1	Summary of main characteristics and references of the climatic datasets . .	193
7.2	Summary of positive Mann-Kendall Trend on land use and land cover clas- sification	205

Résumé

1.1 Aperçu de la télédétection pour l'évaluation hydrologique

La télédétection dans le contexte de l'observation de la Terre consiste à mesurer l'énergie émise et rayonnée par la Terre à l'aide d'un rayonnement électromagnétique pour recueillir des informations sur la surface et le sous-sol. La mesure à travers le spectre électromagnétique permet une grande variété de mesures sur plusieurs sections du spectre électromagnétique. Les mesures de télédétection à partir de satellites dépendent de deux principaux types de capteurs utilisés dans la collecte de données, tels que les capteurs passifs et actifs. Les interactions entre les surfaces et les capteurs passifs/actifs seront différentes selon les surfaces observées. Les capteurs passifs détectent la lumière du soleil réfléchie par les surfaces de la Terre ou le rayonnement thermique naturellement émis par les objets. Les capteurs actifs génèrent leur énergie électromagnétique et la transmettent à la cible étudiée. Cette capacité permet d'effectuer des mesures qui pénètrent dans les nuages et dans l'obscurité loin de l'énergie du soleil.

Fait intéressant, les applications de télédétection par satellite mettant l'accent sur l'hydrologie de la surface terrestre ont été introduites par le lancement réussi du premier satellite de technologie des ressources terrestres (Landsat-1). Le développement de techniques d'évaluation des états et des flux hydrométéorologiques a été l'un des principaux axes de la recherche en télédétection liée à l'hydrologie. La surveillance des événements hydroclimatiques tels que la sécheresse à l'aide d'une estimation par satellite passif

à micro-ondes est basée sur la faible émissivité des masses d'eau. Cela est dû aux différences de propriétés diélectriques entre l'eau et le sol ou la végétation, en particulier aux basses fréquences. La combinaison de données provenant de plusieurs gammes spectrales a ouvert de nouvelles opportunités pour développer des méthodologies produisant des données hydroclimatiques globales. Les revendications de la combinaison active et passive de la télédétection dans le but de surveiller l'humidité du sol Babaeian et al. (2018).

Plus précisément, dans les études liées à l'hydrologie, l'énergie solaire réfléchie est utilisée pour des études sur la qualité de l'eau ainsi que pour la cartographie de la neige, l'analyse de la végétation et de la couverture terrestre. De plus, l'humidité du sol et la neige utilisent l'émission thermique dans les micro-ondes et l'infrarouge pour la température de surface. La télédétection permet une mesure et une analyse simultanées en temps réel de la surface tout en obtenant des informations sur la variabilité spatiale et temporelle. La télédétection par satellite permet une surveillance continue à l'échelle mondiale, tandis que les observations terrestres conventionnelles sont généralement effectuées à intervalles réguliers avec une couverture spatiale limitée.

Les techniques de télédétection et les applications et la modélisation de la télédétection par satellite pour la gestion de l'environnement se sont améliorées ces dernières années. L'intégration de différentes techniques telles que l'intelligence artificielle (IA) et les approches d'apprentissage automatique dans l'interprétation des données de télédétection n'a fait qu'améliorer la convivialité des produits de télédétection à diverses fins environnementales. De plus, les progrès dans le développement des capteurs ont également amélioré la détection, en utilisant des capteurs à haute résolution spectrale. Ils sont parfaits pour surveiller les phénomènes spatiaux, en particulier les événements très variables tels que les précipitations, l'évapotranspiration, l'humidité du sol, les sécheresses et les inondations.

La télédétection a permis des avancées significatives dans la compréhension du système climatique et de ses changements en mesurant et quantifiant les processus et les états spatio-temporels de l'atmosphère, des terres et des océans. Notre compréhension du système climatique et de ses changements s'est considérablement améliorée grâce aux capacités et aux produits de télédétection. Dans les études sur le changement climatique, la télédétection par satellite est essentielle aux observations du système climatique. Il per-

met la collecte de données sur la surface, le sous-sol et l'atmosphère de la Terre à distance grâce à des capteurs embarqués sur des satellites. La couverture géographique mondiale et à petite échelle inégale des observations satellitaires permet d'obtenir de nouvelles informations. L'utilisation de satellites permet de surveiller les conditions et les processus atmosphériques, terrestres et océaniques à diverses échelles spatio-temporelles. La télédétection est également utile pour développer des modèles climatiques. Par exemple, les données climatiques satellitaires sont régulièrement utilisées pour recréer la dynamique du système climatique et améliorer les projections climatiques. Cela est dû à leur acceptabilité générale et à leur fiabilité à fournir les informations nécessaires aux modèles climatiques. Ainsi, contribuer de manière significative à notre compréhension du système climatique est basé sur des données d'observation et des simulations de modèles. En plus de mesurer les fluctuations climatiques et les états spatio-temporels de l'atmosphère, des terres et des océans.

1.2 Variabilité climatique végétation et stress hydrique

La variabilité climatique affecte le système hydrologique pour qu'il soit dynamique sur une gamme d'échelles de temps, exerçant une pression sur le système dans le passé par des situations d'inondation et de sécheresse. Les effets de la variabilité climatique actuelle peuvent être exacerbés par le réchauffement climatique anthropique. Les émissions de gaz à effet de serre aggravent le changement climatique et que ce changement ou cette oscillation des modèles climatiques aura un impact significatif sur les conditions environnementales futures. Plusieurs rapports indiquent que le cycle hydrologique est l'une des composantes physiques mondiales qui seraient touchées par le changement climatique Bai et al. (2019); Tabari (2020). D'autres impacts négatifs ont déjà été enregistrés à travers le monde Margaryan et al. (2022); Yang et al. (2019); Visser et al. (2019). Les altérations des processus des composants du cycle hydrologique ont entraîné une modification des régimes de précipitations et une augmentation de l'évapotranspiration due à un réchauffement accru. Modifiant ainsi la dynamique au sein de l'écologie et de l'hydrologie. Ce changement dans la dynamique du système écologique détermine la quantité d'humidité que les plantes peuvent extraire des sols profonds et supérieurs et en-

suite transpirer l'humidité dans l'atmosphère. De même, l'augmentation des températures continue de battre des records mondiaux, les précipitations, les tempêtes, les ouragans plus violents, les inondations submergeant les villes, les incendies de forêt, la famine, les sécheresses et l'assèchement des lacs et des rivières sont quelques-uns des impacts négatifs du changement climatique. En outre, l'intensification de l'érosion des sols côtiers due aux précipitations de forte intensité et à l'élévation du niveau de la mer augmente dans le monde entier. Le changement climatique naturel résultant de l'augmentation de la température augmente le taux d'évaporation et de transpiration. Cependant, ils sont plus difficiles à améliorer.

Par conséquent, il est prévu que la portée géographique des impacts puisse s'étendre. Les tendances actuelles devraient augmenter en intensité, comme les zones subissant une tendance à l'assèchement en raison du changement climatique. L'extraction de l'eau à usage humain devrait connaître une nouvelle pénurie d'eau.

Comprendre la contribution anthropique et naturelle est essentiel pour proposer des solutions et évaluer l'impact du changement climatique sur le système hydrologique. La contribution anthropique diffère des contributions naturelles. La contribution anthropique comprend la construction sur les canaux et les trottoirs, la réduction des forêts et l'extraction de plus d'eau que la production nécessaire de gaz à effet de serre (GES) qui contribuent de manière significative à l'augmentation de l'ET Talebmorad et al. (2021); Menzel et Bürger (2002) et augmentation de la température Cassia et al. (2018). Fait intéressant, il a été suggéré que la réduction du changement climatique anthropique pourrait atténuer l'impact naturel du changement climatique Bjelle et al. (2018); Takemura et Suzuki (2019); Gu et al. (2018). Cependant, la recherche pour quantifier la dynamique et les déterminants environnementaux de la variation des systèmes hydrologiques est généralement complexe. L'une des raisons est que plusieurs mesures sont nécessaires à partir des nombreuses variables qui contribuent à l'impact de l'hydrologie sur le changement climatique. Des études opportunes et continues peuvent contribuer à la détection précoce des tendances hydrologiques. L'observation et le calcul de divers facteurs, tels qu'un changement dans la tendance des précipitations, qui ont un impact sur d'autres variables telles que les eaux souterraines, permettent aux scientifiques et aux analystes environnementaux de suggérer ou de concevoir une stratégie d'atténuation. Par con-

séquent, la mesure des différences spatio-temporelles en hydrologie sur une large gamme d'échelles géographiques est impérative pour améliorer la compréhension et la gestion hydrologiques.

Le rôle de la végétation dans l'évapotranspiration, la condensation et la quantité de précipitations a été documenté par Hesslerová et al. (2019). Un phénomène directement lié à la quantité d'humidité transpirable. Il existe des preuves que la quantité de précipitations s'est améliorée dans les zones de grande couverture végétale dense par rapport aux zones avec moins de couverture végétale. Wang et al. (2020); Duncan et al. (2019); Spracklen et al. (2018).

L'évapotranspiration est au cœur du cycle hydrologique en raison de sa capacité à représenter la disponibilité en eau et la demande en eau atmosphérique. L'augmentation de l'évapotranspiration et la diminution des précipitations sont les pires scénarios pour l'approvisionnement en eau Bormann (2005); Abtew et Melesse (2013) ; Rajabi et al. (2022). L'augmentation de la température, de l'humidité, du rayonnement et de la vitesse du vent entraînera une variabilité accrue et élevée de l'évapotranspiration. En d'autres termes, il ne fait aucun doute que l'évapotranspiration et les précipitations jouent un rôle vital dans la subsistance de l'écosystème. Ces impacts sont imputables au lien intrinsèque entre les précipitations qui tombent sur le sol, l'infiltration profonde dans les eaux souterraines, le ruissellement et les pertes par évaporation et transpiration.

Ce qui précède est modifié à un rythme alarmant par les activités anthropiques et naturelles. Cependant, ces dynamiques spatio-temporelles interconnectées dans l'interaction hydrologique déterminent dans une plus large mesure la disponibilité de l'humidité. Notamment, la dégradation inévitable de l'environnement, comme les sécheresses, commence après des périodes prolongées sans précipitations. Dans cet événement, l'écologie et l'hydrologie (écohydrologie) se combinent pour soutenir la biodiversité en fournissant un environnement stratégique bénéfique pour la prospérité des plantes et des animaux. Alors que la recherche sur l'interaction hydrologique augmente, des appels stridents ont été lancés pour une meilleure reconnaissance et des politiques d'atténuation visant à réduire le réchauffement climatique anthropique qui aggrave le changement climatique.

Un fait saillant du changement climatique est sa capacité à induire des fluctua-

tions de température. Une augmentation de la température, une diminution de l'humidité et une diminution des précipitations contribuent à stimuler l'évapotranspiration. Cependant, lorsque ces phénomènes se prolongent pendant de longues périodes, un impact négatif commence à se manifester dans l'environnement. L'augmentation de la température rend les plantes et les sols arables susceptibles de dépasser leur fléau de tolérance, ce qui entraîne souvent la mort des plantes et la dégradation de l'environnement. L'interconnexion naturelle hydrologique a rendu difficile l'étude isolée. Une étude holistique prenant en compte toutes les composantes d'un système écohydrologique est souvent nécessaire pour comprendre les relations et l'influence de chaque variable sur les autres. Le « continuum sol-plante-atmosphère » (SPAC) est un concept crucial dans les études sur l'utilisation de l'eau par les plantes. Wood et al. (2008). Fait intéressant, presque tous les composants hydrologiques individuels peuvent être mesurés isolément. Cependant, la mesure simultanée de plusieurs variables est encouragée. Une longue période de mesure est également nécessaire pour étudier l'influence de facteurs tels que les saisons. Par conséquent, le changement climatique hydrologique met l'accent sur certains aspects des interactions entre les arbres forestiers et l'hydrologie, en particulier la transpiration.

1.3 Le contexte de l'impact du changement climatique sur l'hydrologie évaluation du système

La mesure de l'impact climatique sur l'hydroécologie est difficile en raison de leurs dépendances interconnectées, parfois difficiles à isoler. Les mesures peuvent être effectuées à l'aide d'équipements au sol ou d'observations par satellite. Les variables hydrologiques et hydroclimatiques peuvent être mesurées in situ. Certaines pratiques de mesure traditionnelles incluent l'utilisation d'une station météorologique avec un thermomètre, un pluviomètre, une jauge d'état-major et une jauge à crête, un évaporimètre, etc. La méthode de covariance d'Eddy s'est avérée être la mesure au sol la plus fiable de l'évapotranspiration. L'évapotranspiration peut également être estimée à l'aide de méthodes bien planifiées basées sur des processus en mesurant des variables associées telles que le rayonnement solaire. De même, Penman (1948), Thornthwaite (1948), Hargreaves et Samani (1982) et d'autres ont établi que ces méthodes d'estimation de l'évapotranspiration sont valides. La

plus populaire parmi ces méthodes d'estimation est la méthode Penman-Monteith (PM) recommandée par la FAO. Les données ET de télédétection provenant de l'observation par satellite ont été traitées sous ces algorithmes. En outre, l'approche des systèmes de télédétection fournit des sources de données alternatives. Le principal avantage des techniques de télédétection est leur large couverture et la capacité d'effectuer une détection à différentes échelles spectrales, des capteurs améliorés et une résolution spatiale et temporelle élevée. Cependant, pour être fiables, les données de télédétection nécessitent une validation avec la jauge ou d'autres données in-situ.

L'évaluation hydrologique est réalisée en paramétrant les processus hydrologiques régionaux ou mondiaux à différents niveaux à l'aide d'une série de modèles de mécanismes physiques couplés. Il applique des approches mathématiques ou statistiques pour examiner la rétroaction ou les réponses des systèmes hydrologiques et écologiques. Cela permet également de prévoir des scénarios futurs. Il est basé sur la compréhension que les rétroactions et les interconnexions dans les systèmes climatiques, hydrologiques et écologiques déterminent l'évolution des conditions environnementales globales au fil du temps. En outre, la saisie de plusieurs paramètres hydrologiques et climatiques connexes est nécessaire en raison de la complexité de l'évaluation des changements hydrologiques et climatiques. D'autres méthodes telles que les apprentissages basés sur les processus, statistiques, automatiques et profonds ont toutes été appliquées aux modèles hydrologiques de changement climatique dans le but de comprendre leur dynamique spatio-temporelle (Granata (2019); Ardabili et al. (2019); Klotz et al. (2021); de la Fuente et al. (2019); Hussain et al. (2020); Saggi et Jain (2019); Ferreira et da Cunha (2020)). Un test statistique qui montre les relations et les tendances, comme l'analyse de régression et le test de tendance de Mann-Kendall, fait partie des tests statistiques les plus importants utilisés pour évaluer les impacts du changement climatique sur le système hydrologique.

Des algorithmes d'apprentissage automatique tels que la Forest random, la régression logistique, tree decision, la support vector machine, etc., ont tous été utilisés pour évaluer ou prédire les impacts du changement climatique sur les systèmes hydrologiques. De plus, les prévisions hydrologiques du changement climatique peuvent être faites en utilisant une approche de modélisation prédictive telle que CMIP(s).

L'indice de précipitations standardisé (SPI) et l'indice d'évapotranspiration des

précipitations standardisé (SPEI), l'indice de sévérité de la sécheresse de Palmer (PDSI), l'indice de végétation par différence normalisée (NDVI) et l'indice de végétation amélioré (EVI) sont quelques indices utilisés pour évaluer l'état hydrologique. En termes de relations hydrologiques avec l'écologie, cela aide à surveiller les impacts du changement climatique entraînant une dégradation de l'environnement telle que la sécheresse.

1.4 Évaluation hydrologique et du changement climatique dans cette thèse

Cette thèse a pour objectif de démêler les impacts potentiels du changement climatique sur la dynamique spatio-temporelle du système hydrologique du Nigeria en évaluant la tendance à long terme de ses différentes composantes. La première tentative a consisté à valider 16 produits de précipitations satellitaires (SPP) comprenant des ensembles de données satellitaires, de jauge et de réanalyse. Les ensembles de données ont été validés avec les données de précipitations des stations de référence de jauge 11 à travers le Nigeria de 2000 à 2012. Cela est devenu important après qu'il a été découvert qu'il manquait des données précises et opportunes sur les précipitations pour la zone d'étude. L'efficacité de Kling-Gupta (KGE) a été utilisée pour tester la corrélation, le biais et la variabilité du produit. Les résultats ont révélé que la fiabilité substantielle du SPP varie dans l'espace et dans le temps. Il a été découvert que tous les SPP avaient de meilleurs résultats sur une partie du centre du Nigéria pendant la saison sèche. Lorsque les produits satellitaires en temps réel et ajustés ont été comparés, les résultats ont montré que les produits ajustés avaient un meilleur score KGE. L'évaluation a également montré que la fiabilité des extractions multi-satellites intégrées pour les produits de la mission mondiale sur les précipitations (IMERG) était cohérente avec celle de leur prédécesseur l'analyse des précipitations multi-satellites (TMPA) de la mission de mesure des précipitations tropicales (TRMM). Enfin, les meilleurs scores globaux ont été obtenus à partir des précipitations d'ensemble pondérées multi-sources (MSWEP) v.2.2 et IMERG-F v.6. Les deux produits sont donc suggérés pour des études hydrologiques ultérieures.

Deuxièmement, l'indice standard des précipitations (SPI) et l'indice standard des

précipitations et de l'évapotranspiration (SPEI) ont été utilisés pour évaluer la situation de la sécheresse au Nigeria entre 1981 et 2019 afin de déterminer la force et le schéma de la sécheresse dans la zone d'étude. Le SPI évalue la sécheresse en se basant uniquement sur les précipitations. Le SPEI, contrairement au SPI, tient compte à la fois de la température et des précipitations, tenant compte en partie des effets du réchauffement climatique et du changement climatique. L'évaluation du niveau d'accord entre SPI et SPEI à différentes échelles de temps, c'est-à-dire (3, 6 et 12 mois), a révélé une forte corrélation de $r = 0,94$. L'évaluation a révélé qu'il y avait eu des épisodes de sécheresse intense entre 1982 et 1984. Plusieurs types de sécheresse étaient présents dans la zone d'étude et à toutes les échelles de temps. Il a été déterminé que l'intensité la plus élevée s'est produite en 1983. Cependant, le dernier événement de sécheresse extrême a été déterminé en 2016. En conséquence, il a été déterminé que la fréquence des sécheresses graves et extrêmes a récemment diminué. Cependant, la fréquence des sécheresses modérées persiste, surtout aux échelles de temps de 3 mois. Selon les résultats de cette étude, il existe généralement un accord satisfaisant entre les cotes SPI et SPEI dans la zone d'étude.

Troisièmement, l'influence climatique sur l'évapotranspiration (ET), un indicateur climatique critique dans l'étude du changement climatique en raison de sa contribution au cycle hydrologique et au bilan énergétique, a été évaluée. L'évaluation devait révéler l'influence des variables climatiques telles que la température, les précipitations, le rayonnement solaire et le vent sur les changements d'évapotranspiration afin de déterminer leurs impacts sur l'ET à travers le Nigéria en utilisant l'estimateur de test de tendance Mann-Kendall (MK) pour la détection des tendances. Les résultats MK ont montré que le rayonnement solaire et la température avaient plus d'influence sur l'ET de la zone d'étude en termes de corrélation et de magnitude.

En conclusion, le changement climatique naturel est plus répandu malgré la grande étendue de changement d'utilisation des terres due aux activités anthropiques. Le rayonnement solaire et la température sont les principaux facteurs exacerbant l'évapotranspiration dans la zone d'étude. De plus, la durée limitée des précipitations de la zone d'étude dans la région écologique du Sahel et de la savane soudanaise aggrave la dégradation hydrologique.

Abstract in English

2.1 Overview of Remote Sensing for Hydrologic Assessment

Remote sensing in the context of earth observation is the measurements of the Earth's emitted and radiated energy using electromagnetic radiation to gather surface and sub-surface information. The measurement through the electromagnetic spectrum allows for a wide variety of measurements across several sections of the electromagnetic spectrum. Remote sensing measurements from satellites depend on two main types of sensors used in data collection, such as passive and active. The interactions between the surfaces and passive/active sensors will differ depending on the observed surfaces. Passive sensors detect sunlight reflected from Earth's surfaces or thermal radiation naturally emitted by objects. Active sensors generate their electromagnetic energy and transmit it to the target under investigation. This ability makes it possible to effect measurements that penetrate clouds and in the darkness away from the sun's energy.

Interestingly, satellite remote sensing applications emphasising land surface hydrology were introduced by the successful launch of the first Earth Resources Technology Satellite (ERTS-1, later renamed Landsat-1). The development of techniques for assessing hydrometeorological states and fluxes has been a key focus of hydrology-related remote sensing research. Monitoring hydroclimatic events such as drought using a passive microwave satellite estimate is based on the low emissivity of water bodies. This is due to differences in dielectric properties between water and soil or vegetation, particularly at

lower frequencies. Combining data from multiple spectral ranges has opened new opportunities to develop methodologies producing global hydroclimatic data. Claims of remote sensing active and passive combination with the aim to monitor soil moisture abound Babaeian et al. (2018).

Specifically, in hydrology related studies, the reflected solar energy is utilised for studies on water quality as well as snow mapping, vegetation and land cover analysis. Also, soil moisture and snow use the thermal emission in the microwave and infrared for surface temperature. Remote sensing enables concurrent real-time measurement and analysis of the surface while yet obtaining information about spatial and temporal variability. Satellite remote sensing enables continuous monitoring on a global scale, while conventional land-based observations usually are made at regular intervals with limited spatial coverage.

Remote sensing techniques and, precisely, satellite remote sensing applications and modelling for environmental management have been improving in recent years. Integrating different techniques such as Artificial Intelligence (AI) and machine learning approaches in interpreting remotely sensed data has only improved the usability of remote sensing products for various environmental purposes. Furthermore, advancements in sensor development have also improved detection, using high spectral resolution sensors. These are perfect for monitoring spatial phenomena, especially highly variable events such as precipitation, evapotranspiration, soil moisture, droughts, and flood.

Remote sensing has provided significant advances in understanding the climate system and its changes by measuring and quantifying processes and spatiotemporal states of the atmosphere, land and oceans. Our understanding of the climate system and its changes has substantially improved due to remote sensing capabilities and products. In climate change studies, satellite remote sensing is essential to climate system observations. It allows data collection on the Earth's surface, subsurface, and atmosphere remotely through sensors onboard satellites. The unmatched global and fine-scale geographical coverage of satellite observations make it possible to get new insights. Using satellites enables the monitoring of atmospheric, terrestrial, and oceanic conditions and processes at various spatiotemporal scales. Remote sensing is also useful in developing climate models. For instance, satellite climate data are regularly used to recreate the dynamics of the

climate system and enhance climate projections. This is due to their general acceptability and reliability in providing the information needed for climate models. Thus, contributing significantly to our understanding of the climate system is based on observational data and model simulations. As well as measuring climate fluctuations and spatiotemporal states of the atmosphere, land, and oceans.

2.2 Climate Variability Vegetation & Water Stress

Climate variability affects the hydrological system to be dynamic on a range of time scales, putting strain on the system in the past through flood and drought situations. The effects of current climate variability may be exacerbated by anthropogenic global warming. It is commonly acknowledged that greenhouse gas emissions are causing climate change to exacerbate and that this shift or oscillation in climate patterns will significantly impact future environmental conditions. There are several reports that the hydrologic cycle is one of the global physical components that would be impacted by climate change [Bai et al. \(2019\)](#); [Tabari \(2020\)](#). Other negative impacts have already been recorded across the globe [Margaryan et al. \(2022\)](#); [Yang et al. \(2019\)](#); [Visser et al. \(2019\)](#). The alterations in hydrological cycle components processes have resulted in changing precipitation patterns and increased evapotranspiration due to increased warming. Thereby altering the dynamic within ecology and hydrology. This shift in ecological system dynamics determines the amount of moisture available for plants to extract from deep and top soils and subsequently transpire the moisture back into the atmosphere. Similarly, increased temperatures continue to break world records, precipitation, storms, more violent hurricanes, floods submerging cities, forest fires, famine, droughts, and drying lakes and rivers are some negative impacts of climate change. Furthermore, the intensification of coastal soil erosion due to high-intensity precipitation and rising sea levels is increasing worldwide. Natural climate change resulting from increased temperature increases the evaporation and transpiration rate. However, they are more difficult to ameliorate.

Therefore, it is anticipated that the geographic range of the impacts may expand. Current trends are projected to increase in intensity, such as areas undergoing a trend toward drying due to climate change. Water extraction for human use is expected to

witness further water scarcity.

Understanding the anthropogenic and natural contribution is essential in proffering solutions and assessing the impact of climate change on the hydrological system. Anthropogenic contribution differs from natural contributions. Anthropogenic contribution includes building on channels, and pavements, forest reduction, and extracting more water than necessary production of greenhouse gases (GHGs) which significantly contribute to ET increase Talebmorad et al. (2021); Menzel and Bürger (2002) and temperature increase Cassia et al. (2018). Interestingly, it has been suggested that reducing anthropogenic climate change (global warming) may lessen the natural impact of climate change Bjelle et al. (2018); Takemura and Suzuki (2019); Gu et al. (2018). However, research to quantify the dynamics and environmental determinants of variation in hydrological systems is usually complex. One of the reasons is that several measurements are needed from the numerous variables that contribute to the climate change impact of hydrology. Timely and continuous studies can help early detection of hydrologic trends. Observation and calculation of various factors, such as a change in precipitation trend, which impact other variables such as groundwater, enables scientists and environmental analysts to suggest or devise a mitigating strategy. Therefore, measuring spatiotemporal differences in hydrology over a wide range of geographical scales is imperative to improve hydrological understanding and management.

The role of vegetation in evapotranspiration, condensation, and precipitation amount has been documented Hesslerová et al. (2019). A phenomenon linked directly to the amount of transpirable moisture. There are proofs that precipitation amount improved in areas of large dense vegetal cover when compared to areas with less vegetal cover Wang et al. (2020); Duncan et al. (2019); Spracklen et al. (2018).

Evapotranspiration is central to the hydrologic cycle due to its ability to represent water availability and atmospheric water demand. Increasing evapotranspiration and diminishing rainfall are the worst-case scenarios for water supply Bormann (2005); Abtew and Melesse (2013); Rajabi et al. (2022). Increases in temperature, humidity, radiation and wind speed will lead to the increased and high variability of evapotranspiration. In other words, there is no doubt that evapotranspiration and precipitation play a vital role in the ecosystem's sustenance. These impacts are traceable to the intrinsic link between

precipitation that falls to the ground, the infiltration deep into groundwater, the runoff and the loss through evaporation and transpiration.

The above is being altered at an alarming rate by anthropogenic and natural activities. However, these interconnected spatiotemporal dynamics in hydrologic interaction determine to a greater extent, the availability of moisture. Notably, inevitable environmental degradation, such as droughts, starts after prolonged periods without precipitation. In this event, Ecology and Hydrology (Ecohydrology) combine to sustain biodiversity by providing a beneficial strategic environment for plants and animals to thrive. As research on hydrologic interaction is increasing, there have been strident calls for better recognition and mitigating policies to reduce the anthropogenic global warming that aggravates climate change.

A significant highlight of climate change is its ability to induce temperature fluctuation. A temperature rise, decrease in humidity, and declining rainfall help to boost evapotranspiration. However, when these phenomena are sustained for extended periods, a negative impact begins to manifest in the environment. Temperature increase makes plants and top soils susceptible to exceeding their bane of tolerance, which often results in plant deaths and environmental degradation. Hydrologic natural interconnectedness made it challenging to study in isolation. A holistic study that considers all components of an eco-hydrological system is often needed to understand the relationships and influence each variable has on others. The 'Soil-Plant-Atmosphere Continuum' (SPAC) is a crucial concept in studies of plant water use [Wood et al. \(2008\)](#). Interestingly, almost all the individual hydrologic components can be measured in isolation. However, simultaneous measurement of multiple variables is encouraged. A long measurement period is also required to study the influence of factors such as seasons. Therefore, the hydrologic climate change emphasises some aspects of the interactions between forest trees and hydrology, especially transpiration.

2.3 The context of Climate Change Impact on Hydrologic System Assessment

Measuring climatic impact on hydroecology is difficult due to their interconnected dependencies, which are sometimes difficult to segregate. Measurements can be done through ground-based equipment or satellite observation. Hydrologic and hydroclimatic variables can be measured in situ. Some traditional measurement practices include using a weather station with a thermometer, rain gauge, staff gauge and crest-stage gauge, evaporimeter etc. The Eddy covariance method has been proven as the most reliable ground base measurement of evapotranspiration. Evapotranspiration can also be estimated using well-planned process-based methods by measuring associated variables like solar radiation. Similarly, [Penman \(1948\)](#), [Thornthwaite \(1948\)](#), [Hargreaves and Samani \(1982\)](#) and others have established that these methods of evapotranspiration estimation are valid. The popular among these methods of estimation is the Penman-Monteith (P-M) method which the FAO has recommended as a trusted option. Remote sensing ET data from satellite observation have been processed under these algorithms. Also, the remote sensing systems approach provides alternative data sources. The main advantage of remote sensing techniques is their broad coverage and the ability to effect detection at different spectral scales, improved sensors and high spatial and temporal resolution. However, for reliability, remote sensing data requires validation with the gauge or other in-situ data.

Hydrological Assessment is achieved by parameterising regional or global hydrological processes at various levels using a series of coupled physical mechanism models. It applies mathematical or statistical approaches to examine feedback or responses from hydrological and ecological systems. It also provides an opportunity to predict future scenarios. It is based on the understanding that feedbacks and interconnections in the climatic, hydrologic and ecologic systems drive the evolution of overall environmental conditions over time. In addition, the input of several related hydrological and climatic parameters is required due to the complexities involved in assessing hydrological and climate change Assessment. Other methods such as the Process-based, statistical, machine and deep learnings have all been applied to hydrological climate change models in an effort to understand their spatiotemporal dynamic [Granata \(2019\)](#); [Ardabili et al. \(2019\)](#); [Klotz](#)

et al. (2021); de la Fuente et al. (2019); Hussain et al. (2020); Saggi and Jain (2019); Ferreira and da Cunha (2020). A statistical test that shows relationships and trends, such as the regression analysis and Mann-Kendall trend test, is among the most prominent statistical tests used in assessing the climate change impacts on the hydrological system.

Machine Learning Algorithms such as random forest, logistic regression, decision tree, support vector machine etc., have all been used to assess or predict the climate change impacts on the hydrological systems. Additionally, hydrological climate change predictions can be made using a predictive modelling approach such as CMIP(s).

The standardised precipitation index (SPI) and standardised precipitation evapotranspiration index (SPEI), Palmer Drought Severity Index (PDSI), Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are a few indices used to evaluate hydrologic status. In terms of hydrological relationships with the ecology, this help to monitor climate change impacts resulting in environmental degradation such as drought.

2.4 Hydrologic & Climate change Assessment in this thesis

This thesis aims to unravel the potential impacts of climate change on the spatiotemporal dynamics of Nigeria's hydrological system by assessing the long-term trend of its various components. The first attempt was to validate 16 satellite-based precipitation products (SPPs) comprising satellite, gauge and reanalysis datasets. The datasets were validated with the precipitation data from 11-gauge reference stations across Nigeria from 2000–2012. This became important after it was discovered that accurate and timely precipitation data for the study area was lacking. The Kling–Gupta efficiency (KGE) was used to test the product for correlation, bias and variability. The results revealed that the substantial SPP reliability varies spatially and temporally. It was discovered that all the SPPs performed better over part of central Nigeria during the dry season. When the real-time and adjusted satellite-based products were compared, the results showed that the adjusted products had a better KGE score. The Assessment also showed that the re-

liability of integrated multi-satellite retrievals for Global Precipitation Mission (IMERG) products was consistent with that of their predecessor Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation analysis (TMPA). Finally, the best overall scores were obtained from multi-source weighted-ensemble precipitation (MSWEP) v.2.2 and IMERG-F v.6. Both products are therefore suggested for further hydrological studies.

Secondly, the Standard Precipitation Index (SPI) and the Standard Precipitation and Evapotranspiration Index (SPEI) were used to evaluate the drought situation across Nigeria between 1981-2019 to determine the strength and pattern of drought in the study area. SPI evaluates drought based solely on precipitation. SPEI, in contrast to SPI, considers both temperature and precipitation, partially accounting for the effects of global warming and climate change. The Assessment of the level of agreement between SPI and SPEI at various timescales, i.e. (3,6 and 12 months), revealed a high correlation of $r=0.94$. The Assessment revealed that there were intense drought episodes between 1982 to 1984. Several drought types were present across the study area and in all the timescales. The highest intensity was determined to have occurred in 1983. However, the last extreme drought event was determined in 2016. As a result, it was determined that the frequency of severe and extreme drought has recently reduced. However, the frequency of moderate droughts persists, especially at the 3-months timescales. According to the results of this study, there is generally a satisfactory agreement between SPI and SPEI ratings in the study area.

Thirdly, the climatic influence on evapotranspiration (ET), a critical climate indicator in studying climate change due to its contribution to the hydrologic cycle and the energy balance, was assessed. The Assessment was to reveal the influence of climatic variables such as temperature, precipitation, solar radiation, and wind against evapotranspiration changes to determine their impacts on ET across Nigeria using the Mann–Kendall (MK) trend test estimator for trend detection. The MK results showed that solar radiation and temperature had more influence on the ET of the study area in terms of their correlation and magnitude.

In conclusion, natural climate change is more prevalent despite anthropogenic activities' large expanse of land use change. Solar radiation and temperature are the prominent factors exacerbating evapotranspiration in the study area. Additionally, the

study area's limited precipitation duration experience in the Sahel and Sudan Savannah ecological region aggravates hydrological degradation.

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Introduction

3.1 Overview

In this chapter, the background of the thesis is introduced. The concepts of remote sensing and climate change impact the hydrologic cycle, and the resulting land precipitation alteration, land use, and land cover change are presented. The role of vegetation soil-water interaction and their alterations are also highlighted. Additionally, background information on drought assessment, hydrological data needs and data types are discussed. Finally, the main aim of this thesis, the scope, the study area, and the structure are all presented.

3.2 Remote Sensing (RS) capabilities

The growing need to monitor, measure and track the dynamics of change in Earth's properties has inspired several developments. One such development in science is remote sensing systems. Remote sensing, by definition, is the science of gathering information about an object without physically touching the target of interest. The term was first mentioned in the 1950s by Evelyn Pruitt of the then U.S Office of Naval Research as cited in [Short \(2003\)](#). This is accomplished by sensing and recording reflected or emitted energy and then processing, analysing, and applying the data to extract useful information. In this thesis, the remote sensing we are interested in will focus on sensing Earth's properties, especially as it concerns hydrology, ecology, climate change and water resources using data from satellite sensors.

Satellite remote sensing began in the 1950s, following the Soviet Union’s launch of Sputnik-1, the world’s first man-made satellite, into space on October 4, 1957. Since then, satellite technology has advanced rapidly, particularly in the last few decades, providing valuable information for a wide range of Earth sciences (i.e., Hydrology, Geology, oceanography, and changes in land/land cover). Satellite remote sensing has provided significant advances in understanding the climate system and its changes by measuring and quantifying processes and spatiotemporal states of the atmosphere, land and oceans. Satellite remote sensing applications focusing on land surface hydrology began with the successful launch of the first Earth Resources Technology Satellite (ERTS-1, later renamed Landsat-1) on March 23, 1979, [Lauer et al. \(1997\)](#).

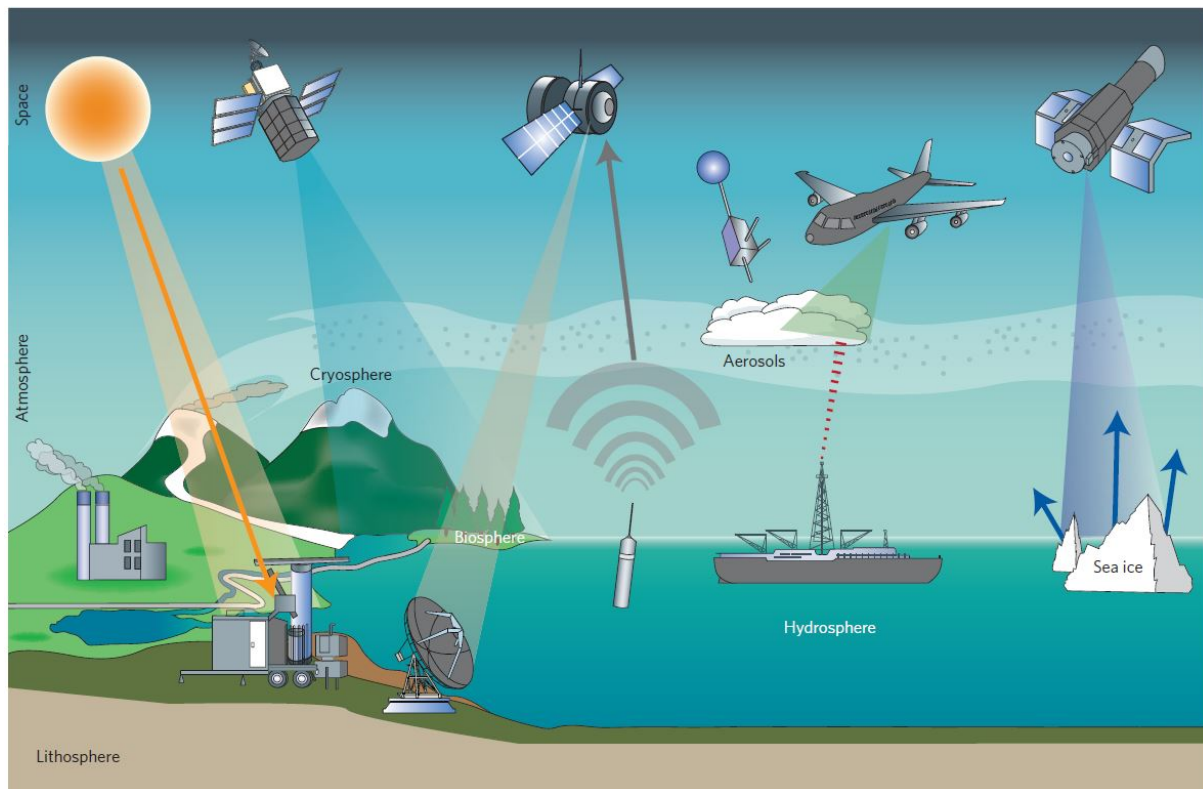


Figure 1: A schematic diagram showing the ability of remote sensing to monitor climate from space. Adapted from [Yang et al. \(2013\)](#)

This opportunity heralded a new era in hydrological research by providing scientists with valuable large-scale observations useful for hydrological dynamics monitoring, especially in areas with limited gauge coverage. In comparison to in-situ hydrological data, satellite remote sensing observations have clear advantages. For instance, while in situ measurements have been around for an extended period and can provide longer data records, they provide limited information about the spatial dynamics of hydrological pa-

rameters (such as evaporation, transpiration, and cloud detection). On the other hand, satellite observations can provide regional and global observations at various wavelengths and spatial resolutions, with uniform quality and rapid data acquisition [Asner and Warner \(2003\)](#); [Morrow et al. \(2019\)](#); [de Leeuw et al. \(2018\)](#). In addition, satellite observations can reach remote or inaccessible areas and provide consistent observations worldwide.

Remote sensing measurements from satellites depend on two main types of sensors used in land surface satellite remote sensing: passive and active. The interactions between the surfaces and passive/active sensors will differ depending on the observed surfaces. Passive sensors detect sunlight reflected from Earth's surfaces or thermal radiation naturally emitted by objects. Active sensors generate their electromagnetic energy and transmit it to the target under investigation. When incoming energy interacts with the target, it produces backscattered energy, which is reflected back to the sensor for measurement. Optical observations are those obtained by measuring the surface reflectance from the Sun. As a result, optical imagery depends on the Sun and is susceptible to cloud cover. Nevertheless, optical observations are frequently used in applications such as surface water monitoring, disaster monitoring, inundation mapping, and detecting land surface change [Albertini et al. \(2022\)](#). Active sensors emit radar beams that are not obstructed by clouds, and radar imagery can be acquired at any time, in any weather condition, and without regard for the Sun [Marino et al. \(2012\)](#).

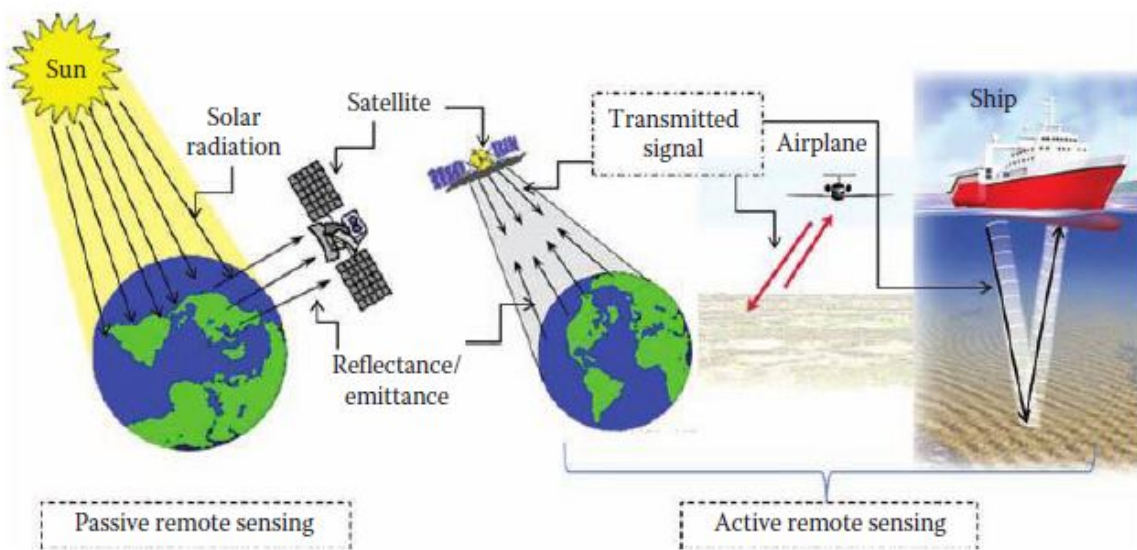


Figure 2: Illustration of passive vs active remote sensing with different platforms. Adapted from [Thenkabail \(2018\)](#)

Further advancements in the abovementioned sensors have propelled remote sensing studies on surface water and soil moisture. Surface water can be monitored locally and globally using optical sensors mounted on satellites. For repeated extensive area observations, passive and active microwave remote sensing sensors can be installed on high-altitude platforms, such as satellites, and can measure the surface soil moisture (0–5 cm). A soil's dielectric characteristics are influenced by how much water is in it. The microwave measurement is based on the dielectric properties and several other physical factors. The relevance of the dielectric characteristics also depends on the wavelength and sensor type. Longer-wavelength (> 5 cm) instruments can detect a deeper layer of soil with greater sensitivity and have fewer issues with the atmosphere and vegetation [Jackson et al. \(1996\)](#). The passive data interpretation algorithms currently in use for bare soil and plants have been thoroughly evaluated and are adaptable to various situations. This is because, The amount of water that percolates into the soil and replenishes the water table is regulated by soil moisture, as opposed to the amount that contributes to surface runoff and channel flow [Lakshmi \(2013\)](#). Across the globe, remote sensing studies of soil moisture include [Mohanty et al. \(2017\)](#); [Wagner et al. \(2007\)](#); [Lakshmi \(2013\)](#), and provide important information in hydrological [Zhuo and Han \(2016\)](#); [Wanders et al. \(2014\)](#), and drought assessment [Ahmadalipour et al. \(2017\)](#); [West et al. \(2019\)](#); [Ford and Quiring \(2019\)](#); [Jiao et al. \(2021\)](#). Also, the relationships between soil moisture, precipitation, and vegetation health have been studied across the globe using remote sensing [Sehler et al. \(2019\)](#).

The use of visible/infrared satellite observations to detect surface water began with Earth Resources Technology Satellite (ERTS-1, later renamed Landsat-1) data for flood mapping in several locations. Many satellites equipped with optical instruments have been launched since then, providing regional and global imagery at various spatial and temporal resolutions. Some satellite observations provide free access to data to the user community (i.e. National Oceanic and Atmospheric Administration (NOAA) / The Advanced Very High-Resolution Radiometer (AVHRR), Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), and Sentinel-2) and have been widely used for flood and surface water monitoring applications. The temporal coverage of these satellites, such as Landsat, makes them suitable for climate studies. Others, such as Sentinel-2, launched in 2015, is the most recent satellite that provides freely visible observations at 6-day

temporal resolution. In addition, the Sentinel-2 satellites' MultiSpectral Instrument (MSI) provides observations with spatial resolutions ranging from 10 m to 60 m. This high spatial resolution is advantageous for interpreting hydrologic features. Despite these benefits, satellite remote sensing has some limitations. A satellite system is costly and developing, building, testing, launching, and operating the system is lengthy and complicated. As a result, many countries could not afford their satellites capable of providing observations. In addition, satellite technology fabrication, communication and monitoring skills are scares giving the proficiency and licences of operation to a few technologically advanced countries. Even though data from satellite platforms often requires in-situ validation before their general acceptability and is sometimes difficult to interpret, particularly with radar images. However, the benefits and success of remote sensing opportunities outweigh their difficulties.

3.3 Climate Change Impact on Hydrology & Water Resources

IPCC et al. (2007) defined climate change as the Long-term changes in the Earth's climate dynamics. In recent years, these changes have been increasingly linked to the growth of human industrial activity and the consequent rise in the concentration of greenhouse gases like carbon dioxide (CO_2) and methane (CH_4), Nitrous oxide N_2O as well as aerosols in the atmosphere. The continuous rise in greenhouse gases by humans is one of the main factors sustaining climate change exacerbation. The occurrence and availability of water resources are impacted by changes in local and global climate, as well as in the magnitude and pattern of temperature and rainfall. Water is an essential resource for both human needs and environmental services Clifton et al. (2018); Vose et al. (2016); Hartter et al. (2018); Kerns et al. (2018).

The question of how much more impact on hydrological components could result from climate change and how these can be mitigated has led climate scientists to develop models such as the international Coupled Model Intercomparison Project (CMIP) in order to predict future climate trends. Climate research organisations worldwide have conducted

climate change simulations for CMIP6 using a preset selection of these scenarios. The prominent scenarios are the Representative Concentration Pathways (RCP) and Shared Socioeconomic Pathways. Results from these models suggest that immediate action towards curbing the negative impacts of climate change should receive full attention if the target reduction of global warming to less than 2°C, based on the current warming trend. This is because the current scenarios depict various socioeconomic advancements as well as various pathways for atmospheric greenhouse gas concentrations.

Human activities such as fossil fuel combustion produce greenhouse gas emissions that blanket the planet, trapping heat from the Sun and increasing temperatures. For instance, carbon dioxide and methane are produced while burning coal, cooling or heating a building. Carbon dioxide can also be released during forest and land clearing. Waste landfills and animals primarily produce methane emissions. Among the significant emitters are energy, industry, transportation, buildings, agriculture, and land use. A recent finding is that the Earth has warmed by around 0.7°C since the late 1800s [Tom \(1999\)](#). As emissions continue to increase globally due to energy and food demand, the most recent ten years (2012–2021) have consistently been the warmest ever recorded on Earth. This has led to intense droughts, water scarcity, destructive fires, rising sea levels, flooding, melting polar ice, catastrophic storms, and declining biodiversity, which are currently some of the effects of climate change. It is worrisome because global GHG emissions keep increasing. Long-lasting droughts put people at risk of starvation. At the same time, conditions like sea level rise and saltwater intrusion have progressed to the point of forced migration [McGregor \(1994\)](#); [Atapattu \(2009\)](#). As asserted in [Change \(1990\)](#), climate change is causing changes in the global hydrologic cycle. Multiple lines of evidence show gradual and, in some cases, rapid changes in the global hydrologic cycle due to climate change. The regional signal, on the other hand, is more significant because different changes in river discharge trends and the occurrence of hydrological extremes (e.g., floods, droughts) are found in different regions of the world [Wijngaard et al. \(2017\)](#); [Wang et al. \(2008\)](#); [Taye et al. \(2011\)](#); [Vicuña et al. \(2013\)](#); [Mamo et al. \(2019\)](#); [Burn et al. \(2010\)](#); [Webb \(1996\)](#); [Wilcox et al. \(2018\)](#); [Nka et al. \(2015\)](#); [Casse and Gosset \(2015\)](#); [Shiru et al. \(2018\)](#).

Hydrological extremes such as floods and droughts have become more common

in Nigeria, particularly since the turn of this century. These regional changes, such as the intense drought in the Sahel, will directly influence local sustainability and social development at a regional scale. Therefore to ensure a radiative forcing consistent with the 2°C objective by the year 2100, it would be required to start cutting emissions right now and even reach negative emissions on a world average by 2100.

3.4 Land Use / Land Cover & Drought from Climate Change Perspective

Changes in land use and land cover have an impact on both environmental quality and quality of life, both of which have an impact on human well-being. Human land use causes changes in land cover, which can harm biodiversity. Land use changes can impact runoff water's volume, timing, and quality [Goonetilleke et al. \(2005\)](#); [Miller et al. \(2002\)](#); [de Mello et al. \(2020\)](#). The proportion of impervious surface is higher in more developed land uses (areas where water can not soak into the ground, such as roadways, parking lots, and building roofs). Rainstorm runoff volume increases with impervious surfaces, increasing the risk of flooding and the number of pollutants transported to rivers and lakes. Human land use also disrupts natural land cover, increasing the likelihood of soil erosion into streams and lakes.

Land cover is essential in global carbon cycles because more natural landscapes can capture and store carbon in the soil, reducing carbon dioxide levels in the atmosphere [Bhattacharyya et al. \(2008\)](#); [Bossio et al. \(2020\)](#). When vegetation or soil is cut, stored soil carbon can be released back into the atmosphere. Several studies have investigated the social and economic factors influencing land use and land cover change. The net flux of carbon from land use and landcover change (LULCC) accounted for 12.5 % of anthropogenic carbon emissions from 1990 to 2010 [Houghton et al. \(2012\)](#).

Changes in the land surface can have an impact on local precipitation and temperatures. The impact of vegetation patterns and soil composition on evaporation and convection, or the rise of air, can influence cloud formation and precipitation [Manoli et al. \(2016\)](#); [Ray et al. \(2006\)](#). The type of land cover present in a given region determines the

effect of land cover on climate. For example, barren lands heat up faster and can transfer this heat to the lower atmosphere. Changes in land surface temperature can affect local temperatures not only in forests and agricultural land but also in cities. For example, average temperatures in a city's downtown areas can rise due to the high density of construction materials such as pavements and roofs. In other words, many researchers have discussed this situation in urban heat islands. This refers to the large amount of heat generated from urban structures as they consume and re-radiate solar radiation [Rizwan et al. \(2008\)](#), compared to lower temperatures in surrounding rural areas. Highlighting a significant anthropogenic contribution to aggravating climate change.

Land use and land cover play a vital role in global energy redistribution. Vegetal land cover is significant in ET and precipitation by transpiring water vapour into the atmosphere. Around the globe, the vegetal cover is rapidly depleted, thus impeding transpiration. Forest vegetation induced ET enhancement, resulting in a positive precipitation response [Li et al. \(2018\)](#); [Malhi et al. \(2002\)](#). The removal of vegetal cover through clearing for agriculture and sizeable urban development leaves the topsoil bare and sets a suitable condition for other forms of degradation to commence. However, it is not all forest loss that occurs as a result of anthropogenic degradation. Presently, severe land use and land changes due to natural climate change, such as forest fires, are increasing globally. Moreover, forests lost due to plants lacking moisture or exceeding the bane of tolerance result in further catastrophic devastation, including droughts.

Forests are more efficient in transpiration processes, which involve the transpiration from plants during photosynthesis that helps to cool the surrounding air. The direct and indirect influence of climate on the vegetation or other features that cover the land causes adverse climate impacts on land cover Ecosystems. Climate change causes changes in water, energy, and carbon fluxes. It may also cause environmental disturbances that affect land cover directly or indirectly. Species, for example, respond to climate change disturbances through migration, extinction, or adaptation to new disturbances. This phenomenon describes the constantly extending desert field across Saharan West Africa. Therefore, as climate variables continue to vary with time and scale, land use and land cover responses are being altered by variables, specifically precipitation and temperature, exacerbating the condition in the world fringe. The cessation of precipitation and intense

temperature increase for an extended period will continue to impact natural land cover regeneration ability, severely impacting hydrologic components in the Saharan and sub-Saharan regions. In addition, there are reports and evidence of drying surface water, such as the case of Lake Chad, resulting in famine and geopolitical conflicts.

3.5 Statement of the problems

The recent extreme weather events, such as increases in temperature, droughts, and flooding, have highlighted the very high costs of climate change to infrastructure and society. The hydrological or hydrologic cycle is a significant component of the global climate system. The climate is affected by several peculiar characteristics of water, particularly its high latent heat of fusion and vaporisation. The enormous latent heat of vaporisation absorbs a significant amount of the incoming solar energy wherever there is water on Earth. Because of this, temperature cycles are typically more evident in deserts than in wet areas.

Although the hydrological cycle is most active over the ocean, a reasonable amount of continental precipitation comes through terrestrial evapotranspiration. In addition, evaporation from interception can be significant. Most of this evapotranspiration occurs through the stomata of plants [Berry et al. \(2010\)](#); [Cascone et al. \(2019\)](#). This is due to their capacity to draw moisture from the soil profile. Evapotranspiration accounts for the majority of the precipitation that falls over the continents. Also, despite being essential to the hydrological cycle, soil moisture storage only makes up a minor portion of the Earth's water reservoir.

Then again, plants modify their stomatal resistance to water transfer based on the amount of soil moisture present. In habitats where water is a scarce resource, the adaptation of vegetation to climate is most apparent. In reality, water availability affects the distribution of forest species worldwide. In addition to being directly impacted by meteorological conditions, most notably through precipitation, soil moisture can also impact these variables by controlling the surface energy balance.

Generally, as a consequence of this intrinsic cycle, lower precipitation causes

lower soil moisture and evaporation, and lower evaporation causes lower precipitation. When this phenomenon is lengthened, it intensifies climate extremes. Groundwater flow, rainfall-runoff and soil moisture are critical variables since they directly regulate water and energy fluxes at the land surface.

The situation in Nigeria is precarious in many ways. The population of Nigeria is about 216 million people (National Population Commission-NPC). This population explosion that started towards the end of the 21st century is a recipe for disaster. The high demand for food and shelter has forced unplanned developments to augment the need for buildings and other sundry constructions. Moreover, unsustainable primitive environmental practices such as open grazing and incessant bush burning for game negatively impact Nigeria's climate by releasing large plumes of carbon dioxide into the atmosphere. [Omann et al. \(2009\)](#); [Travis \(2003\)](#). asserted that anthropogenically driven climatic changes are already considered to pose a major threat to global biodiversity

Then again, the large natural deposits across Nigeria and the subsequent mineral extraction for economic gains mean that large amounts of industrial waste are produced daily. Tin, Columbite, Limestone, and crude oil are extracted in larger quantities across Nigeria. Processes involved in the exploitation and exploration of these mineral deposits from mining and other industrial wastes disposal have been identified to have negative impacts on the Nigerian environment [Aigbedion and Iyayi \(2007\)](#); [Gutti et al. \(2012\)](#); [Ogunro and Owolabi \(2022\)](#).

Meeting the rising population's developmental needs requires large-scale clearing of expansive vegetation, thereby altering part of the hydrological system by removing forests and replacing them with a paved surface that hinders infiltration. There are also indications that some of these activities are the catalyst for exacerbating negative climate change, thereby contributing to atmospheric carbon deposits. Atmospheric carbon dioxide, vegetation removal that affects the ecological status, and altered hydrologic system have significantly contributed to how they have impacted the hydrologic system. The increased impervious surface area associated with urban development contributes to water quality degradation due to non-point source pollution. Forests removal causes weakening and about 25% reduction in precipitation change [Snyder et al. \(2004\)](#); [Beringer et al. \(2005\)](#); [Snyder \(2010\)](#). The hydrological effects of climate change and urbanisation are

having a significant impact on future water resource management.

Consolidating on some existing findings within the study area, this thesis will use remote sensing and gauge data and various statistical and machine learning methods to examine the implication of the highlighted climate change aggravating the factors promoting Nigeria's drought.

3.6 Scope of this thesis

Nigeria's terrestrial hydrological system is one of the most significant natural resources of the nation. However, with mean annual precipitation varying from about 4000 mm to 250 mm/year across the country from the north to the South, the variation has been projected to result in different environmental problems [Dike et al. \(2015\)](#). As a result, most parts of Nigeria have been projected to suffer precipitation scarcity. In contrast, some parts will experience the adverse effects of increased precipitations such as flooding and rainstorms [Dike et al. \(2015\)](#); [Joseph \(2012\)](#). There are concerns that the country's hydrological systems are altering at an alarming rate [Ojoye et al. \(2016\)](#); [Joshua \(2021\)](#); [Merem et al. \(2019\)](#). For example, the hydrological agency of Nigeria consistently foresees severe floods along the banks of some of the country's major rivers.

In addition, anthropogenic such as dam construction and other developmental activities and the naturally changing climate contribute to the alteration in the nation's hydrologic system [Ngatcha \(2009\)](#). Irrigation is the 2nd largest consumer of surface and groundwater, irrigation schemes across northern Nigeria account for 90% of agricultural water provision within the region. Agriculture frequently has various effects on stream flow, depending on management practices, including irrigation, crop rotation, and the level of soil disturbance and surface degradation.

Investigating the role of vegetation as an independent component of the hydrologic system of Nigeria demands a holistic approach. The hydrological situation in parts of the study area is already in jeopardy. Water resources in the northern region are among the most over-stressed aquifers in the world [Jabbo et al. \(2022\)](#); [Nur et al. \(2012\)](#). Drying surface water, famine, and crop failures have degenerated into clashes between some

farmers and herders communities in many parts of the study area. Increased water stress is anticipated for the future even without considering future climate change because of the rising water demand brought on by the anticipated growth in population and irrigated agriculture. Therefore, information on water quantity and their temporal change is constantly needed to support policies and management plans for sustainable development

3.7 Aim & Objectives of the study;

This thesis mainly aims to use remote-sensing products to identify climate change effects across Nigeria, worsening the hydrologic situation resulting in drought. The following objectives will be pursued;

- To validate 16 selected satellite precipitation datasets covering products from the following missions and reanalysis (TRMM, PERSIAN, CMORPH, GPM, MSWEP) across sixteen years using available precipitation gauge datasets for the study region;
- To assess the dryness of the study area using drought indices such as the standard precipitation index (SPI) and standard precipitation and evaporation index (SPEI) across thirty-nine years;
- To analyse the climate trends in the study area by evaluating the influence of climatic variables such as solar radiation and temperature on the production of evapotranspiration with the view towards ascertaining the variable with significant influence on land use changes and evapotranspiration spatiotemporal dynamics.

For this thesis, there is no one methodology adopted. Instead, each chapter has been processed and discussed as an article. Therefore, the methods adopted in the articles are based on the focus of each article and the specific topic the article is trying to address.

3.8 Study Area

Nigeria is a country in West Africa, located within latitude 4°.00-14°.00 north of the equator and longitude 3°.00-15°.00 east of the meridian. It is bordered to the north by the Niger Republic and the Chad Republic, east and West by Cameroon and Benin Republic, and south by the Atlantic Ocean [figure 3](#).

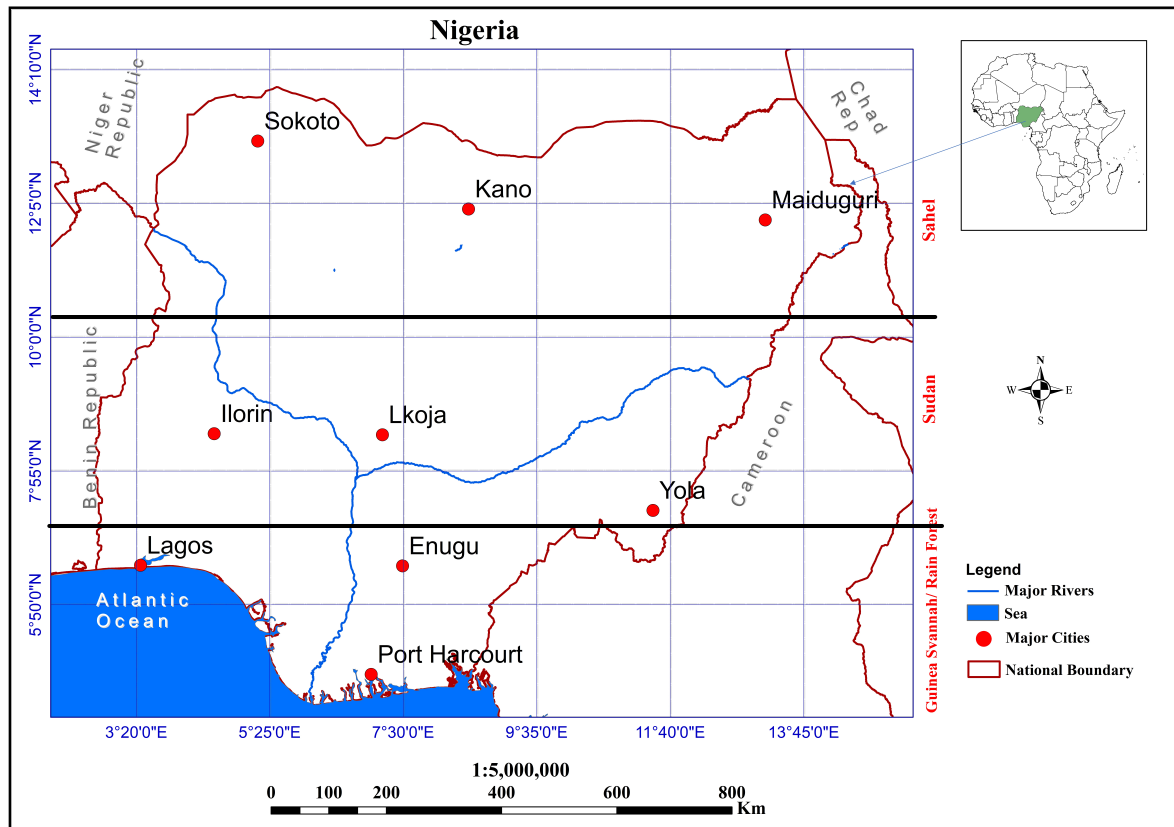


Figure 3: A location map of Nigeria showing the ecological zones. Precipitation amount varies from the Guinea Savannah/Rain forest region with a high volume of precipitation most part of the year to the Sahel region with scanty precipitation; source: *The author*.

The topography of Nigeria is generally flat towards the South and the far North. However, there are a few highlands with elevations above 1000 meters, such as the Mambila and Adamawa highlands and the Jos Plateau [figure 4](#). There are also the Obudu highlands on the southern border with Cameroon [figure 4](#). Parts of the Southwest consist of complex and rugged rocky terrain. This region consists of undulating terrain that increases in elevation towards the north. The coastal lowlands are located in the Southwest, South-south and Southeast, primarily covered in mangrove and swamp forests.

Generally, the South comprises swampy coastal terrains stretching inland for

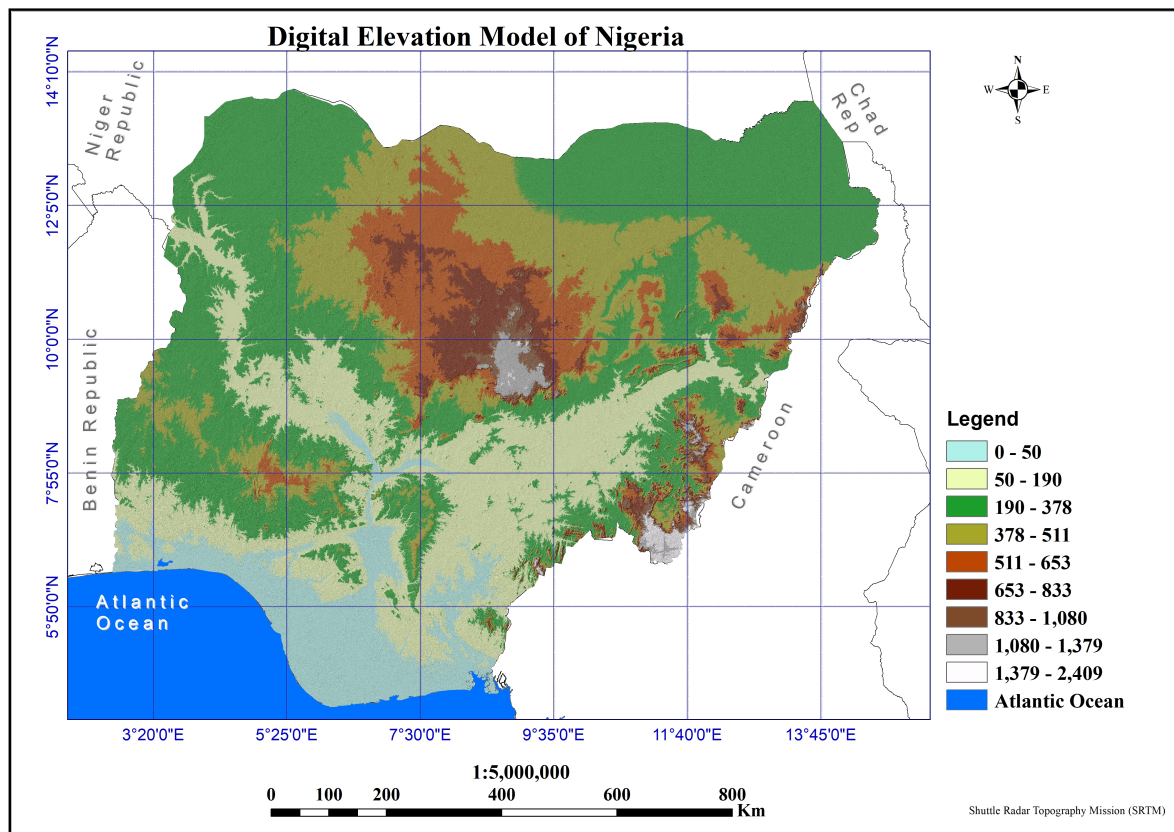


Figure 4: Map of Nigeria showing the digital elevation model; source: *The author*.

roughly ten kilometres [figure 4](#). The elevation rises towards the northern boundary at forty to fifty meters above sea level. The most important rivers are the Niger and the Benue [figure 3](#). The Niger River and its tributaries provide water for various activities, including irrigation, especially in the semi-arid Northern region. Both have formed a confluence in the low-lying plains of the north-central town of Lokoja

Vegetation types across Nigeria vary from the Sahel in the northwest Sudan Savannah stretching to some of the north-western, north-central, and north-eastern parts of Nigeria [figure 3](#). The Guinea/rainforest region starts from the southern part of the middle belt, extending into the stretch of the Niger Delta in the South. As with the vegetation, the topography varies within the country [figure 4](#).

Nigeria has a precipitation regime that varies spatially and temporally. Annual precipitation varies from about ≤ 900 mm/year in the northern region to over 4000 mm/year in the southern part [figure 5](#). Climatologically, Nigeria can be divided into three main climatic zones: (i) the Guinea Coast (4° – 8° N), (ii) the Savannah (8° – 11° N), and

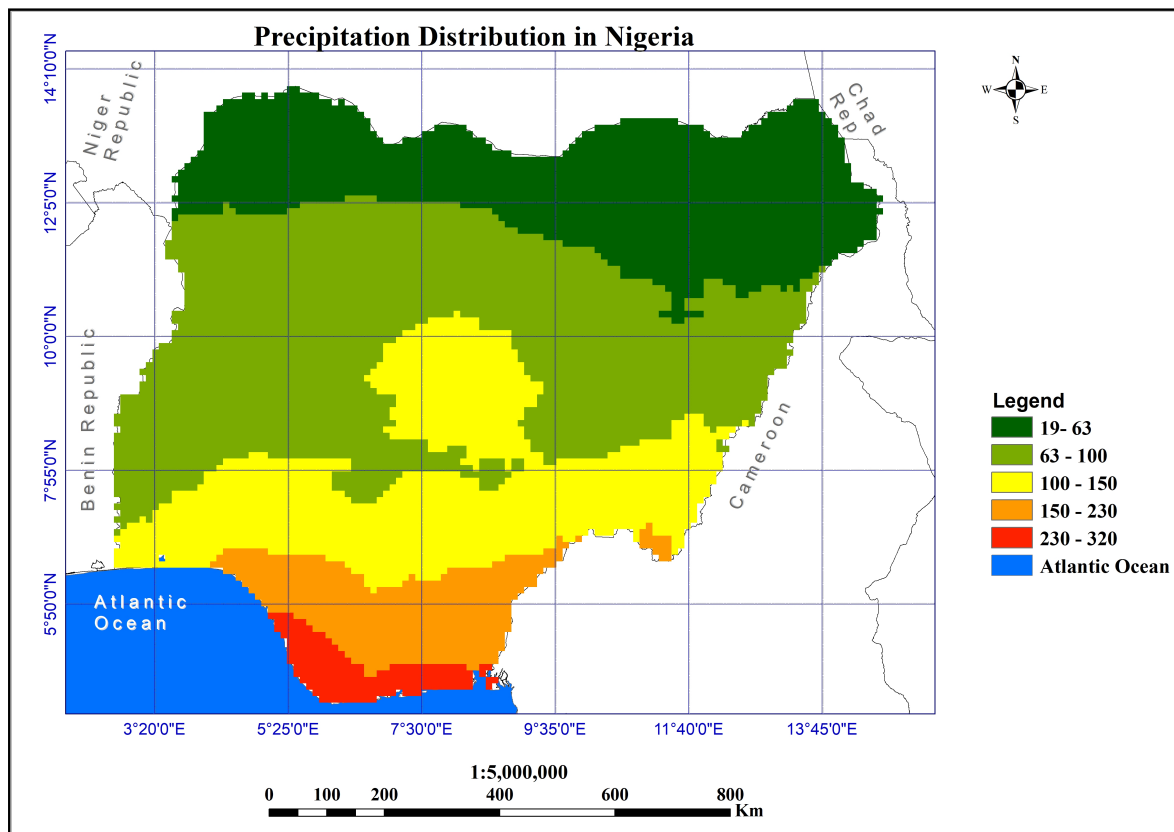


Figure 5: Map of Nigerian showing precipitation distribution; source: *The author*.

(iii) the Sahel (11° – 16° N) [Abiodun et al. \(2012\)](#); [Akinsanola et al. \(2017\)](#). Precipitation starts around March/April in the Guinea region and ends by October each year. However, in both Savannah and Sahel regions, precipitation sets off around May/June and ends in September (Figure 1). The Guinea and Savannah areas experience double maxima, with a small break in August (Figure 1), known in Nigeria as August break [Akpodigaga-a and Odjugo \(2010\)](#). It is worth noting that generally, in Nigeria, precipitation is governed by the actions of the West African monsoon, characterised by variations in the maritime and continental air masses, referred to as south-westerly and northeasterly winds, respectively [Chineke et al. \(2010\)](#). This monsoon action summarises the known rainfall regime known in Nigeria.

Humidity is high most of the year, although this drops in the winter. The colder months are December and January, when night-time temperatures are frequently low, marking a significant reduction in humidity. Temperature is high in the Sahel and Sudan Savannah, sometimes reaching 32°C [figure 6](#). As a result, northern Nigeria experiences a dryer climate, recording annual low precipitation compared to the South. The harmattan

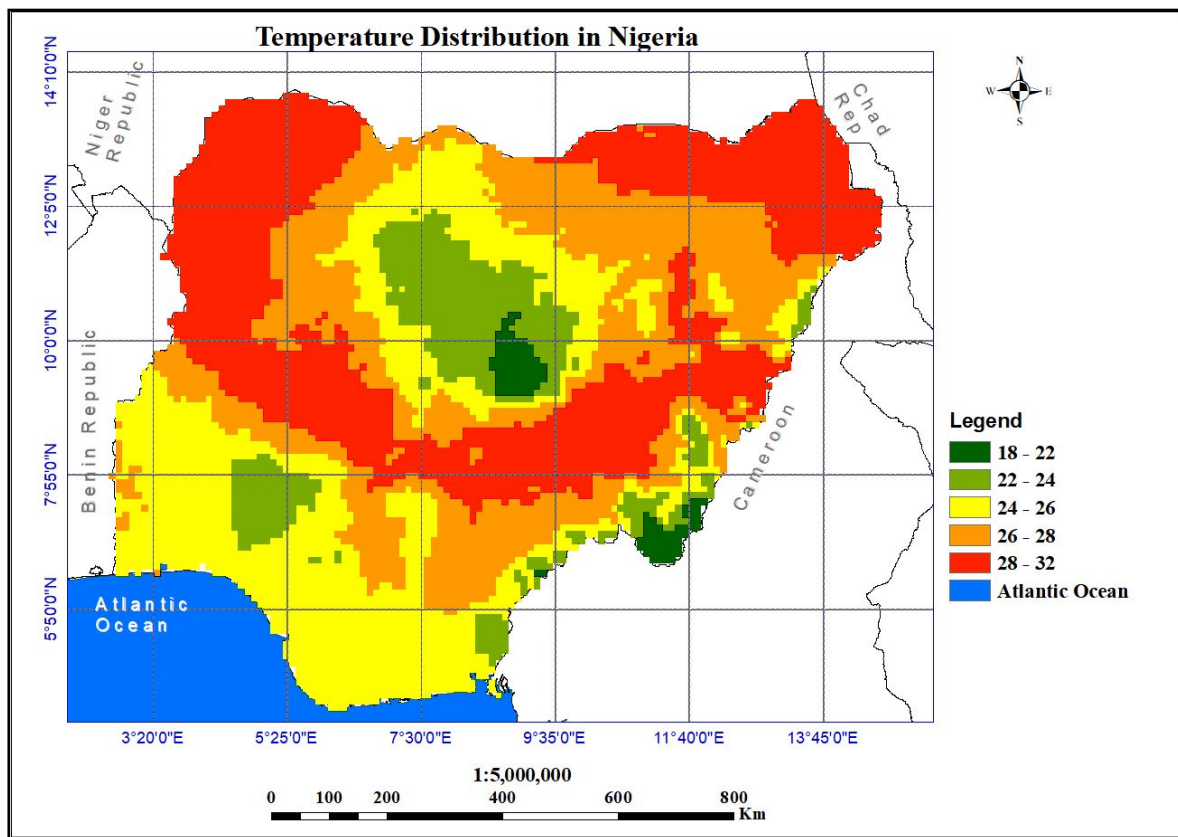


Figure 6: Map of Nigeria showing temperature distribution; source: *The author*.

wind, a dry northeasterly wind that blows from the Sahara desert, reaches Nigeria's coast from December through February. The harmattan's impacts are most noticeable in the country's north and gradually lessen Southwards.

3.9 Dissertation structure

The chapters in this thesis have the structure of an article. Apart from chapters 2 & 3, which provided background information about the concepts and context of the thesis, chapters 4-6 discussed individual analyses of components linking precipitation quantities, climate change, and drought.

Chapter 1 is the extended abstract in English with all its references, of which a copy has been made in French under the heading "Résumé".

Chapter 2 introduced the thesis and provided background information, the context, and the importance of remote sensing techniques and products in climate change studies. Notably, as it concerns the measurement and monitoring of hydrologic components. The aim and objectives will also be discussed in this chapter as the overall importance of this thesis in Nigeria.

Chapter 3 provided a review of state-of-the-art and emerging trends on the concepts adopted in this thesis. This chapter further discussed the concept of remote sensing technology in hydrology, land use, land cover change, climate change assessment, as well as hydrological cycle components such as evapotranspiration and precipitation. Furthermore, this chapter discussed the measurement, analytical methods, and instrumental systems used to collect the data that form the basis for subsequent analysis in the thesis.

Chapter 4 focused on validating satellite remote sensing and reanalysed precipitation datasets with measurements from gauge stations. This approach is to determine the best satellite product that will subsequently aid in an area-wide assessment of climate change's impact on the hydrological variables.

Chapter 5 assessed the wetness and dryness of the study area with a specific interest in the drought situation in the past thirty-nine years. Examined how frequent droughts have occurred and their intensity at different timescales. Determined if droughts had the capability to affect the socioeconomic activities and the hydrological status in the study area.

Chapter 6 used statistical analysis to examine the influence of climatic variables such as temperature, precipitation, solar radiation, and wind speed on evapotranspiration production in the study area. Each variable is compared to the present land use and land cover of the area to determine which land use is being exacerbated by a particular variable.

The final chapter, chapter 7 focused on the conclusions reached after all the assessments had been concluded.

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State of the Art

4.1 Overview

In this chapter, the thesis will explore existing knowledge on remote sensing assessment of the extent of climate change impacts on hydrologic variables and leading to droughts. The concepts of ecology-hydrology and the vegetation-land-atmosphere-water interaction will be examined. The concepts of climate change will be discussed. Furthermore, different methods of estimating ET will be discussed due to the role of Evapotranspiration (ET) in surface energy balance and climate change. Also, numerous techniques used to measure and estimate evapotranspiration will be discussed. Remote sensing techniques, land use, and land cover's role in climate change and drought will be discussed. Different indices and methods of assessing drought will be discussed. The existing research and emerging hydroclimatic and hydro-ecologic systems trends will be discussed. The ultimate goal of this chapter is to present whether the natural and climate change impacts captured by past spatiotemporal analysis would have been exacerbated in recent times.

4.2 Hydrological Systems & Climate Drivers

The hydrologic system is an interrelated intrinsic component where water constantly changes location and state within the atmosphere, land and terrestrial ecosystems within their intrinsically connected catchments. The related water distribution interconnected system consists of surface runoff, groundwater flow, and interaction with atmospheric water [Winter \(2001\)](#). In this phenomenon, water movement from the land, plants, animals

and the ocean surface returns to the atmosphere and back in the form of precipitation in a continual and intricate cycle within the Earth's atmosphere. Quantifying the volume of water available in a particular phase of the hydrological cycle, such as those help up in ice caps and groundwater, is essential for water managers and sustainable water planning. The quantification of the hydrologic cycle is calculated using the water balance equation as follows;

$$P = Q + I + ET + \Delta S \quad (4.1)$$

where;

P = Precipitation;

Q = Surface runoff;

I = Infiltration;

ET = Evapotranspiration;

ΔS = change in storage (in soil or the bedrock)

An illustration of the hydrologic cycle showing the hydrologic cycle components and the global water storage capacity is presented in [figure 7](#), and [table 4.1](#). Processes labelled include; precipitation, condensation, evaporation, evapotranspiration (from trees into the atmosphere), surface runoff, groundwater and stream flow, infiltration, percolation and soil moisture.

In the hydrological cycle, liquid water flows across the land as runoff [Markstrom et al. \(2008\)](#), into the ground infiltration [Horton \(1933\)](#), some of which flows deep through the ground as groundwater [Horton \(1933\)](#). The groundwater is extracted by plant uptake through plant roots. That extraction is lost through transpiration into the atmosphere. Most of the runoffs flow into the ocean and evaporate back into the atmosphere directly from the ocean surface. Also, solid ice and snow can turn directly into a gaseous state through *sublimation*.

In general, this continuous cyclical movement is the main source of ecosystem sustainability and has been regarded as "the bloodstream of the biosphere" [Gleeson et al. \(2020\)](#). However, across the globe, the impacts of the changing environment on the hydro-

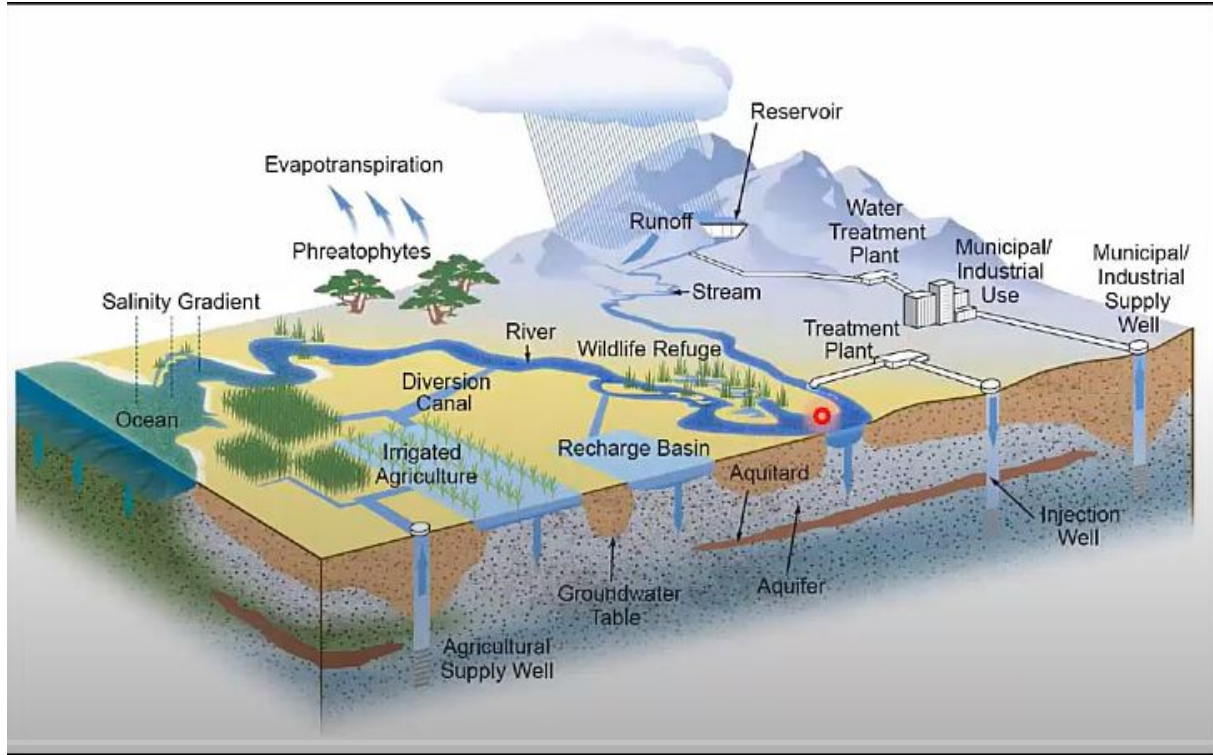


Figure 7: Water cycle showing the hydrologic cycle components. Adapted from <https://water.ca.gov/library/modeling-and-analysis/>

logic cycle have revealed complexities in trends, such as an increase in Evapotranspiration (ET) and precipitation [Zhang et al. \(2020\)](#); [Taye et al. \(2018\)](#); [Cakir et al. \(2019\)](#), surface and groundwater [Rozemeijer et al. \(2021\)](#); [Zamanirad et al. \(2018\)](#). Under global warming and increasing water conservation facilities, water-cycle processes become more complex and are increasingly influenced by climate change and human interference, [Sheil \(2018\)](#); [Allan et al. \(2020\)](#); [Liu et al. \(2019\)](#). The water that evaporates from the oceans and land surfaces is transported across the planet by atmospheric circulation as water vapour. This water condenses to form clouds and precipitates as rain or snow. Trees and vegetation block some precipitation, while some provide runoff on the land surface. Some of the precipitation infiltrate into soils, recharges groundwater, or discharges into streams and flows out into the oceans.

The hydrologic cycle describes the water processes that occur above in the atmosphere, below as groundwater, and on the surface. The importance of land surface in this process is an essential part of the hydrologic cycle. Examples include interception, runoff, infiltration, and water discharge. The sensitivity of hydrologic components to the land surface has been reported by [Music and Caya \(2009\)](#); [McColl et al. \(2017\)](#). To com-

Table 4.1: Global Water Resources Allocation. Source: [Gleick \(1996\)](#)

Global Water Distribution	Vol (1000 km ³)	Percentage of Total Water (%)	Percentage of Freshwater (%)
Oceans, Seas, and Bays	1,338,000	96.5	-
Ice Caps, Glaciers, and Snow	24,064	1.74	68.7
Groundwater	23,400	1.7	-
Fresh	(10,530)	(0.76)	30.1
Saline	(12,870)	(0.94)	-
Soil Moisture	16.5	0.001	0.05
Ground ice and Permafrost	300	0.022	0.86
Lakes	176.4	0.013	-
Fresh	(91.0)	(0.007)	.26
Saline	(85.4)	(0.006)	-
Atmosphere	12.9	0.001	0.04
Swamp Water	11.47	0.0008	0.03
Rivers	2.12	0.0002	0.006
Biological Water	1.12	0.0001	0.003
Total	1,385,984	100.0	100.0

pletely understand the hydrologic cycle processes, which span a variety of time periods and spatial variability, the cycle must be considered as a whole. In these processes, water plays various roles that, in some situations, can have opposite impacts. For instance, the evaporation process favours surface cooling, but the atmosphere's water vapour is a potent greenhouse gas that almost doubles the warming effect of carbon dioxide [Sherwood et al. \(2018\)](#); [Manabe \(2019\)](#); [Aresta et al. \(2021\)](#).

Again, considering that Earth's water is stored in different reservoirs, the largest reservoir being the ocean, providing about 1 335 million km³) of water. The smallest is the atmosphere, with a millionth of that of the ocean. The remaining water is stored as snow, ice in glaciers and permafrost. Other reservoirs include lakes and rivers and underground storage like groundwater and soil moisture. Therefore different reservoirs and their role in climate change will be discussed in 4.2.1 to 4.2.3

4.2.1 Atmosphere

The atmospheric reservoir is ten times smaller than the fluxes. Due to this distinction, water vapour has a limited residence period in the atmosphere before condensing and precipitating [Hense et al. \(1988\)](#). However, [Bengtsson \(2010\)](#); [Bodnar et al. \(2013\)](#); [Van](#)

Der Ent and Tuinenburg (2017) opined that the resident time of water vapour takes a week to 9 days and more Peeters et al. (2020); Bolin and Rodhe (1973), compared to greenhouse gases. Water vapour is a passive component of the troposphere because it is solely determined by temperature and should be viewed as a component of the climatic feedback system Hense et al. (1988). Due to the short lifetime in the atmosphere, water vapour will significantly affect the climate system. For instance, it will affect cloud formation and the radiative balance. As a result, the hydrological cycle's response to global warming is extensive. In general, wet areas become wetter and dry areas become dryer as a result of the different physical processes that influence the change in water vapour, evaporation and precipitation Bengtsson (2010).

Furthermore, clouds scatter and absorb light, thereby reducing the amount of direct solar energy that the surface receives by reflecting incoming solar radiation, on the one hand. On the other hand, they stop some of the surface energy from being released back into space. Understanding the role of water in cloud characteristics is necessary to comprehend both phenomena. For instance, the distribution of incident energy and that emitted by the surface will be impacted by the size, shape, and phase of the cloud's particles. Whether the surface will warm or cool depends on the height of the cloud and its albedo. The surface temperature will increase if warming occurs. As a result, when a cloud's water content rises, its albedo also rises, reflecting more sunlight, favouring negative feedback and chilling the surface. Therefore the atmospheric water interaction is an essential component when studying climate change response and impacts

4.2.2 Land surfaces

Estimating the resident time of water on land surfaces is essential in determining how long water has been present on terrestrial surfaces. The superficial and deeper layers will differ significantly. Accordingly, the average residence time varies between 12 to more than 100 days Stewart and McDonnell (1991), 1.5 to 10 years, and more McGuire et al. (2005); Maxwell et al. (2016), depending on whether water is considered in the soil, plants, or aquifers Haggerty et al. (2002). Compared to the ocean's influence, the hydrological cycle is affected by mechanisms with more temporal and regional diversity.

For instance, there are more significant temperature changes between day and night. Even when merely taking into account land surfaces, significant variances can be seen. Forests, for example, will have lower amplitudes in daily temperatures than deserts. Similarly, seasonal fluctuations and the availability of rainfall affect water storage. In regions with distinctive seasonal interference, e.g. sub-Saharan Africa, water is stocked in the rainy season (summertime in Europe, America and the northern hemisphere) and released into the atmosphere in the dry season.

Soil moisture and vegetation are essential when discussing land surfaces in the hydrological cycle. While assessing soil moisture, surface and soil parameters must be considered by highlighting the soil type, porosity, density, and water retention capability. The second factor is albedo, or roughness, which affects how water vapour is transported from the surface to the atmosphere during evaporation. The biological elements of vegetation, such as its physiology and morphology, which are crucial to transpiration, require attention when studying soil-water-vegetation interaction as has been proven by [Broksma and Bierkens \(2007\)](#); [Jiao et al. \(2020\)](#).

Evaporation and precipitation are the two main processes that may be determined by examining the flow values. Over the oceans, evaporation outpaces precipitation, but not over land surfaces [Joshi et al. \(2008\)](#). Two additional mechanisms, atmospheric water vapour movement from the ocean to the land and runoff, help to explain these differences. The wind drives the extra evaporation from the oceans, resulting in rainfall over land. As a result, precipitation will be greater than evaporation, and the water will runoff back into the oceans. It is worth noting that water exchanges between the reservoirs, as mentioned above, are frequently accompanied by a shift in the water phase. Examples of processes include evaporation from the surface to create water vapour in the sky, sublimation from the poles and glaciers, condensation to create raindrops, and solidification to create ice crystals.

The atmospheric and surface processes of the hydrological cycle address the combined impact of energy and hydrology. Clouds affect the radiative balance. Water vapour is the most prevalent of the atmosphere's significant gases and has high variability. It is significant as a greenhouse gas [Manabe \(2019\)](#); [Shine and Sinha \(1991\)](#). The stratospheric water vapour feedback, which has the potential to affect the climate system significantly,

is discussed by Kweku et al. (2018); Flohn et al. (1992); Shine and Sinha (1991). Because water vapour is a greenhouse gas, warmer climates will increase water vapour in the stratosphere, which will cause further warming. This feedback was estimated to be $0.173 \pm 0.05 W m^{-2} K^{-1}$ Banerjee et al. (2019).

Regarding surface adjustments, the hydrological cycle is primarily driven by the surface energy balance. Precipitation and evaporation have a close relationship. Therefore, modifying either of these processes will affect the intensity of the hydrological cycle. For instance, a change in evaporation brought on by a shift in net radiation is crucial to the radiative balance.

4.2.3 Oceans

The most extensive surface water storage facility is the ocean. The ocean is vital in the hydrologic cycle due to the amount of evaporation occurring from the ocean's surface. Oceans will favour heat storage because of their size and the excellent thermal inertia they possess. The ocean communicates with the atmosphere by absorbing heat, affecting the global hydrological cycle, and exchanging gases like oxygen and carbon dioxide. The distribution of heat, freshwater, nutrients, and chemical tracers throughout ocean basins and the planet are governed by the mass fluxes of seawater. Since the ocean spans 71% of Earth's surface and holds 97% of the planet's water, it plays a crucial role in the hydrologic cycle. Similarly, the heat transferred through regional and global ocean currents impacts local weather and temperature extremes. Since the 1950s, the ocean has absorbed 90% of the extra heat from the imbalanced radiation brought on by human-caused greenhouse gas emissions Nelson and Nelson (2021); Schlesinger (1986). This oceanic absorption of heat due to global warming considerably slows the rise in air temperature. As a result, coupled ocean-atmosphere interaction strongly links climate variability and climate change to ocean dynamics over more extended periods.

From the biodiversity standpoint, the most significant physical changes include warming oceans, greater climatic variability, increased frequency of extreme events, variations in upwelling, thermal stratification, sea level, sea ice, and the ocean's circulation. Moreover, decreased subsurface oxygen O_2 concentrations result from warming and changed ocean circulation. Ocean water can travel vertically upwelling/downwelling,

mixing, and horizontally ocean currents. Deep and surface circulations are separate in terms of temperature and density variations between ocean layers due to mechanisms that exchange heat and salinity. In addition to affecting how waves are created and how the ocean's surface is circulated, the wind also plays a significant role in atmospheric moisture transfer from the ocean.

More importantly, salinity influences ocean density changes, which is crucial in determining the ocean's place in the hydrological cycle. Capotondi et al. (2012) reported that while not as widespread in space as temperature, salinity significantly impacts stratification shifts in the Arctic, North Atlantic, and Northeast Pacific. While temperature has a negative impact on density in the tropical Atlantic, salinity has a positive impact on density at the surface in the western tropical Pacific. An obvious example is the control of thermohaline circulation Chen et al. (2022). This is the method by which warm water moving north undergoes a decrease in temperature and a rise in salinity. The water consequently sinks and flows back toward the south. The higher layers of the ocean's salinity will decrease if the ice from the Northern ice cap melts, adding fresh water to the salty ocean. The thermohaline circulation pattern and, consequently, the hydrological cycle would change as a result. According to Durack et al. (2012), changes in the hydrological cycle are correlated with changes in ocean salinity patterns. The ocean condition is exacerbated by prevailing climatic conditions within the ocean's location and time or season of the year.

4.3 The climate change

The IPCC's special report IPCC (2018) defined climate change as a change in the state of the climate that is identifiable (e.g., through statistical tests) by changes in the mean and/or variability of its attributes and that lasts for a significant amount of time, usually decades or longer. Natural internal processes, external forcings, or enduring man-made changes in the atmosphere's composition or land use can all contribute to climate change. Similarly, the United Nations Framework Convention on Climate Change (UNFCCC) defined climate change as "a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere, and that is

in addition to natural climate variability observed over comparable time periods [Sands \(1992\)](#). The synchronicity of these definitions is without ambiguity. Hence, climate change brought on by human activities that alter the composition of the atmosphere differs from changes in climate brought on by natural factors.

One of the leading causes of climate change is the increase in greenhouse gases (GHG), and among its many notable effects, such as their contributions to global temperature increases, is well known [Nema et al. \(2012\)](#); [Bretherton et al. \(1990\)](#); [Cassia et al. \(2018\)](#). Many studies have found that greenhouse gas (GHGs)-induced global warming may result in increased surface aridity and droughts in the twenty-first century [Dai et al. \(2018\)](#); [Rongfan et al. \(2021\)](#). The information available from the IPCC on surface temperature estimates shows a corresponding increase in temperature to an unabated increase in GHG accumulations. The fact that climate change depends on a range of causes explains the necessity to work with many scenarios [Moss et al. \(2010\)](#); [Harrison et al. \(2015\)](#), such as the Representative concentration pathways (RCPs) and Shared socio-economic pathways (SSPs). These include not just scientific concerns but also demographic, economic, and technical ones that have the potential to impact the severity of climate change's effects.

The impact of human activity on climate change has been the subject of numerous research. [He and Silliman \(2019\)](#) studied the impairment and decimation of a variety of coastal ecosystems agriculture leading to land degradation, [Arora \(2019\)](#); [Malhi et al. \(2021\)](#), changes in land cover and land use [Borrelli et al. \(2020\)](#); deforestation [Qu et al. \(2020\)](#), industrial activities [Shen et al. \(2020\)](#) and many more. Changes in characteristics of precipitation and evaporation due to natural and human-caused climate change result in water availability changes that have implications for the ecosystem. [Wang et al. \(2018\)](#) claim that in addition to climate explanations like glacier melting, human factors can also account for the observed rising sea level [Syvitski et al. \(2009\)](#), about $\sim 76\%$ since 1960 [Dangendorf et al. \(2019\)](#). [Sahagian \(2000\)](#) suggested that global sea level increased by about 1.75 mm/year, [Peltier and Tushingham \(1991\)](#) and have obtained a net signal of 2.4 ± 0.9 mm/year of sea level rise for the 20th century. A similar observation of 1.5 ± 0.4 mm/year, with a preferred value of 1.75 mm/year, was made by [Trupin and Wahr \(1990\)](#) with anthropogenic contribution attributed to one-third of the total measured sea

level rise Sahagian (2000).

Similarly, studies have established the connection of climate change to changes in precipitation patterns, intensity, extremes, and a rise in atmospheric vapour. There is a clear association between temperature and precipitation, as shown by the several regions where high correlations between these two variables have been found Trenberth and Shea (2005). Increased heating causes more evaporation from the earth's surface that may result in surface drying, increasing the severity and duration of the drought. Precipitation supports the ecosystem through moisture availability. However, global warming is presenting a direct impact on precipitation. A warmer atmosphere has more water Pendergrass (2018), as a result, considerable emphasis is placed on the thermodynamics and kinetics of precipitation. In addition, concerns about anthropogenic climate change have increased the demand for accurate assessment of spatial and temporal variations in precipitation across the globe. Climate change, therefore, is affecting the mechanisms involved in the hydrological cycle. For instance, Sun et al. (2022) linked soil moisture trends are found to rise in the summer around the world. It further explains rising trends in precipitation that outnumber those brought on by evaporation. In fact, evaporation has shown tendencies that might be explained by climate change.

Long-term changes in climatic variables, such as temperature patterns, lead to climate change. The greenhouse gases emission from the earth traps solar heat, resulting in global warming and climate change. The rate of global warming is presently higher than it has ever been. Weather patterns are shifting as a result of warming temperatures, which is also upsetting natural climatic events. Across the globe, this puts all living things, including humans, at grave risk to life on Earth. Across the globe, destructive storms have increased in ferocity and frequency. More moisture evaporates as temperatures rise, aggravating extremely heavy rains and flooding, resulting in more severe storms.

The warming ocean impacts both the intensity and frequency of tropical storms. Warm ocean surface waters are the primary food source for cyclones, hurricanes, and typhoons. Most of the heat from global warming is absorbed by the ocean. Most ocean depths have experienced a significant increase in ocean warming during the past 20 years. The ocean water expands as it becomes warmer. Therefore, as the ocean warms, so does its volume. Sea levels increase due to melting ice sheets, endangering coastal and island

people. These storms frequently demolish homes and towns, resulting in fatalities and significant financial losses. Water supply is changing due to climate change, becoming more scarce in many places. In already water-stressed areas, global warming makes water shortages worse. It also increases the danger of ecological and agricultural droughts, harming crops and making ecosystems more vulnerable. A sizable component of the research done for this thesis looked into how atmospheric variables, which are being altered by climate change, might affect precipitation patterns and encourage drought progression.

4.4 Evapotranspiration

The fundamental engine of atmospheric circulation is radiation. According to Stefan-Boltzmann, any object with a temperature greater than absolute zero (0°C) as cited in [Parry and Charlton \(2011\)](#) will emit radiation. Solar radiation heats the earth's surface. The energy is stored in the form of latent heat in atmospheric water vapour [Pierrehumbert \(2002\)](#). Solar radiation interacts with molecules in the air, the most well-known of which are greenhouse gases (GHGs) and ozone. This modest interaction can significantly impact the earth's climate system regardless of budget. Abrupt or prolonged differences in temperature between land and sea, for example, can induce circulations. The air atmosphere, energy balance and aerodynamic equation are given as follows;

$$R_n - G - \lambda ET - H = 0 \quad (4.2)$$

where;

R_n = net radiation flux;

G = sensible heat flux into the soil;

λET = the latent heat flux;

H = the sensible heat;

Short wave radiation, which is emitted by the sun, and longwave radiation, which is emitted by the earth and its atmosphere, are the two types of radiative forcing oscillating

water and energy balance within the earth's atmosphere Council et al. (2005). Short and long wave spectra have limited overlap, and their interactions with matter are different Spyrou et al. (2013). Kleidon and Renner (2013), suggested that surface warming caused by increased absorbed solar radiation results in a greater sensitivity of the hydrologic cycle. Recent studies Kharin et al. (2013); Pendergrass and Hartmann (2012); Andrews and Forster (2010) suggested that a primary measure of hydrologic cycle intensification is the increase in global-mean precipitation per unit surface warming. The author's claim variation is about 1–3 per cent per kelvin, indicating the relationship between solar radiation and the hydrologic cycle. The impact of solar radiation on the hydrologic cycle cannot be overemphasised. Hence, the emission of thermal infrared radiation, latent heat loss associated with evapotranspiration, and the diffusion of thermal energy into the soil, balance the total radiation absorbed by the surface.

Evapotranspiration is an essential element of the hydrologic cycle, and it is responsible for most of the atmospheric water vapour Maček et al. (2018); Adnan et al. (2020), a critical process of water balance and energy balance Zhao et al. (2013). Evapotranspiration is the sum of water evaporation from soil and ocean, including transpiration from plants and animals Thornthwaite (1948). Water evaporation varies across the globe in reference to different climates. Evapotranspiration can be assessed as Potential Evapotranspiration or Actual Evapotranspiration.

Actual evapotranspiration (ET) is the amount of water that removes from the surface by evaporation and transpiration under prevailing soil, water, and atmospheric conditions. Potential evapotranspiration (ET_p) measures the atmosphere's ability to remove water from the surface by evapotranspiration when there is enough water Thornthwaite (1948). Reference evapotranspiration (ET_o) is the rate of evapotranspiration from a reference surface. For example, a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 sm^{-1} , and an albedo of 0.23 are used as the reference surface. It is described as a vast area of uniformly tall, green, well-watered grass actively growing and covering the ground. The available radiative energy, air temperature, the gradient or deficiency of the relative humidity, and the wind speed are the four fundamental ET_p characteristics that still matter a lot for ET_o . Nevertheless, there is a significant distinction between these ideas, and that is how the land surface is

characterised. The height, type, and uniformity of the crop, as well as the albedo, are fixed parameters, as explained in the specification of the reference surface.

Also, Pan evaporation (ET_{pan}) is another crucial water transfer method. Pan evaporation, according to Kadel and Abbe Jr (1916), demonstrates the combined impact of radiation, temperature, humidity, and wind on evaporation from an open-water surface. Using empirical coefficients, sometimes called pan coefficients, can change its measure to reference evaporation. It must be highlighted, though, that safety measures must be implemented. For instance, the energy exchange between the pan's perimeter and bottom must be considered when determining the energy balance. Additionally, there may be extensive heat storage, resulting in nighttime evaporation as opposed to most crops that transpire throughout the day. Finally, the shallow pan's water and grass's reflection of solar radiation, as well as the quality of the air, will vary in temperature and humidity above both surfaces with turbulence.

4.4.1 Methods for Estimating Evapotranspiration

Evapotranspiration measurement is difficult due to its high variability in space and time. Alternatively, the estimation of evapotranspiration is determined by the data available. Several methods for estimating evapotranspiration exist in the literature, such as Penman Penman (1948); Thornthwaite (1948); Blaney and Criddle (1962); Jensen and Haise (1963); Penman-Monteith as cited in Howell and Evett (2004); Priestley and Taylor (1972); Hamon (1961); Hargreaves and Samani (1982). Other conventional methods of measurements, such as the use of Eddy Covariance (EC) devices, weighing lysimeters, the Energy Balance Bowen Ratio (EBBR), and scintillometer, are operationally capable of supplying accurate estimates of ET_a over homogeneous surfaces.

ET is usually estimated from fundamental equations, observation of contributing climatic variables, remote sensing and Land Surface Models (LSMs) techniques. The energy balance equation is given as follows;

$$R_n = H + LET + G \quad (4.3)$$

where;

R_n = net radiation

H = sensible heat flux

L = latent heat of vaporisation

ET = actual evaporation

G = soil heat flux

Similarly, ET can be obtained from the water balance using the following equation;

$$P = ET + Q + \frac{dw}{dt} \quad (4.4)$$

where;

P = precipitation

Q = runoff

dw/dt = change in soil moisture storage

The ability to estimate at many spatial scales is one of the key benefits of utilising this method. Interestingly, many empirical techniques have been developed to calculate evapotranspiration from various meteorological factors over the past years. Some of them used a combination of an energy balance and an aerodynamic equation to calculate evaporation from open water and bare soil, as well as transpiration from grass and vegetated areas. Most of these equations modified the now well-known Penman equation [Penman \(1948\)](#).

$$E_p = \frac{1}{\lambda \rho_w} \frac{s R_n + c_p \rho_a (e_a - e_d) / r_a}{s + \gamma (1 + \alpha r_c / r_a)} \quad (4.5)$$

where;

E_p = Potential Evapotranspiration in m/s

λ = Latent heat coefficient in J/kg

ρ_w = Density of Water in Kg/m³

R_n = Net radiation in W/m²

s = Slope of the temperature-saturated vapour pressure curve in kPa/K

c_p = Specific heat of air at constant pressure J/(kg K)

ρ_a = Density of air kg/m³

e_d = Actual vapour pressure of the air kPa

e_a = Saturation vapour pressure for the air temperature kPa

γ = Psychrometric constant kPa/K

r_a = Aerodynamic resistance s/m

r_c = Bulk Surface resistance s/m

α = Stomatal resistance coefficient.

4.4.2 Energy Balance Bowen Ratio (EBBR)

Another important method of measuring surface moisture is the Bowen Ratio [Bowen \(1926\)](#). Energy Balance Bowen Ratio (EBBR) links turbulent fluxes to surface temperature and humidity gradients. It is most frequently used in meteorology and hydrology and is calculated as follows;

$$B = \frac{H}{E} = \frac{-pc_p K_h dT_a/dz}{-(L\rho\varepsilon/P)K_v de/dz} \quad (4.6)$$

where;

c_p = specific heat of air

e = air vapour pressure

ε = ratio of the molecular weights of wet and dry air

K_h = eddy diffusivity for heat

K_v = eddy diffusivity for water vapour

L = latent heat of vapourisation

P = atmospheric pressure

ρ = air density

T_a = air temperature

z = height.

Where equation 4.6 is substituted into the energy balance, 4.7 produces BREB, 4.8 G is

the soil heat flux density at the surface, and Q^* is net radiation, and 4.9 provides the BREB gradient form.

$$Q^* + G + H + E = 0 \quad (4.7)$$

$$E = -(Q^* + G)/(1 + B) \quad (4.8)$$

$$E = \frac{-(Q^* + G)}{1 + \frac{C_p K_H dT_a/dz}{(L\varepsilon/P)K_v de/dz}} \quad (4.9)$$

In BR, the sensible heat flux density, H , and latent heat flux density, E , are expressed by their respective transport or gradient. Bowen ration the type of heat transfer (i.e., sensible heat (differences in temperature absent of evapotranspiration) and latent heat are the two types of heat transmission that can take place (the energy required during a change of state, without a temperature change). The Bowen ratio is frequently used to determine the amount of heat lost (or acquired) in a substance; it is the ratio of energy fluxes caused by sensible heat and latent heating, respectively, from one state to another. As a result, these gradients can be used to achieve evaporation.

When B approaches -1 in equation 4.6, that is, when $-E$ is about equivalent to $+H$ becomes unstable in equation 4.8. This circumstance frequently happens around sunrise and sunset when Q^* is low. To analyse E at certain times, other approaches must be utilised. According to Fritschen and Fritschen (2005), this approach makes the following assumptions; first is that steady-state conditions exist. Secondly, transport is one-dimensional, and thirdly, the surface is homogenous (i.e., sensible heat, water vapour, and momentum sources and sinks are indistinguishable). However, the Bowen ratio is a poor choice of variable for use in formulas, especially for arid terrain. Because of this, the term describing the proportional contributions of the turbulent energy fluxes to the surface energy budget, the evaporative fraction, is occasionally a better choice.

Furthermore, the assumption of steady-state circumstances appears to preclude transitory conditions at the surface; yet, in agronomic work, no severe errors occur because $\frac{1}{2}$ hourly or hourly values are typically calculated. On the assumption of one dimen-

sion, vertical gradients are assumed to be zero in one-dimensional transport. If there are horizontal gradients, significant inaccuracies may happen. When the airflow comes into contact with changes in surface roughness, moisture, or temperature, horizontal gradients may develop. Wind speed, air temperature, and vapour profiles change as the air flows downwind to account for the new surface. On the assumption that the surface is homogeneous, orchards with large gaps between the trees and skip-row plantings might not be uniform. Due to soil and plant heterogeneity, natural surfaces such as grasslands, forests, and deserts might not be uniform. However, vegetative covers on agricultural land can be considered homogeneous. Additional instrumental sites for spatial sampling may be needed for nonhomogeneous surfaces.

Interestingly, BREB methods have been deployed for various studies involving surface-atmosphere energy exchange, water budget, and climate change. Göckede et al. (2017) in their assessment concluded that warmer conditions were found throughout the soil profile, profound shifts in soil temperatures, modification of the snow cover period, and shifts towards taller vegetation. Ren et al. (2022) conducted energy distribution measurements and observations characteristic of semi-arid and semi-humid farmland ecosystems and found that sensible heat flux in the semi-arid farmland was the main consumer of available energy. In the semi-humid area, latent heat flux in summer had the dominant role in energy distribution (mean β 0.71). It is worth mentioning that the higher BR values cause the available energy to shift more in favour of the sensible heat flux, which may signal water stress and/or drought stress. Other studies include estimating evapotranspiration in artificial environments such as screen houses by Dicken et al. (2013), where they revealed a good agreement between the latent heat flux calculated using the Bowen ratio approach and that derived from Eddy Covariance measurements.

Evapotranspiration estimation in various environmental factors, such as climate change studies, requires extra care when it comes to selecting a proper measurement method. For example, using the Bowen ratio to estimate ET has provided varying results, as shown from the research cited, due to its ability to switch performance under certain conditions whereby the evaporation rate increased as the net irradiance increased and vice versa. Therefore much care is required in instrumentation and calibration of equipment for optimal results as well as adequately scaled spacing to obtain the best result.

4.4.2.1 Eddy covariance (EC)

Montgomery (1948); Swinbank (1951); Obukhov (1951) as cited in Foken et al. (2012) devised the eddy covariance method for monitoring exchanges of heat, mass, and momentum between a flat, horizontally homogenous surface and the surrounding environment (1951) Foken et al. (2012). The turbulent transport theory is the foundation of this methodology. In these circumstances, net transport between the surface and atmosphere is one-dimensional. The covariance between the quantity of interest and turbulent vertical wind variations can be used to determine the vertical flux density. While studies in the 1980s focused on the turbulent fluxes of momentum, sensible, and latent heat across heterogeneous surfaces, early micrometeorological experiments from the 1950s to 1970s were made to examine fundamental characteristics of air turbulence on homogeneous surfaces Foken et al. (2012). These studies served as the foundation for a large number of subsequent micrometeorological studies, which required experts in sensor handling and micrometeorology.

In the 1990s, a new generation of sonic anemometers, infrared gas analysers for carbon dioxide and water vapour, and the first complete software packages for the eddy covariance method were developed, paving the way for continuous eddy flux measurements McMillen (1988). The ecological community began using the eddy covariance approach to quantify the water and carbon dioxide exchange between an ecosystem and the atmosphere in the early 1990s. Installation of the first measuring towers began for what would eventually become the global FLUXNET network Baldocchi et al. (2001) as cited in Foken et al. (2012) and writing of introductions to novel techniques for non-micro meteorologists.

The covariance of measured heat and moisture fluxes with the vertical wind speed is used to calculate sensible heat flux and evaporation rate. For complete definitions of layers in the atmosphere, eddy covariance measurements are often conducted in the surface boundary layer. Which are 20–50 m high in the event of unstable stratification and a few tens of meters high in the case of stable stratification. Fluxes in the surface layer are roughly constant with height; hence, measurements made in this layer indicate the fluxes from the underlying surfaces that are of interest. Using the eddy covariance approach to

estimate the fluxes is appropriate, given that air turbulence is the predominant transport mechanism in this situation.

4.4.2.2 Lysimetry

Lysimetry is another essential technique to study water and soil balances. It is a standard tool for measuring evaporation. The technique entails monitoring a tank's water level changes while managing water storage, drainage, and precipitation. This technique aids in studying the amount of water taken in by soil by irrigation or precipitation and, consequently, how much of the water is lost through plant uptake, evaporation and drainage. The lysimeter technique uses large sensors to measure soil water content, temperature, GHG concentration and emission, carbon dioxide, etc. Depending on their complexity, lysimeters come in a variety of forms. We can distinguish between weighable and non-weighable items, for instance.

In contrast to the second kind, which merely provides the drainage rate, the first kind directly measures precipitation, drainage, and changes in water storage. In order to measure the water content and precipitation, respectively, the user will need to do the remaining measurements using additional tools like a neutron probe and a rain gauge. Several research studies have been done across the globe using the Lysimetry technique. In addition, the Lysimetry equipment can be installed with different soil types. For instance, these methods have revealed crop performances under different soil types and crops in the same environment, [Bello et al. \(2019\)](#); [López-Urrea et al. \(2021\)](#). Although large weighing lysimeters are considered the ultimate standard for measuring ET, their installation and upkeep are costly [Moorhead et al. \(2017\)](#).

4.4.2.3 Scintillometer

Another method of measuring ET is by using a scintillometer. A scintillometer measures the structure parameter of the refractive index of air caused by changes in humidity, pressure and temperature. Scintillometers assess contributions to fluxes over a set path length. The dynamics of how radiant energy from the sun is dispersed to the land surface

are explained by the energy balance. The energy balance equation is frequently used with scintillometer observations to compute ET using the following equation;

$$LE = R_n - H - G \quad (4.10)$$

where;

R_n is the net radiation (W/m^{-2});

LE = the latent heat flux (W/m^{-2});

H = the sensible heat flux (W/m^{-2});

G = the soil heat flux (W/m^{-2}).

In this approach, the sun's energy is either reflected or absorbed. The R_n , which represents the portion absorbed, is positive when energy goes toward the surface (the plant canopy) and negative when it moves away from it. The R_n that has been absorbed can subsequently be dispersed to the soil as G , the air as H , or it can be used to power the evaporation of water as LE .

Scintillometer uses a beam of electromagnetic radiation with a known wavelength transmitted over a considerable distance to measure agricultural and other landscapes (100 m–4.5 km). A predetermined route length separates the transmitter and receiver of a scintillometer. As the beam passes through air eddies, it experiences variations in beam intensity due to diffraction and absorption. The refractive index of air, which may be used to compute the structural parameters for temperature and humidity, and H , can be determined using these changes or scintillations. Surface fluxes of sensible heat, latent heat and momentum can be determined from the obtained structure parameter of temperature, structure parameter of the refractive index and inner scale of turbulence, respectively, by applying Monin–Obukhov similarity theory (MOST) [De Bruin \(2002\)](#). The benefits of Scintillometer over traditional point source measurements are the ability to quantify fluxes across shorter distances and at elevations closer to the surface. In addition, they derive fluxes over large distances, enabling data collection at various time scales [Moorhead et al. \(2017\)](#). However, they do not offer a direct measurement of H , requiring additional information, which increases the uncertainty of H .

Different types of scintillometers have been deployed in measuring ET for various environmental reasons, such as in water deficit arid region and climate change studies, and by many authors [Valayamkunnath et al. \(2018\)](#); [Aguirre et al. \(2020\)](#); [Saadi et al. \(2018\)](#); [Han et al. \(2019\)](#); [Han et al. \(2019\)](#); [Moorhead et al. \(2017\)](#). The conclusions reached by some of these authors proved that Scintillometers are reliable over a wide area covering a large spatial extent, a watershed or basin, and on varied climatic conditions.

4.5 Remote Sensing-Based Drought Monitoring

The demand for better and comprehensive synchronous measurement of spatial events led to the development and advancements in remote sensing technology. Accurate estimations of water supply and demand are necessary to assess freshwater availability. The energy and atmospheric controls on terrestrial evapotranspiration (ET), which directly links climate and the water-energy-food nexus, are characterised by atmospheric evaporative demand (AED) [Wang et al. \(2010\)](#); [Yang et al. \(2021\)](#). Therefore, understanding AED's fluctuation is crucial for forecasting the unpredictability of water demand and estimating aridity leading to droughts in the current climate change situation.

Drought occurrences are anticipated to intensify and occur more frequently as our climate changes. In the past 50 years, remote sensing has allowed researchers to observe and estimate significant drought-related trends on a regional scale. This substituted researcher's reliance on conventional site-based measurements. In addition, remote sensing introduction has proven crucial in areas lacking in-situ monitoring stations and inadequate data availability. As a result, nearly all facets of the spread of drought are now represented in available remotely sensed data sets, improving human understanding of the phenomenon. In fact, the magnitude of remote sensing satellites, platforms, techniques and data available has made it possible for extensive covering and near-real-time monitoring of droughts as they develop and progress in their intensity and magnitude.

This paradigm shift in drought monitoring methods happened at the turn of the 20th century, coinciding with earth observation and remote sensing technologies developments, such as the 1972 debut of the NASA Landsat series [Huang and Fipps \(2006\)](#);

Menarguez (2015). A broad mix of contextual data is provided for drought monitoring via remote sensing-based techniques, which additionally monitor the Earth’s surface variables such as vegetation health and water levels Menarguez (2015). The need to reduce and mitigate the impacts of droughts requires effective drought and climate change variability monitoring. Therefore, remote sensing has revolutionised the area by making it possible to track crucial drought-related variables at broader temporal and spatial scales than was previously achievable with conventional techniques Bhaga et al. (2020).

While droughts are complex phenomena that spread in a variety of ways and have a wide range of characteristics, they are typically categorised into one of four categories: meteorological, agricultural, hydrological, and socio-economic (which represent the effects on the human population and society) Society (2013). These drought categories pertain to various methods of measurement and identification rather than being independent categories.

Drought propagation is the progression of a precipitation deficit (i.e., rainfall below average) through the rainfall regime, commencing with meteorological drought and progressing to hydrological drought if conditions persist Van Loon (2013). Regional climate, and local catchment characteristics, such as geology, vegetation cover and type, soils, topography, and human activity, might affect how a drought spreads.

Remote sensing is a valuable technique in monitoring various drought-related variables due to the complex nature of drought, event heterogeneity, and multiple propagation channels and influences. As defined in the introduction of this thesis, remote sensing techniques employ measurements of the properties and characteristics of its target using sensors. Active and passive sensors that capture data across the electromagnetic spectrum have been used to enhance understanding and guide environmental management decisions since remote sensing applications in drought monitoring were first developed.

4.5.1 Active microwave observations

Active microwave estimates derived from Synthetic Aperture Radar (SAR) satellite instruments for surface water extent and flood estimation have shown great promise. Active

sensors using electromagnetic radiation with a wavelength between 1 mm to 1 meter and frequency interval from 40,000 to 300 Hz can penetrate clouds and operate day and night, making them extremely useful for measuring flood extent. These sensors can also penetrate vegetation Wagner et al. (2007).

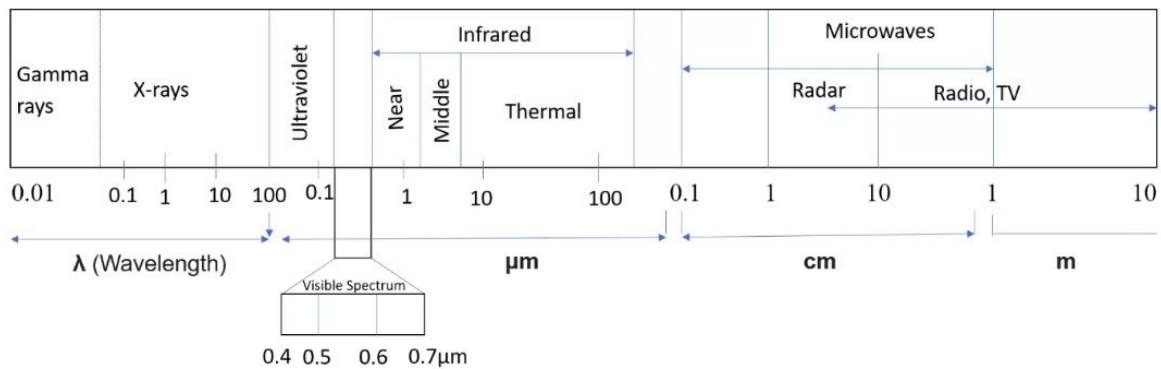


Figure 8: Electromagnetic spectrum (EMS) showing the different sections of the spectrum. The microwave region is from 0.1cm to 1m. Adapted from; <https://geolearn.in/microwave-remote-sensing/>

Hydrological components and drought monitoring include using the Microwave Integrated Drought Index (MIDI), the Tropical Rainfall Measuring Mission (TRMM) derived precipitation, and the Advanced Microwave Scanning Radiometer for EOS (AMSR-*E*) derived soil moisture, Zhang and Jia (2013). In addition, AMSR-*E* derived land surface temperature from monitoring short-term drought Zhang and Jia (2013). Liu et al. (2013); Andela et al. (2013) suggested that microwave-based vegetation monitoring in remote sensing of drought is a rapidly expanding and significant field.

Surface water mapping using active microwave satellite observations is based on extremely low backscatter coefficients over water bodies when observed off-nadir Prigent et al. (2007). When the incidence angle is off-nadir, the energy sent by the active instruments is reflected in the specular directions, resulting in a very low backscatter coefficient at the satellite sensors. Nevertheless, wetland detection becomes site-specific when vegetation is present because nonspecular returns (multiple scattering) pollute the signal and increase the backscattering coefficient Prigent et al. (2007). This situation makes surface waterbodies distinct when viewed on an image, e.g., water bodies appear very dark in SAR imagery.

Other hydrological hazards around the world, such as flooding have been estimated using SAR observations from various satellites, including ERS-2 [Kasischke et al. \(2003\)](#); [Giustarini et al. \(2011a\)](#); [Giustarini et al. \(2011b\)](#) JERS-1 [Hess et al. \(2015\)](#); [Parrons et al. \(2019\)](#), ENVISAT [Giustarini et al. \(2011a\)](#); [Giustarini et al. \(2011b\)](#); [Hess et al. \(2003\)](#), RADARSAT-1 [Iris et al. \(2019\)](#); [Rahman and Thakur \(2018\)](#). Despite all the benefits highlighted above, global mapping of hydroclimatic events using SAR observations is limited due to several reasons. One of the problems is that SAR observations are more difficult to interpret than visible/infrared observations because the backscatter coefficients are affected by complicated mechanisms. Again, the effect of wind on the backscatter coefficient over water surfaces, the double-bounce scattering mechanism and the similarity between water and flat dry surfaces have all been identified as impediments. However, the benefits provided by active microwave sensors outweigh the impediment. [Xing et al. \(2018\)](#) explained that some impediments could be ignored.

4.5.2 Passive microwave observations

Contrary to the active sensors discussed above, passive sensors record the electromagnetic energy released or reflected by the Earth's surface in their range of view. Also, unlike active ones, passive remote sensing sensors do not direct their energy toward the surface or object being studied. Instead, sunlight the target reflects is the natural energy source used in passive remote sensing. Because of this, it can only be used when there is adequate sunshine, as there won't be anything to reflect in darkness. A good example is the longest-running Earth-observing mission, Landsat. Landsat stands out among passive sensor examples used in remote sensing. The long period of earth observation has provided tons of satellite data of the globe, allowing us to examine how the Earth has changed over 50 years. This has provided researchers and scientists with information relevant to various earth science applications such as drought monitoring, vegetation health, ecology, forestry and agriculture, marine sciences, meteorology, etc.

Monitoring hydroclimatic events such as drought using a passive microwave satellite estimate is based on the low emissivity of water bodies. This is due to differences in dielectric properties between water and soil or vegetation, particularly at lower frequen-

cies. Although passive microwaves can provide global coverage, the spatial resolution is coarse, preventing them from being used for higher spatial resolution applications Sabaghy et al. (2018). In addition, this low spatial resolution presents significant ambiguities in complex areas of open water bodies and other types of environments such as soil and vegetation. However, Some researchers combined passive microwave with active microwave and visible/NIR satellite estimates to develop methodologies producing global hydroclimatic data. In passive remote sensing, various band combinations are used to measure the obtained quantity through multispectral or hyperspectral sensors. The number of channels used in these combinations varies (two wavelengths and more). The range of bands includes spectra visible to humans and those invisible (visible, IR, NIR, TIR, microwave).

According to Babaeian et al. (2018) Sentinel-1, the advanced microwave scanning radiometer-earth observing system (AMSR-E), soil moisture and ocean salinity (SMOS), soil moisture active passive (SMAP), and other satellites with active and passive microwave sensors have all been launched to monitor soil moisture. Other studies that utilised passive sensors in climate change and drought include; Konings et al. (2019); Hu et al. (2019); Becker and Schmidhalter (2017); Xu et al. (2018); AghaKouchak et al. (2015). For example, the inclusion of TIR makes it possible to estimate the earth's surface temperature, an important parameter when discussing climate change. Colliander et al. (2017) assessed for active-passive for accuracy and validity and concluded that both satisfied all the standards. There has also been an attempt to compare active and passive sensors' capabilities in monitoring drought Eswar et al. (2018); Bai et al. (2018).

In general, all water detection methodologies are based on the absorption of water bodies in visible and near-infrared wavelengths Aggarwal (2004). Other remote sensing methods for estimating hydrologic components, such as the surface water extent using visible and NIR satellite imagery, are well established and considered reliable at local and regional scales. As long as clouds do not obscure the surface water target or dense vegetation. Water bodies absorb nearly all incoming energy in the near and shortwave infrared wavelengths, resulting in little to no reflection to satellite sensors as the wavelength increases. The Normalised Difference Vegetation Index (NDVI) Tucker (1979), the Normalised Difference Water Index (NDWI) McFeeters (1996), the Modified Normalised Difference Water Index (MNDWI) Xu (2006), and the Automated Water Extraction Index

(AWEI) Feyisa et al. (2014) are examples of such indices. These water indices have been tested with various types of visible/infrared satellite imagery, including NOAA/AVHRR Bryant (2003); Jain et al. (2006), MODIS Chandrasekar et al. (2010); Chen et al. (2005), Sentinel-2 Du et al. (2016), and Sentinel-1 and Landsat Bao et al. (2018); Konapala et al. (2021). These results demonstrated a high level of classification accuracy. However, given the speed at which technology is developing, it is crucial to constantly analyse and consider past and present events and potential future developments, especially in this rapid climate change era.

4.5.3 Land Use & Land Cover in Climate Change & Drought

Forests and agricultural land have received the majority of attention in research on the effects of climate change on land use. This is in part due to anthropogenic land use activities such as agriculture. Although, other factors, such as rainfall patterns and climate variation, can impact temperature changes that lead to droughts. For example, increasing nighttime temperatures can impact biological functions like respiration and may lower the perspective of plants, thereby lowering their bane of tolerance.

Notably, numerous studies abound worldwide to better understand the contribution of land use leading to drought Qi et al. (2020); Ty et al. (2022); Biazin and Sterk (2013); Ding et al. (2021). Furthermore, the frequency, severity, and duration of natural and man-made fires, as well as a potential rise in sea levels and floods, particularly in coastal areas, are additional potential effects of climate change on land cover. Given all the aforementioned considerations, the net effect on agriculture in a particular location could be either favourable or unfavourable. If a region's agriculture becomes less productive due to climate change, more farmland will be put to other purposes or left barren. Lands that are now forested may be converted to agricultural usage. This condition is often detrimental to a region's overall land use status, making recovery and reforestation impossible and exposing the current land use to the actions of climate change impacts.

Again, increasing population density leads to increased demand for development and housing Güneralp et al. (2020), contributing to the worsening climate change progression due to significant residential energy demands. As noted by Goldstein et al.

(2020), residential energy use accounts for 20% of greenhouse gases in the United state. As more significant development and land fragmentation occur, additional human settlements indirectly impact the land cover. Furthermore, rising temperatures will worsen the consequences of urban heat.

A more unpredictable global climate is predicted for the future [Junk et al. \(2013\)](#); [Dai \(2011\)](#); [Eckstein et al. \(2019\)](#). Natural ecosystems will be under more stress as a result. Species that depend on untouched, natural habitats will have difficulty surviving droughts and storms, especially where the habitat is only present in sparsely distributed areas. On the other hand, if these ecosystems are interconnected, they will be more resistant to climate change, allowing populations to travel and repopulate areas affected by drought or intense storms. Planning for land use to avert climate change impacts may include establishing habitat corridors to link isolated areas with adequate habitat.

As a result of climate change, certain agricultural areas will be more suited for production while others will be in less arable conditions. If productivity is permitted to fluctuate in reaction to the changing climate, the effects of climate change on agriculture will be reduced. This situation will further create a problem for the land cover. The climate of certain land may change in the future, making it ideal for agriculture in some areas. Similarly, forest territory dominated by less desirable species may increase in value in the future, and vice versa. Settlements will have less flexibility to adapt to sea level rise if land use policies prohibit building along the shore. A rise in storm intensity, which would increase flash flooding, is one potential effect of climate change.

Studies around the globe suggested that the net flux of carbon from land use and landcover change (LULCC) accounted for 12.5% of anthropogenic carbon emissions from 1990 to 2010 [Houghton et al. \(2012\)](#), carbon emission from deforestation and degradation in the tropic $\sim 1.4 \pm (0.5) \text{ PgCyr}^{-1}$ [Houghton et al. \(2012\)](#). Therefore, proactive land use planning can be adopted to prepare for and respond to climate change and reduce the potentially harmful effects resulting from land use and land cover alterations.

4.6 Current Trends on Hydrological Assessment for Drought Identification

Hydrological assessment is accomplished by parameterising regional or global hydrological processes at various levels using coupled physical mechanism models. It is the application of mathematical or statistical approaches to examine feedback or responses from hydrological systems. Similarly, it provides an opportunity to anticipate a little-known outcome. It is based on the understanding that feedbacks and interconnections in the climatic, hydrologic and ecologic systems drive the evolution of overall environmental conditions over time. Therefore, regular assessments of the hydrological system are required to provide insights into the present and expected environmental conditions. For instance, in a watershed, the interplay between hydrological, climatic, and ecosystem processes can be used to model the regional multi-component hydrologic cycle, considering the scale and magnitude of events over time.

The possible implementation of conceptualised modelling is due to the hierarchical structure connected to multiple physical processes in hydro-ecology. In addition, the intricacies linking hydro-ecology to rapidly changing global climate point to the fact that there is a gap in understanding the impacts of climate change on hydrological systems. A few hydrological models have covered surface flow and infiltration capacity models, atmospheric transport such as evapotranspiration, and groundwater modelling. However, hydrology modelling is complex and has drawn constant criticisms from scientists from other fields, such as mathematics and physics.

The dominant drive inspiring the research in hydro-ecologic model development has been to identify which model will give more compatible results with observation. For instance, event-based hydrologic models are often used for flood design, and assessment [Stephens et al. \(2018\)](#). However, this is difficult due to the divergent global spatial distribution of features. Water resident time, change in state transformation techniques, volume/amount and temperature all impact the efficiency of a particular hydrologic or hydro-ecologic model. Some hydro-ecologic models are complex, while some are simple. A complex hydro-ecological model requires the input of many parameters and high computational costs. However, some scientists have argued that even a complex model does not

provide better results. Simple and easy-to-interpret models requiring empirical equations for a simplified condition may still be the first choice when choosing a model because they incur moderate computational costs [Song et al. \(2015\)](#).

Model applications in hydro-ecology encompass every facet of the hydrological system. This has led to physical-based hydrodynamic models such as HEC-HMS, SWAT, MIKE, ADCIRC, Delft3D, HEC-RAS, MIKE SHE, HBV model, TOPMODEL etc. Conceptual models such as Fuzzy logic and Auto-regressive integrated moving average (ARIMA) model, Unit Hydrograph, and Support Vector Machine (SVM) have all been applied in hydrological modelling.

As many studies have shown that Identifying the important parameters affecting hydro-ecologic performance, thereby limiting model optimisation and uncertainty quantification is essential in hydro-ecologic assessment. Hydroecological models used in studying the processes governing impacts of climate change and urban development on water resources and projecting potential ranges of impacts from future change scenarios have recently received attention. This is because the level of uncertainties is amplified at each stage of the process, from scenario generation to scale issues, hydrological process simulation, and management implications [Praskievicz and Chang \(2009\)](#). Some studies [Praskievicz and Chang \(2009\)](#); [Wicks and Bathurst \(1996\)](#); [Massmann \(2020\)](#); [Sisay et al. \(2017\)](#); [Dwarakish and Ganasri \(2015\)](#) have shown that geology, land use, latitudinal position and topography have all been named as significant factors influencing the accurate modelling of hydrological systems. Despite these, scientists are faced with several uncertainties and complexities when modelling a scenario in research for answers. [Efstratiadis and Koutsoyiannis \(2010\)](#) have proposed alternative techniques for dealing with conflicting and non-commensurable criteria in hydrologic modelling.

Under global warming and an increase in the number of water conservation facilities, water-cycle processes become more complex and are increasingly influenced by climate change and human interference. Hence, there is a need for more significant research to understand the hydrologic cycle and ecological processes and their responses to human interferences and environmental changes through independent assessment of the contributing factors such as evapotranspiration, precipitation and temperature. The impact of the changing environment on the hydrologic cycle needs to be investigated

through mechanisms, techniques, and an efficient modelling methodology.

Drought signals can develop from anomalous atmospheric moisture (such as precipitation deficits) and spread through the hydrological system, where they can lead to a scarcity of usable water for terrestrial purposes (such as soil moisture, groundwater, and streamflow). Therefore, several drought indices have been established, each with advantages and disadvantages, to better monitor and capture the complex drought conditions with various causes and characteristics. Other prominent drought indicators include the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Index and the Standardized Precipitation Evapotranspiration Index (SPEI). Normalised Difference Vegetation (NDVI), Vegetation Condition Index (VCI), Normalised Difference Water Index (NDWI), Modified Normalised Difference Water Index (MNDWI) and a lot more.

Most of these indices are in use, depending on the purpose of the research. Standard Precipitation and Evapotranspiration Index (SPEI) are the most commonly used drought assessment indices worldwide. SPI evaluates drought based solely on precipitation. SPEI, in contrast to SPI, takes into account both temperature and precipitation, partially accounting for the effects of global warming. The SPEI is made to determine drought by taking into account both precipitation and potential evapotranspiration (ET_p). The SPEI thus captures the primary effect of rising temperatures on water demand, in contrast to the SPI. The SPI is based on the long-term precipitation record for the study period and is then fitted to a probability distribution to ensure the mean SPI is zero for the study period, and location [McKee et al. \(1993\)](#). To measure and evaluate the geographical and temporal drought features across diverse regions, [Palmer \(1965\)](#) created the Palmer Drought Severity Index (PDSI). It calculates the supply and demand for moisture in soil layers using temperature and precipitation data. It is widely acknowledged that PDSI is more of a drought indicator when taking into account water shortages over extended periods [Keyantash and Dracup \(2002\)](#), which commonly ranges from 9 to 18 months depending on the hydrometeorological characteristics of the region [Guttman \(1998\)](#). Despite the fact that various Palmer index variations, such as the Z index and Palmer Hydrological Drought Index (PHDI), may suggest a different time scale from the original version [Karl \(1986\)](#). However, they do not substantially make the time scale as flexible as in SPI. SPI and SPEI can be calculated in addition to mod-

ifications. [Noureldeen et al. \(2020\)](#) integrated the standard precipitation index (SPI), standard precipitation evapotranspiration index (SPEI), and Vegetation Condition Index (VCI) anomaly to assess drought in the Sahelian countries. [Anyamba and Tucker \(2005\)](#) calculated the Normalised Difference Vegetation Index (NDVI) using NOAA/AVHRR data in the Sahel.

4.6.1 Assessing Climate Change Impact on Hydro-ecology

The scientific study of climate change has a long history dating back to the distant past. For example, more than a century ago, [Fourier \(1827\)](#) as cited in [Fleming \(1999\)](#) noted that the Earth is a greenhouse with an atmosphere that prevents infrared radiation from escaping. Shortly after then, the overriding importance of water as a greenhouse gas was recognised. This was followed by [Arrhenius \(1896\)](#) articles presenting the first model of the impact of carbon dioxide (CO₂) in the atmosphere on terrestrial temperature. These discoveries have continued to this day. Despite the recent global awareness of the implications of rapid climate change, there seem not to be many options left, and the factors exacerbating climate change scenarios are only increasing.

The main concepts for evaluating climate change impact include changes in climatic variables such as temperature. For example, factors leading to an increase in temperature are assessed by evaluating the changes in the system, such as identifying what role evapotranspiration plays in temperature increase and what could likely be the result of temperature increase on precipitation and runoff. Unfortunately, information on climate change impacts on hydro-ecology is significantly distortions in many regions, especially the developing world.

Since the climate variability associated with the increase and decrease of climatic variables has continued unabated. The climate phenomenon will likely worsen existing natural resource strains while also creating new ones [IPCC \(2012\)](#). Climate change impacts on hydrological systems have been reported on various hydrological and ecological components such as precipitation patterns, surface water, wetlands, groundwater etc.

Around the globe, water resources such as rivers are among the ecosystems most

sensitive to climate changes Visser et al. (2019b); Li and Fang (2021); Rafiei-Sardooi et al. (2022). Climate change would also impact groundwater Nguyen (2020); Cuthbert et al. (2019). Thus, it is through freshwater resources, particularly rivers, that some of the most significant impacts of climate change will be felt.

In an attempt to assess the influence of climate change on hydro-ecology Barnett et al. (2004); David (2018); adopted quantitative assessments of climate-driven environmental impacts in the United States of America (USA) in order to provide useful information to regional state and local decision-makers. They observed general large-scale warming of about 1-2 °C over the West of the USA. Visser et al. (2019a). Brown et al. (2020) used regression and correlation analyses to examine the relationships between sub-arctic riverbank erosion and seasonal hydrology. In addition, Satgé et al. (2017), when they used satellite remote sensing products to investigate the drying of Poopó Lake in Bolivia, reported that out of the three reoccurring droughts between 1990 and 2015, two are associated with negative annual rainfall anomalies in 1994 and 1995. Their study finds that anthropogenic impacts through agricultural activities are significant factors contributing to the regional desertification and the recent disappearance of Poopó Lake in Bolivia.

In Europe, Marcinkowski and Mirosław-Świątek (2020), preferred mathematical models to better understand ecosystem functions and their interactions across different spatial and temporal scales by anastomosing river system in north-eastern Poland where a significant loss of the anabranches has been observed. A combination of modelling approaches, the Soil and Water Assessment Tool (SWAT software) coupled with the HEC-RAS one-dimensional unsteady flow model, was applied to reveal the projected changes of two future times, 2021–2050 and 2071–2100, under the Representative Concentration Pathway 4.5 using an ensemble of nine EURO-CORDEX model scenarios. Their results showed that low flow conditions in the anastomosing section of the Narew National Park will remain stable in 2021–2050 compared to current conditions and will slightly increase in 2071–2100. Nerantzaki et al. (2019) used a Karst-SWAT model combined with 11 climate change scenarios to assess surface and karstic spring flow in Crete, a Mediterranean, karst-dominated island in the Mediterranean. Their Water Exploitation Index to describe the spatial variability of future water stress on Crete revealed a projection of a decrease in

both surfaces and karstic spring flows around 2060.

Other attempts have been made at both regional and global scales to assess the levels of climate change impacts on the hydrological system. In Asia, [Liu et al. \(2021\)](#) used a coupled model to investigate the potential responses of lake water level, flow field and pollutant migration to the changing climatic factors. They observed from the result that hydrodynamics and water quality are more sensitive to rainfall change than temperature change. Their result further showed that the effect of wind field appears to be more pronounced than temperature. Similarly, [Momblanch et al. \(2020\)](#) used the water resource systems modelling approach to evaluate freshwater ecosystem service (fES) across the full range of plausible future scenarios to identify the likely (worst-case) climate change scenarios triggering the most significant impacts on the capacity of adaptation to enhance fES. They observed that the current and future states of the fES depend on the spatial patterns of climate change and the impacts of infrastructure management on river flows.

Studies across Africa showed that climate change's impact on water resources would intensify even into the future if the practices exacerbating the situation are not ameliorated. For example, [Thompson et al. \(2021\)](#) assessed climate change impact on freshwater ecosystem alteration of Upper Niger Basin in the inner Niger Delta using General Circulation Model (GCM)-related uncertainty in environmental flows at 12 gauging stations in the Upper Niger Basin within the Inner Niger Delta using the Ecological risk due to the Flow Alteration method and a hydrological model forced with projections from 12 GCM groups for RCP 4.5 in the 2050s and 2080s. They observed that the risk varies between GCM groups and stations and increases into the future. Similarly, [Taye et al. \(2018\)](#) observed that projections for the future of the Awash basin, Ethiopia, show an increase in water deficiency due to a projected increase in temperature and decrease in precipitation. [Manful and Opoku-Ankomah \(2021\)](#) also observed a shift and shortening of rainy seasons, and an increase in the frequency of dry spells occurring within the rainy seasons is forecast under climate change scenarios.

Only a few studies have holistically studied climate change's impact on hydrological systems in Nigeria. However, several studies exist that studied related components and, in some cases, two of the related components together [Ogunrinde et al. \(2021\)](#); [Ak-](#)

inwumi et al. (2021). Izah et al. (2022) highlighted poor management methods of sewage, solid wastes and industrial effluents, oil spill events, dredging, makeshift or artisanal refinery, and water transportation are among the man-induced activities that often alters river water quality. Adeyeri et al. (2020) assessed the impact of human activities and rainfall variability on river discharge as a result of the contributory effects of rainfall variability and human influences using daily rainfall and discharge data between 1971 and 2013. Furthermore, linking anthropogenic impacts by evaluating historical human presence using generalised variance, double mass curve, and the wavelet spectral methods. They discovered that a relationship exists to support that breakpoints correspond to dam construction times within the basin. Mayomi et al. (2018) also reported the drastic decrease of Lake Chad, with only about 2% of the Lake still within the shores of Nigeria. Although, several authors have blamed human action as the cause of the drying of Lake Chad. However, the general rainfall variability and high temperatures experienced in the region did little to help recharge the Lake. The climate change impacts on hydrological systems in Nigeria typify actual climate change scenarios of increasing and decreasing precipitation. While some authors have reported a decrease and drying, some have reported a projected increase in future precipitation, especially in southern Nigeria Hassan et al. (2020).

Interestingly, the several methods and modelling frameworks in existence to assess the impact of climate change on hydrological systems has opened up discussion on their accuracy and effectiveness in the methods and data inputs. In other words, there are substantial concerns about the appropriate approach for integrated assessment of climate change's impact on the hydrological system. Especially given the rising complexity of hydro-ecological modelling Visser et al. (2018). Generally, recent assessments and modelling approaches show promise to a long-standing debate of whether the methodologies and modelling are fit to produce good results when data conditions vary.

The impact of climate change on hydrological response has been the subject of many qualitative investigations. The hydrological effects are less well understood and rarely quantified due to the high spatiotemporal uncertainties. As a result, the influence of climate change on hydrological response remains unknown, as are the consequences for prolonged poor ecosystem services.

4.6.2 Assessing Anthropogenic Impacts

Anthropogenic activities such as industrial and agricultural processing have been blamed for the rise in anthropogenic global warming resulting in climate change. Anthropogenic global warming theory explains how anthropogenic forcings that show evidence of a causal effect of greenhouse gases (GHGs) have resulted in the current long-term rise in the earth's atmosphere due to industrial and agricultural activities [Ruddiman \(2003\)](#) [Malla et al. \(2022\)](#). This claim is further supported by the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), citing available data that persistent human-induced causes exacerbate climate change [Trenberth \(2018\)](#).

The scientific proof is clear, the accumulation of GHGs occurring at the earth's surface is warmed up by absorbed solar radiation. Furthermore, observations suggest that the climate is changing incredibly quickly, about ten times faster than natural climate changes since the end of the last ice age, judging from paleoclimatic observations [Wuebbles \(2018\)](#). According to [Ruddiman \(2003\)](#), the anthropogenic era is assumed to have begun 150 to 200 years ago, when the industrial revolution began creating CO₂ and CH₄ at rates high enough to change their atmospheric compositions. In fact, [Kimball and Idso \(1983\)](#); [Malla et al. \(2022\)](#) stated that the earth's average surface temperature has risen by around 1.18 degrees Celsius since the late nineteenth century, owing primarily to rising carbon dioxide emissions into the atmosphere.

Humans rely on rivers and their ecosystems for a wide range of services, such as freshwater supply for human consumption, construction and irrigation. Human factors which are responsible for hydrological disturbances include; (i) Dam construction; (ii) Land use change; (iii) Inter-basin water transfer; (iv) Overgrazing. Monitoring the effects of these variables on the hydrological system requires a wholesome approach capable of segregating the contribution of each variable to the hydrological system. Furthermore, such analysis requires a sophisticated hydrological model capable of clearly presenting the time-space interaction of each component and the magnitude of their influence on the hydrological system. Unfortunately, the detailed database needed for such sophisticated analysis is lacking in many world regions. This made it challenging to quantify water resources availability, status and spatiotemporal changes occurring within the hydrological

system within the study area.

Again, with the global population estimated at over 7 billion by 2020. This would further increase the demand for water and resources drawn from the hydro-ecologic system. The population growth has increased the demand for shelter, which requires a large clearing of vegetal cover and several encroachments into a watercourse. The need for food and water to support the growing population has impacted the hydro-ecologic system variables. As a result, the rate of change in these variables is enormous.

Global energy demand has led to several Dam construction [Sternberg \(2010\)](#); [Zarfl et al. \(2015\)](#). This is affecting some of the ecohydrological variables. Moreover, energy demand and processing are sending GHGs to the atmosphere at an alarming rate [Mousavi et al. \(2020\)](#). There are also indirect activities producing GHGs, such as ranching, that produce enormous amounts of methane from cows, which cause a temperature rise that increases ET and subsequent change in precipitation pattern and wind velocity. Considering the direct human activities that impact the hydrological system, none of the points mentioned above appears to decrease anytime soon with the current global trend in population growth and energy demand.

4.6.3 Earth Observation in Hydro-ecologic Studies

Since its inception, remote sensing has proven to be an effective means of acquiring glacier data. The introduction of Geographic Information Systems (GIS) and Global Positioning Systems (GPS) has provided an excellent technique for analysing obtained data for effective monitoring and mapping of the earth's surface and subsurface temporal dynamics. Land surface temperature from thermal infrared data, surface soil moisture from passive microwave data, snow cover from visible and microwave data, water quality from visible and near-infrared data, and predicting landscape surface roughness using lidar are a few remote sensing capabilities in hydrological study.

These state-of-the-art technologies have provided numerous variables for estimating hydrological fluxes, such as evapotranspiration, precipitation, ice snow, snowmelt

and runoffs. In addition, remote sensing allows for large-scale monitoring of hydrological status variables [Tang et al. \(2009\)](#); [Hall et al. \(2011\)](#).

GIS application in hydrological modelling includes (1) model parameter estimation with the aid of remotely-sensed satellite data; (2) real-time forecasting of several hydrological parameters; (3) Time series assessment of scenarios leading to climatic and environmental change predictions using various satellite data as input. The latter applications are becoming more critical because remote sensing techniques have the ability: (i) to measure spatial, spectral and temporal information; and (ii) to provide data on the state of the earth's surface. It's also a dynamic field, with new sensors, platforms, and application techniques developed to provide hydrologists with new data and perspectives on the landscape to assess the earth's surface. In addition, remote sensing can monitor hydrological conditions and changes by observing changes in their states over time and place.

4.6.4 Process Based Hydrological in Assessment

Parameterising the relationship between human activity and hydrological variables due to several complex and uncertain inputs and processes that vary with time-space and quantities is imperative but difficult. Therefore, a lack of measurement on some variables poses problems to the modelling approach, resulting in inadequate model input. Another major problem is the lack of information on simultaneous occurrences such as the production of GHGs and Dam construction affecting hydrological systems concurrently. In an attempt to elaborate on the hydrological and hydrological modelling framework, a coupled method to assess the impact of climate change on hydro-ecological response quantitatively has been proposed by [Visser et al. \(2019b\)](#).

Statistical is a popular method to identify affected variables and attribute the rate of human activities to hydrological changes. Statistical methods have proved sufficient in testing hydrological hypotheses: statistical time series analyses and fitting regression between dependent and independent variables. In addition, several indices have been developed over the years, such as NDWI (normalised difference water index), NDVI (normalised difference vegetation index), climatic water balance, and continuity equations that

incorporate drainage basin characteristics and changes etc. In some cases, more than one model is needed to assess climate change's impact on hydro-ecology, i.e. coupled model intercomparison projects (CMIP). However, in assessing the hydrological condition of an area, a deeper analytical insight can be achieved, especially when the analysis is on a basin scale by combining climate change and anthropogenic factors from the same period.

4.6.5 Artificial Intelligence Hydrological Studies

Machine learning and Deep Learning are becoming increasingly important ways to produce accurate hydrological predictions across a wide range of spatial and temporal scales. Also, machine learning algorithms make it possible to obtain time series forecasting models characterised by very high accuracy and precision. For example, [Granata \(2019\)](#) have applied machine learning algorithms to estimate evapotranspiration. Recently, hydrologists have witnessed intensification in the applications of deep learning and reinforced while exploring space-time variation in hydrologic modelling. [Ardabili et al. \(2019\)](#); [Klotz et al. \(2021\)](#); [de la Fuente et al. \(2019\)](#); [Hussain et al. \(2020\)](#); [Saggi and Jain \(2019\)](#); [Ferreira and da Cunha \(2020\)](#) have all applied deep learning in modelling hydrological events for different reason such as climate, runoff, hydrological time series prediction and evapotranspiration.

With the growing attention that deep learning is getting in this century, more focus will be on harmonising different models to explain extreme hydrological events in regions with uniform characteristics.

4.7 Drought Impacts in Sub-Saharan Africa

Across the Sahel region, severe droughts of high intensity and magnitude characterised the 1970s and 1980s. Several estimates suggest that the loss of lives and properties due to the drought was as high as 10 billion dollars. Since then, the Sahel has suffered droughts of varying magnitudes to date. Several efforts have been made to minimise the effects of drought in the Sahel region. The drought had led to severe farmer's and herder's conflicts

due to drying water resources in the region. Severe land degradation from infrequent precipitation patterns is an all-natural contributor [Noureldeen et al. \(2020\)](#); [Jnr \(2014\)](#). Human contributions such as unsustainable agriculture and nomadic overgrazing practice have been pointed as the defaulting factors exacerbating the drought situation in the Sahel [Jnr \(2014\)](#). Anthropogenic and climatic influences may interact or act independently of one another. A combination of these variables leads to a decline in plant cover and an imbalance between cultivated fields and fallow areas, which are crucial for preserving soil fertility and minimising erosion losses.

Interestingly, there are also efforts to understand what causes the drought in the Sahel and its trend. The suggestion that drought in the Sahel is meteorological as a function of prolonged reduced rainfall has led to the use of standardised rainfall anomalies to understand drought propagation in the Sahel to indicate drought severity. This approach has been criticised due to variations in the period of standardisation. Similarly, spatial aggregation, another method employed to study drought in the Sahel, has been criticised for its ability to ignore critical local variations such as human impact. However, [Agnew and Chappell \(1999\)](#) investigated these two approaches and suggested a new drought classification in the Sahel. [Herrmann et al. \(2014\)](#) went further to integrate human perception to aid in interpreting evidence from remote sensing-derived trends. However, they discovered that the coarse NDVI had suggested a regreening trend in part of the Sahel. Interestingly, this regreening indicated an improvement in environmental conditions. This conclusion upheld earlier finding in the region [Herrmann et al. \(2005\)](#).

Remarkably, other methods include the regional climate model [Saley et al. \(2019\)](#); empirical data [Igbatayo \(2018\)](#); remote sensing [Hermans and McLeman \(2021\)](#); [Ibrahim et al. \(2018\)](#); [Mishra et al. \(2023\)](#); [Wu et al. \(2022\)](#); fuzzy rule-based [Abdourahmane and Acar \(2019\)](#). Surprisingly, the application of artificial intelligence in studying drought in the Sahel is lacking to a greater extent.

Several studies have been conducted in Nigeria on the propagation, intensity, magnitude and duration of drought land use and land cover change. Each of the studies has been for a specific reason characterising drought based on indices [OLAGBAIYE et al. \(2021\)](#); [Ogunrinde et al. \(2020\)](#); assessing droughts impacts [Hassan et al. \(2019\)](#); [Ibrahim et al. \(2018\)](#). Although a recent study by [Gbetkom et al. \(2023\)](#) pointed to a glimmer of

hope in the Sahel, rainfall fluctuation remains persistent.

4.7.1 Conclusion

Finally, this study looks at the interaction between natural and anthropogenic climate change on Nigeria's hydrological systems by assessing the hydrologic cycle's components and hydroclimatic and hydroecological variables responsible for the present hydrological status of Nigeria. These factors interchangeably impact the stability of the ecosystem. For instance, [Sheil \(2018\)](#) claimed that a novel theory—the 'biotic pump'—suggests that evaporation and condensation can significantly influence atmospheric dynamics. This theory partly suggests that high evaporation and extensive natural forests guarantee a stable and high throughput in the hydrological cycle [Makarieva and Gorshkov \(2010\)](#). This highlights the influence a component has on the hydrologic system. However, natural climate change forcings and radical inputs from the global energy balance also impact the hydrologic cycle.

From the above discussion, it is clear that human and natural events introduce disturbances. However, the spatiotemporal phenomenon in the reviewed articles showed that the majority of the negative impacts detected had occurred where human footprints are significant, as has been observed by the authors. Significant efforts have also been made to ameliorate the rate of changes in recent times. In addition, there is greater awareness presently of cutting energy demands that accelerate GHGs and embrace green and clean energy. In the next chapter, we will assess the performances of some satellite precipitation products, comparing them with in-situ datasets collected from selected gauge stations across the meteorological zones of Nigeria. This would be needed in order to ascertain the best satellite products that would be used as an alternative dataset for further studies that would be carried out in this thesis.

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Validation of Satellite Precipitation Products for Rainfall Analysis in Nigeria

5.1 Overview

In this chapter, we will discuss the validation of some selected satellite precipitation products (SPP) with datasets covering Nigeria. This approach became necessary due to the lack of a free and reliable precipitation dataset. The dataset validation was done by comparing the modelled datasets from the SPPs to the observation from selected gauge stations across Nigeria using Kling-Gupta Efficiency (KGE) score. About three satellite products were adjudged to good correlation with the gauge stations. Those were recommended for further studies. This chapter has already been published in a journal (Remote Sens. 2020, 12(23), 3964; <https://doi.org/10.3390/rs12233964>) and as such, it would be discussed as an article.

5.2 Introduction

5.2.1 Precipitation Monitoring across Remote Regions

Accurate measurements of precipitation across space and time remain essential to assess its deficits and abundance. Such measurements allow for tracking the state of precipitation and its overall effect on hydro-ecological systems and water resource management [Ayehu et al. \(2018\)](#); [Liu et al. \(2019\)](#). At the global level, precipitation information is necessary for sustainable socio-economic growth, especially in countries with lower rainfall regimes and in some developing nations that depend on rainfall for socio-economic purposes such as agriculture [Asfaw et al. \(2018\)](#); [Taxak et al. \(2014\)](#). The high spatial and temporal variability of precipitation requires a formidable network of gauge installations to monitor the occurrence and intensity of rainfall effectively. However, in many countries, precipitation information has traditionally been collected from a sparsely distributed network of gauge stations. The scarcity of large numbers of these gauges has resulted in spatially and temporarily discontinuous observations [Duan et al. \(2019\)](#); [Fenta et al. \(2018\)](#). Some authors [Karimi and Bastiaanssen \(2015\)](#); [Maggioni et al. \(2016\)](#); [Paredes Trejo et al. \(2016\)](#) also claimed that the socio-economic and challenging terrain contexts had hindered the installation and management of gauge stations, emphasising data breaches in many locations. In this context, precipitation data from gauge station observations are inadequate in many parts of the developing world [Dinku et al. \(2018\)](#); [Harrison et al. \(2019\)](#). Hence, there is a need to fill the data gap created in the absence of reliable precipitation from the gauge stations.

5.2.2 Satellite-Based Precipitation Estimate Prospect

Recent advancements in remote sensing technologies have led to the development of satellite precipitation products (SPP) which measure precipitation on a regular grid globally [Jiang and Bauer-Gottwein \(2019\)](#); [Kidd et al. \(2018\)](#), offering ample opportunity to overcome the problems associated with traditional gauge measurements. In recent decades, several efforts to improve SPPs in terms of precipitation accuracy, temporal and spatial resolution, and extension of temporal coverage have been presented.

The first generation of SPPs started with the Tropical Rainfall Measuring Mission (TRMM) launched in 1997 by the National Aeronautics and Space Administration (NASA), and the Japan Aerospace Exploration Agency (JAXA). Over the last 20 years, TRMM multi-satellite precipitation analysis (TMPA) [Huffman et al. \(2007\)](#); [Huffman et al. \(2010\)](#), Climate Prediction Centre MORPHing (CMORPH) [Joyce et al. \(2004\)](#), and precipitation estimation from remotely sensed information using artificial neural networks (PERSIANN) [Sorooshian et al. \(2000\)](#) SPPs have been developed based on the TRMM to deliver precipitation estimates at the 0.25° grid scale.

The second generation of SPPs, the Global Precipitation Mission (GPM), was launched in 2014 to overcome the technical difficulties arising from ageing mechanisms and sensors of the TRMM to ensure the continuation of precipitation data acquisition. The second generation of SPPs included the integrated multi-satellite retrievals for GPM (IMERG) [Huffman et al. \(2015\)](#) and Global Satellite Mapping of Precipitation (GSMaP) SPPs which deliver precipitation estimates at a finer grid scale (0.1°) than the first generation of SPPs.

At the same time, the third generation of SPPs took advantage of previous SPPs and missions to estimate precipitation over a larger time window; hence, the long-term SPP generation. This is the case of PERSIANN-Climate Data Record (PERSIANN-CDR), multi-source weighted-ensemble precipitation (MSWEP), Climate Hazards Group Infrared Precipitation (CHIRP) with station data (CHIRPS) available at a global scale, tropical applications of meteorology using satellite and ground-based observation (TAM-SAT), and African Rainfall Climatology (ARC v.2), only covering the African continent. Despite continuous efforts to improve SPP reliability, these products are subject to uncertainties in space and over time due to technical issues relating to sensitivity to the topography, i.e., [Prakash et al. \(2014\)](#); [Satgé et al. \(2016\)](#), surface temperature and emissivity contrast, i.e., [Satgé et al. \(2017a\)](#); [Paiva et al. \(2011\)](#); [Tian et al. \(2007\)](#), and regional differential climatologic context, i.e., [Dinku et al. \(2007\)](#); [Hirpa et al. \(2010\)](#); [Satgé et al. \(2018\)](#). In these circumstances, numerous studies on the reliability of SPPs in many parts of the world have provided vital information to potentially interested users [Sun et al. \(2018\)](#). This effort comes with the first studies reporting on the first generation of SPPs based on the TRMM, i.e., [Bookhagen and Burbank \(2006\)](#); [Milewski et al.](#)

(2015); Satgé et al. (2017b); Ullah et al. (2019); Yong et al. (2012); Hussain et al. (2018).

Then, from 2014, studies started to report on the second generation of SPPs based on the GPM. These studies highlight the potential benefits of the GPM over the TRMM Satgé et al. (2017b); Hussain et al. (2018); Gaona et al. (2016); Liu (2016); Prakash et al. (2016); Rozante et al. (2018); Salles et al. (2019); Xu et al. (2019). At the same time, other studies reported on long-term SPPs to monitor drought processes and precipitation trends in order to understand the sensitivity of water resources to ongoing climate variability potential Arvor et al. (2017); Bai et al. (2020); Novella and Thiaw (2013).

5.2.3 Toward a Broad Overview of Satellite-Based Precipitation Reliability across Nigeria

As indicated earlier, most of the available studies reported on the reliability of a single SPP group such as TRMM, GPM, and long-term. Although all the SPPs have been available since the start of the satellite precipitation mission (2000–present), it is essential to compare their reliability to indicate the most reliable SPP among the available products. In this circumstance, such effort is only possible by crossing results from studies in different regions and temporal windows. However, such action prevents a robust comparison, as SPP sensitivity to the regional meteorological, topographic, and land cover characteristics induce substantial space and time reliability variation Satgé et al. (2018); Satgé et al. (2019a); Beck et al. (2017). A recent study comparing seven satellite-based precipitation datasets over two distinct areas with similar precipitation patterns (i.e. South American Andean Plateau and Pakistan) shows that the most reliable SPP from one region to another is different Satgé et al. (2021).

In Nigeria, there are few studies focusing on SPP validation, but each has a specific purpose. For instance, using gauge data as a reference, Semire et al. (2013) Abiola et al. (2013), evaluated one first-generation SPP (TMPA v.7) using gauge data as a baseline. Similarly, Akinyemi et al. (2019) Akinyemi et al. (2020) evaluated one long-term SPP (CHIRPS) along with RFE 2.0, and Usman et al. (2018) analysed four SPPs' (TAMSAT v.2, ARC v.2, TMPA v.7, and CHIRPS v.2) ability to follow spatiotem-

poral precipitation trends in northern Nigeria. Consequently, the reliability assessment of SPPs across Nigeria is limited in terms of products (TAMSAT v.2, ARC v.2, TMPA v.7, CHIRPS v.2) and spatial coverage.

5.2.4 Study Objectives

The main goal of this study is to assess for the first time the performances of sixteen SPPs (including TRMM, GPM, and long-term SPPs) over Nigeria for thirteen years. This study also addresses the improvement of first- to second-generation SPPs (TRMM to GPM) and to compare these products with the recently released long-term SPP for a standard observation period.

In a general context, this study will provide useful information to guide potential interested SPP users at the time of choosing the most efficient SPPs for their research but also precious information for SPP team developers to improve future SPP generation.

5.3 Materials

5.3.1 Rain Gauge Observations

Gauge precipitation observations were collected from eleven (11) meteorological stations ([figure 9](#)) managed by the Nigerian Meteorological Agency (NIMET). NIMET uses measuring cylinders attached to rain gauges for measuring rainfall in the majority of their stations across Nigeria. Precipitation is measured daily and further harmonised into a weekly and monthly dataset. Although the gauge reference data were not collected from all stations across the country, the selected gauge stations are well distributed from the Sahel to the southern part of the Guinea/rainforest region.

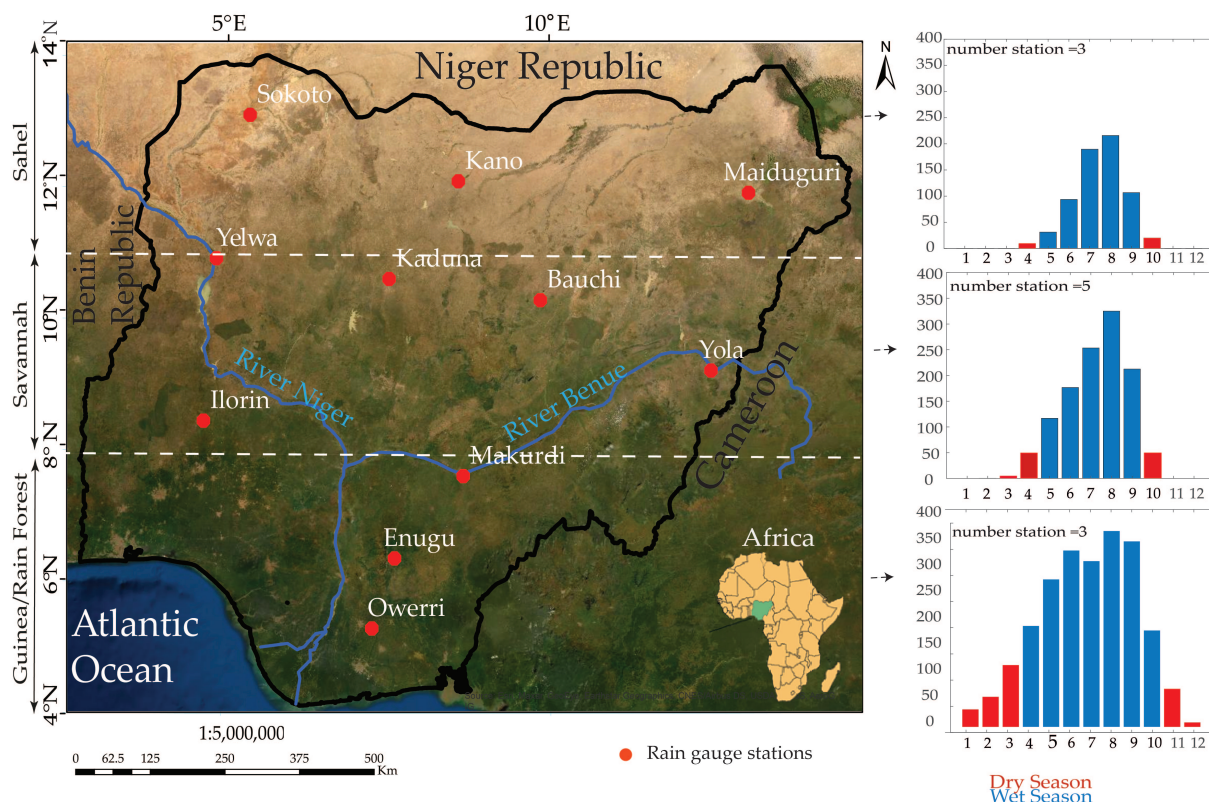


Figure 9: A map of Nigeria showing the locations and names of reference meteorological gauge stations and precipitation distribution among the meteorological zones of the country

5.3.2 Brief Descriptions of the Satellite-Based Precipitation - Products

Table 5.1 shows the main characteristics of the sixteen Satellite-based Precipitation Products (SPPs) used in this work. The SPPs were downloaded from their host websites which are free and open source. The 16 considered SPPs include:

- The Tropical Rainfall Monitoring Mission (TRMM) covering the last 20 years at 0.25° spatial resolution;
- The Global Precipitation Mission (GPM) covering the previous 20 years at 0.1° spatial resolution;
- The long-term datasets are reanalysed retrospectively (40 years).

The first and second SPP generation (TRMM and GPM) combine passive (and active) microwaves (PMWs) with infrared sensors on board a Low Earth-orbital (LEO) satellite and geostationary satellite, respectively, to retrieve precipitation estimates. This

combination aims to optimise precipitation estimates and fill space and time gaps related to the limited overpass of the LEO satellite.

The long-term SPPs merge reanalysis datasets derived from physical and dynamic models with satellite-based precipitation estimates. The reanalysis datasets are available for a larger temporal window than the PMW and IRs sensor used for TRMM and GPM SPPs. Therefore, the long-term SPPs offer more extensive temporal coverage than TRMM and GPM SPPs. Generally, the relationship between reanalysis datasets and satellite-based precipitation estimates from TRMM SPPs and IR-based precipitation estimates is known for a standard period of observation. This information encourages retrospectively reanalysed estimates of past precipitation events. Finally, it is worth mentioning that most of the considered SPPs also include a gauge-based precipitation dataset to calibrate the precipitation estimates. Therefore, the 16 considered SPPs include (1) only satellite-based SPPs (PERSIANN-RT, TMPA-RT v.7, IMERG-E, and -L v.6), (2) satellite-based SPPs adjusted with gauge information, such as TMPA-Adj v.6, IMERG-F v.6, CMORPH-CRT and -BLD v.1, TAMSAT v.3, and ARC-2, and (3) SPPs including both satellite and reanalysis datasets with or without gauge adjustment (CHIRP v.2, CHIRPS v.2, PERSIANN-CDR, and MSWEP v.2.2).

For more information about the considered SPPs, readers should refer to the main references listed in [table 5.1](#).

[Figure 10](#) shows the mean annual precipitation retrieved from the 16 SPPs, which revealed the south–north precipitation pattern that is controlled by the moisture-laden southwest trade winds across Nigeria. The mean yearly precipitation from the satellite-based products demonstrates a similar precipitation trend, where a decrease in precipitation corresponds with an increase in latitude. The Guinea/rainforest region experiences an annual mean of about 6000 mm within the considered period, whereas the annual mean precipitation in the Sahel is about 370 mm.

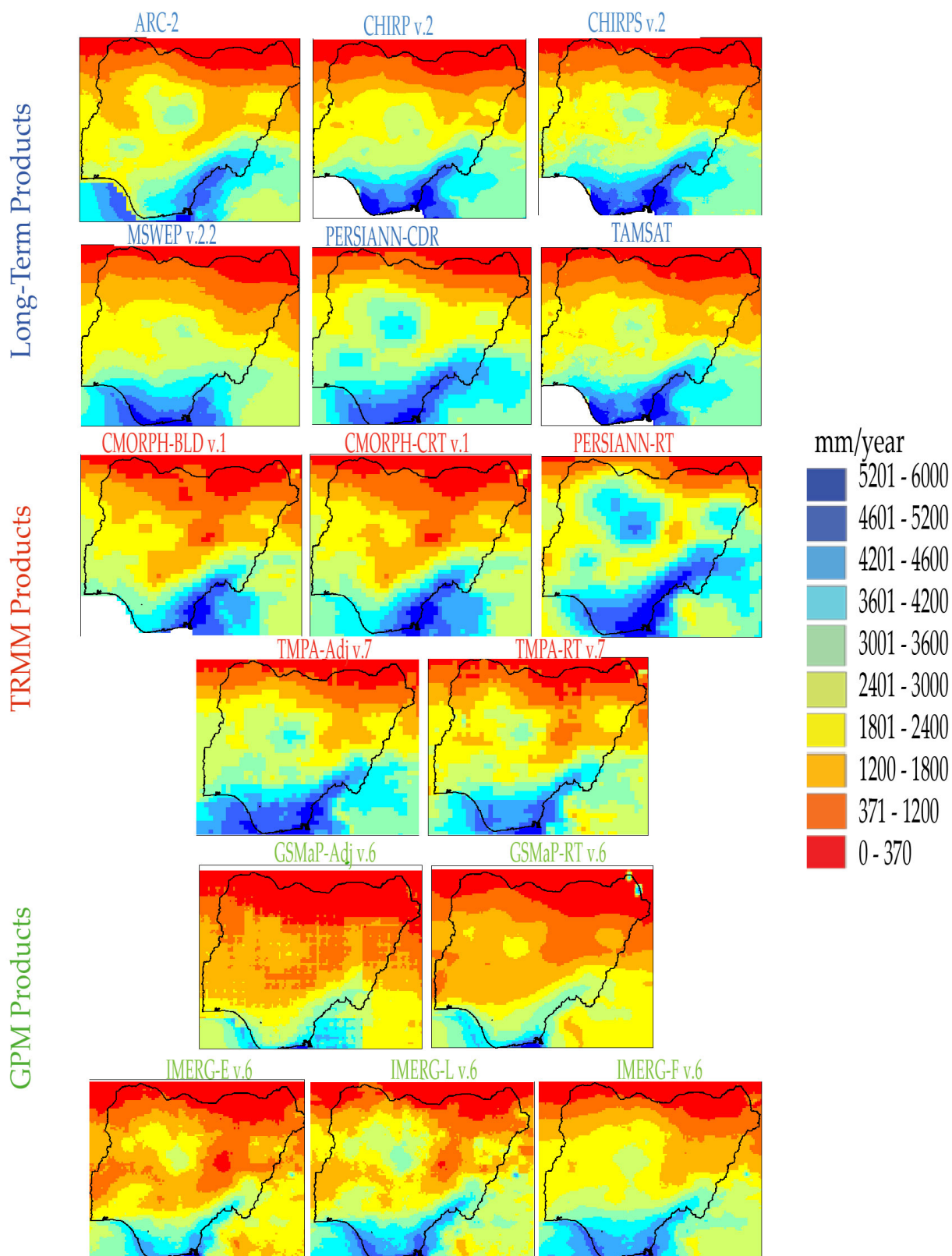


Figure 10: Mean yearly precipitation retrieved from all the satellite-based precipitation products (SPPs) at their original grid size from 2000–2012

Table 5.1: Summary of main characteristics and references of the SPPs. The acronym S, R, G in the data column description stands for satellite, reanalysis, and gauge information; spatial coverage refers to the absolute maximum and minimum latitude with precipitation information, and latency refers to the time delay for data availability.

SN	Acronym	Name	Period	Data	Spatial Coverage	Spatial Resolution	Temporal Resolution	Latency	Link	Reference
1	ARC-2	Africa Rainfall Climatology v.2	1983-Present	S, G	Africa	0.1° x 0.1°	Daily	2 days	ftp://ftp.cpc.ncep.noaa.gov/fews/fewsdata/africa/arc2/	Novella and Thiaw (2013)
2	CHIRP v.2	Climate Hazards Group InfraRed v.2	1981-Present	S, R	50°N x 50°S	0.05°	Daily	2 Days	ftp://ftp.chg.ucsb.edu/pub/org/chg/products	Funk et al. (2015)
3	CHIRPS v.2	Climate Hazards Group Infrared v.2 with Station	1981-Present	S, R, G	50° x 50°	-	Daily	1 month	ftp://ftp.chg.ucsb.edu/pub/org/chg/products/	Funk et al. (2015)
4	MSWEP v.2.2	Multi-Source Weighted Ensemble Precipitation v.2.2	1979-Present	S, R, G	Global	0.1°	3 hourly	A few months	http://www.gloh2o.org/	Beck et al. (2019b)
5	PERSIANN-CDR	Precipitation Estimates from Remotely Sensed Information using Artificial Neural Network and Climate Data Record	1983-Present	S, G	60°N-60°S	0.25°	Daily	3 months	https://chrsdata.eng.uci.edu/	Ashouri et al. (2015)
6	PERSIANN-RT	Precipitation Estimates from Remotely Sensed Information using Artificial Neural Network (Real-Time)	2003-Present	S	60°N-60°S	0.25°	1 hourly	2 days	https://chrsdata.eng.uci.edu/	Sorooshian et al. (2000); Hsu et al. (1997)
7	TAMSAT v.3	Tropical Applications of Meteorology using Satellite and Ground-Based Observations v.3	1983-2018	S, G	Africa	0.0375°	Daily	3 days	https://www.tamsat.org.uk/about	Maidment et al. (2014); Tarnavsky et al. (2014)
8	CMORPH-BLD v.1	Climate Prediction Center MORPHing (Satellite-Gauge Merged) v.1	2002-Present	S, G	60°N-60°S	0.25°	Daily	10 months	ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPHv1.0/	Xie et al. (2017)
9	CMORPH-CRT v.1	Climate Prediction Center MORPHing (Bias Corrected) v.1	2002-Present	S, G	60°N-60°S	0.25°	Daily	6 months	ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPHv1.0/	Xie et al. (2017)
10	TMPA-Adj v.7	TRMM Multi-Satellite Precipitation Analysis Adjusted v.7	1998-Present	S, G	50°N-50°S	0.25°	Daily	3 months	https://earthdata.nasa.gov/	Huffman et al. (2010)
11	TMPA-RT v.7	TRMM Multi-Satellite Precipitation Analysis Real-Time v.7	2000-Present	S	60°N-60°S	0.25° x 0.25°	Daily	1 day	https://mirador.gsfc.nasa.gov/	Huffman et al. (2010)
12	GSMaP-Adj v.6	Global Satellite Mapping of Precipitation Standard Adjusted v.6	2002-2012	S, G	60°N-60°S	0.1°	Hourly	3 days	ftp://hokusai.eorc.jaxa.jp/standard/v6/	Kubota et al. (2020); Ushio et al. (2009)
13	GSMaP-RT v.6	Global Satellite Mapping of Precipitation Standard v.6	2002-2012	S	60°N-60°S	0.1°	Hourly	3 days	ftp://hokusai.eorc.jaxa.jp/standard/v6/	Ushio et al. (2009); Christian et al. (2000)
14	IMERG-E v.6	Integrated Multi-Satellite Retrievals for GPM Early Run	2000-Present	S	60°N-60°S	0.1° x 0.1°	30 min	4 h	http://disc.sci.gsfc.nasa.gov/	Christian et al. (2000)
15	IMERG-F v.6	Integrated Multi-Satellite Retrievals for GPM Final Run	2000-Present	S	60°N-60°S	0.1° x 0.1°	30 min	3 months	http://disc.sci.gsfc.nasa.gov/	Christian et al. (2000)
16	IMERG-L v.6	Integrated Multi-Satellite Retrievals for GPM Late Run	2000-Present	S, G	60°N-60°S	0.1° x 0.1°	30 min	12 h	http://disc.sci.gsfc.nasa.gov/	Christian et al. (2000)

5.4 Methods

5.4.1 Database Pre-Processing

The datasets were aggregated into a monthly dataset to match the rain gauge data and resampled to the 0.1° grid cell size to enable consistent comparison between all SPPs. The bilinear average (interpolation) is used for SPPs with grid cell size $< 0.1^\circ (> 0.1^\circ)$ Beck et al. (2017); Satgé et al. (2020).

5.4.2 SPP Assessment

The Kling–Gupta efficiency (KGE) was used to compare the SPPs with rain gauge measurements. KGE is an objective function introduced by Gupta Gupta et al. (2009), that combines the correlation coefficient (r), bias (β), and the ratio of variability (γ). The KGE function was necessary since water resource management requires a reliable representation of precipitation temporal dynamics as measured by the correlation coefficient (r) and volume as explained by bias (β) and variability (γ). Both aspects (temporal dynamics and volume) might be relevant for different purposes, as potential readers might be interested in an efficient representation of one or another element in the function of the foreseen utilisation of SPPs. The equations are expressed as follows.

$$\text{KGE} = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (5.1)$$

where (r) denotes the ratio between the observation and the modelled correlation coefficients, (β) is the ratio between the observed and the modelled means, and (γ) is the ratio of the estimated and observed coefficients of variation.

$$r = \frac{1}{n} \sum_1^n \frac{(O_n - \mu_o) * (S_n - \mu_s)}{\sigma_o * \sigma_s} \quad (5.2)$$

$$\beta = \frac{\mu_s}{\mu_o} \quad (5.3)$$

$$\gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \quad (5.4)$$

where μ and σ are the distribution mean and standard deviation, respectively; s and o indicate the estimate and the reference, respectively. From Equation (1), r, (β), and Vr analyses of the products were carried out for all the months within the period 2000-2012, as well as the dry and wet seasons. The values of the involved coefficients in KGE, r, (β), and (γ), were computed at each grid cell location to observe the spatial reliability of the SPPs, and their median values were adopted for regional-scale observation.

5.5 Results

5.5.1 SPP Reliability on the National Scale

Monthly and seasonal performances of the SPPs in terms of KGE, correlation coefficient (r), bias (β), and variability ratio (γ) for the 2000-2012 period are expressed in [figure 11](#). With a KGE value inferior to 0.4, TMPA-RT v.7 and PERSIANN-RT were unable to represent the regional monthly precipitation. Interestingly, the gauge adjustment applied for TMPA-Adj v.7 drastically increased KGE from < 0.4 (TMPA-RT v.7) to 0.81 (TMPA-Adj v.7). Similarly, the gauge-adjusted version of IMERG-F v.6 presented a higher KGE score (0.82) than the only satellite-based version, IMERG-E v.6 (0.69) and IMERG-L v.6 (0.71). Actually, IMERG-F v.6 is the second most reliable SPP just after MSWEP v.2.2, which presents the highest KGE score (0.83).

MSWEP v.2.2, CHIRPS v.2, and PERSIANN-CDR precipitation estimates are derived from several gridded precipitation datasets (P-datasets) from satellite, reanalysis, and gauges. CHIRPS v.2 and PERSIANN-CDR include only one gauge-based P-dataset each (CHPclim and GPCP, respectively), while MSWEP v.2.2 includes three gauge-based P-datasets (GPCP, GPCC, WorldClim). They also include fewer satellite- and reanalysis-based P-datasets than MSWEP v.2.2. This difference in terms of input numbers can partially explain the better reliability of MSWEP v.2.2 in comparison to CHIRPS v.2, PERSIANN-CDR, and all the considered SPPs in this study. Notably, MSWEP v.2.2

and CHIRPS v.2 use precipitation estimates from some of the considered SPPs as input data (GSMaP-RT v.6 and TMPA-RT v.7 for MSWEP v.2.2 and TMPA-Adj v.7 for CHIRPS v.2). Thus, as "level-2" versions of these specific SPPs, they provide more reliable precipitation estimates. Interestingly, even if IMERG-F v.6 does not consider such a multi-source approach, it still offered precipitation estimates almost as reliable as MSWEP v.2.2. Therefore, the IMERG technique is up-and-coming and recommended in future multi-source precipitation datasets.

Most of the P-datasets were well correlated to the reference (> 0.8) except PERSIANN-RT and TMPA-RT v.7 (0.79 and 0.62, respectively). The gauge-adjusted versions presented a higher correlation than their non-adjusted version, as observed for IMERG-F v.6 (TMPA-Adj v.7) when compared to IMERG-E and -L v.6 (TMPA-RT v.7). Interestingly, IMERG-F v.6 presents a slightly superior correlation value compared to MSWEP v.2.2, which both offer the highest score.

Non-adjusted SPPs, PERSIANN-RT, TMPA-RT v.7, and IMERG-E and -L v.6 overestimate precipitation amount. The gauge-based adjustment efficiently removed the bias, as observed with a bias value close to 1 for TMPA-Adj v.7 and IMERG-F v.6. In a general way, all SPPs using gauge-based datasets present reasonable bias values ($0.85 >$ and < 1.15). However, the gauge-based adjustment in GSMaP-Adj v.6 introduced a lower bias (0.85) when compared to the non-adjusted version of GSMaP-RT v.6 (0.91). The bias values, as seen here, confirmed previous studies which highlighted deficiencies in the adjustment of GSMaP SPPs across Africa, such as [Satgé et al. \(2020\)](#), and [Beck et al. \(2019a\)](#).

Regarding the V_r , all SPPs presented a V_r close to one except for PERSIANN-RT and TMPA-RT v.7, which underestimated precipitation variability ($V_r < 0.85$). However, these SPPs are also the less efficient ones in terms of KGE, correlation, and bias.

On a seasonal basis, a robust trend was observed for all SPPs, with the highest reliability (as expressed by KGE) during the wet season compared to the dry season. Differences between wet and dry month-based KGE values are essentially linked with significant differences in r values for both seasons. In contrast, similar (β) and V_r values were observed for both wet and dry months. This seasonal variation is linked to the

monthly precipitation total distribution [Satgé et al. \(2021\)](#). Across Nigeria, the monthly precipitation totals are unevenly distributed between the maximum and minimum values during the dry and wet seasons as shown in ([figure 9](#)). This feature tends to increase correlation and therefore the KGE value during the dry season. As this distribution is even better when considering the whole period, the all-month r increases, thereby increasing the KGE.

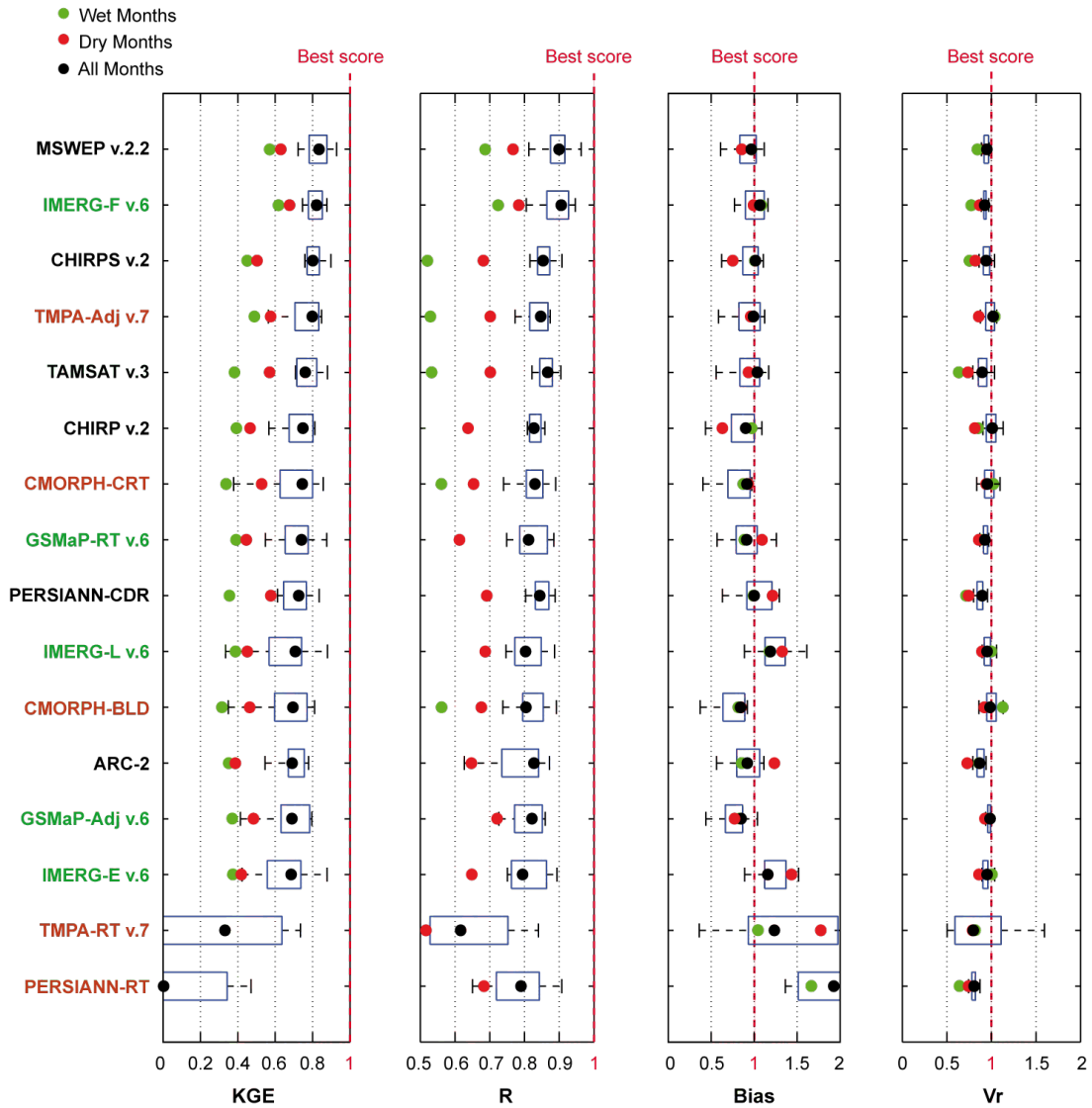


Figure 11: Box plot statistical summary of (a) Kling–Gupta efficiency (KGE), (b) correlation coefficient (r), (c) bias (β), and (d) variability ratio (V_r), based on the sixteen SPPs and eleven gauging stations across Nigeria. The performances in terms of KGE, correlation coefficient, bias, and variability ratio of all SPPs across all months are highlighted in black, while their seasonal performances are highlighted in green and red for the rainy and dry seasons, respectively. The SPPs in black represent the long-term group, while the Tropical Rainfall Measuring Mission (TRMM) is in red and the Global Precipitation Mission (GPM) is in green

5.5.2 SPP Reliability for Different Climatic Regions

In this section, the values of the statistical scores (KGE, r , " β ", and V_r) calculated at the locations of the gauges and for the three Nigerian climatic regions are presented (figure 13 - figure 15).

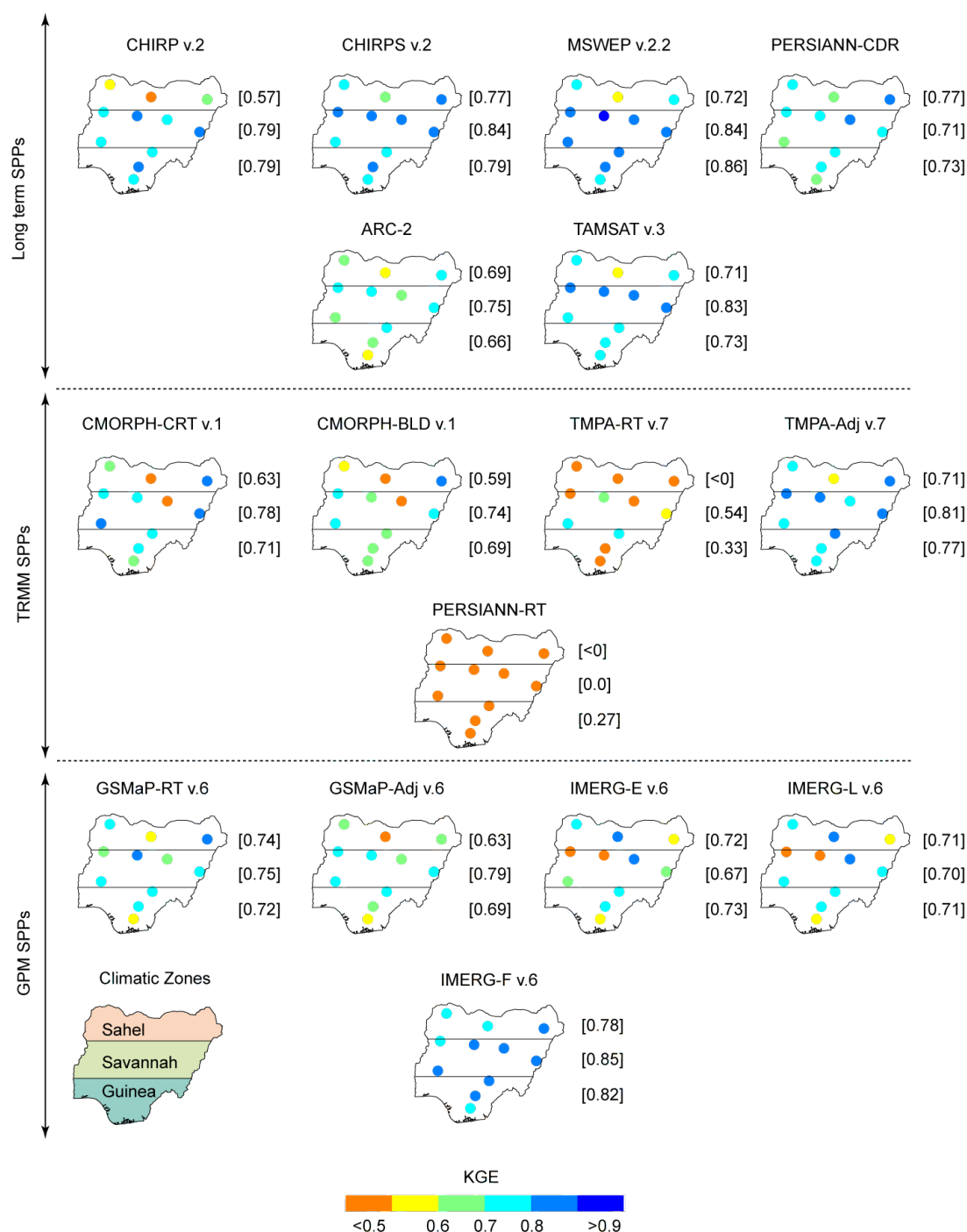


Figure 12: KGE values obtained at the grid cell level of all the SPPs corresponding to gauge stations in the period 2000-2012. The SPPs are grouped according to their respective categories, and the gauges are separated by the country's ecological zones

The KGE values obtained from all considered SPPs at the eleven gauge locations are reported in [figure 12](#). The benefits of the gauge adjustment process observed at the regional scale are observed at all gauge locations when considering TMPA-Adj v.7 and IMERG-F v.6 in comparison to TMAP-RT v.7 and IMERG-E and -L v.6, respectively. Regarding GSMaP SPPs, the adjustment is only significant across the Savannah region.

The most efficient SPP varies according to the considered region. With a KGE of 0.77, 0.77, and 0.78, respectively, PERSIANN-CDR, CHIRPS v.2, and IMERG-F v.6 present the most efficient values across the Sahel region. In contrast, MSWEP v.2.2, CHIRPS v.2, and IMERG-F v.6 showed the highest KGE score over the central Savannah region (0.84, 0.84, 0.85). Finally, across the southern Guinea region, MSWEP v.2.2 is the most efficient SPP (KGE=0.86).

Generally, all SPPs presented lower KGE scores for the gauges located in the northern Sahel region. Passive and active microwave (PMW) sensors onboard a low Earth-orbital (LEO) satellite are the main input for precipitation estimates for most of the considered SPPs (TMPA, CMORPH, IMERG, GSMaP, CHIRP, and MSWEP v.2.2). The orbital trajectory of the LEO satellite limited the number of overpasses and thus hardly captures short precipitation events which are typical in a semi-arid context, as observed across the Sahel region [Gebregiorgis and Hossain \(2012\)](#); [Tian et al. \(2009\)](#). To fill the gaps, IR sensors on board geostationary satellites (continuous observation in time) are commonly used to augment the primary input during the second step. Contrarily, PERSIANN-CDR uses IR information as the input of an artificial neural network trained with precipitation estimates obtained by PMW sensors. Using IR data as the main input allows for a continuous observation, which seems adapted to the arid context of the Sahel region. Indeed, PERSIANN-CDR is the SPP providing the highest KGE score for the Sahel region. It is worth mentioning here that TAMSAT v.3 also used IR data as the main input for its precipitation estimates. TAMSAT v.3 used a cloud temperature threshold calibrated in space and time with gauge records. The heterogeneous distribution of the African rain gauges might introduce uncertainty in the threshold value for some regions, as observed across the Sahel region.

As observed for the KGE, the adjusted version of TMPA-Adj v.7 and IMERG-F v.6 presented higher r values for all regions and considered stations in comparison

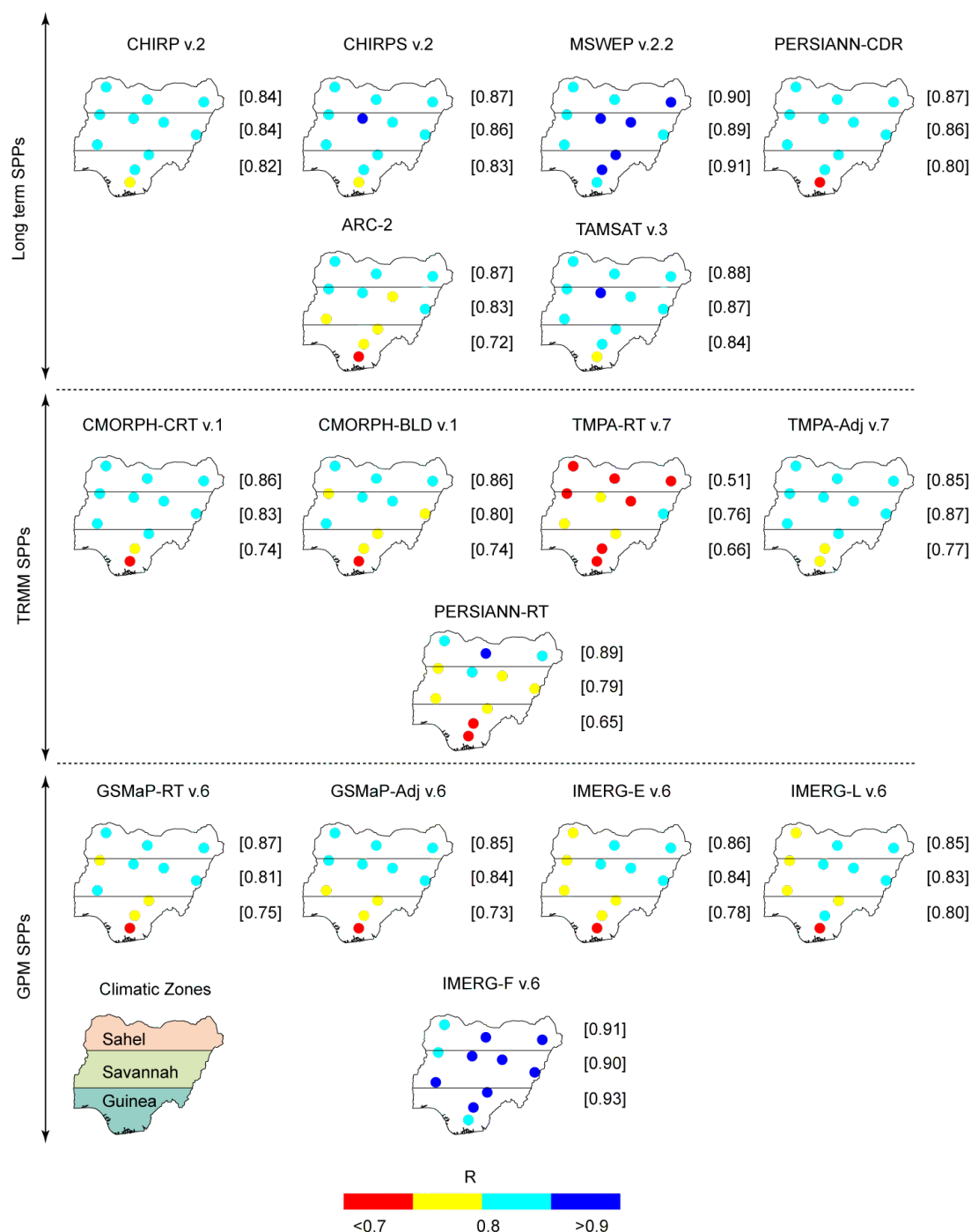


Figure 13: R scores obtained at the grid cell level of all the SPPs corresponding to gauge stations in the period 2000-2012. The SPPs are grouped according to their respective categories, and the gauges are separated by the country's ecological zones. Values in brackets are the average of the scores obtained inside the same ecological zone

to TMPA-RT v.7 and IMERG-E and -L v.6, respectively. The adjustment on GSMaP shows more contrast, with a clear improvement (degradation) observable across the Sahel (Guinea) region. Interestingly, except for MSWEP v.2.2 and IMERG-F v.6, which exhibit a higher correlation for all considered grid cells and regions, the SPPs presented lower

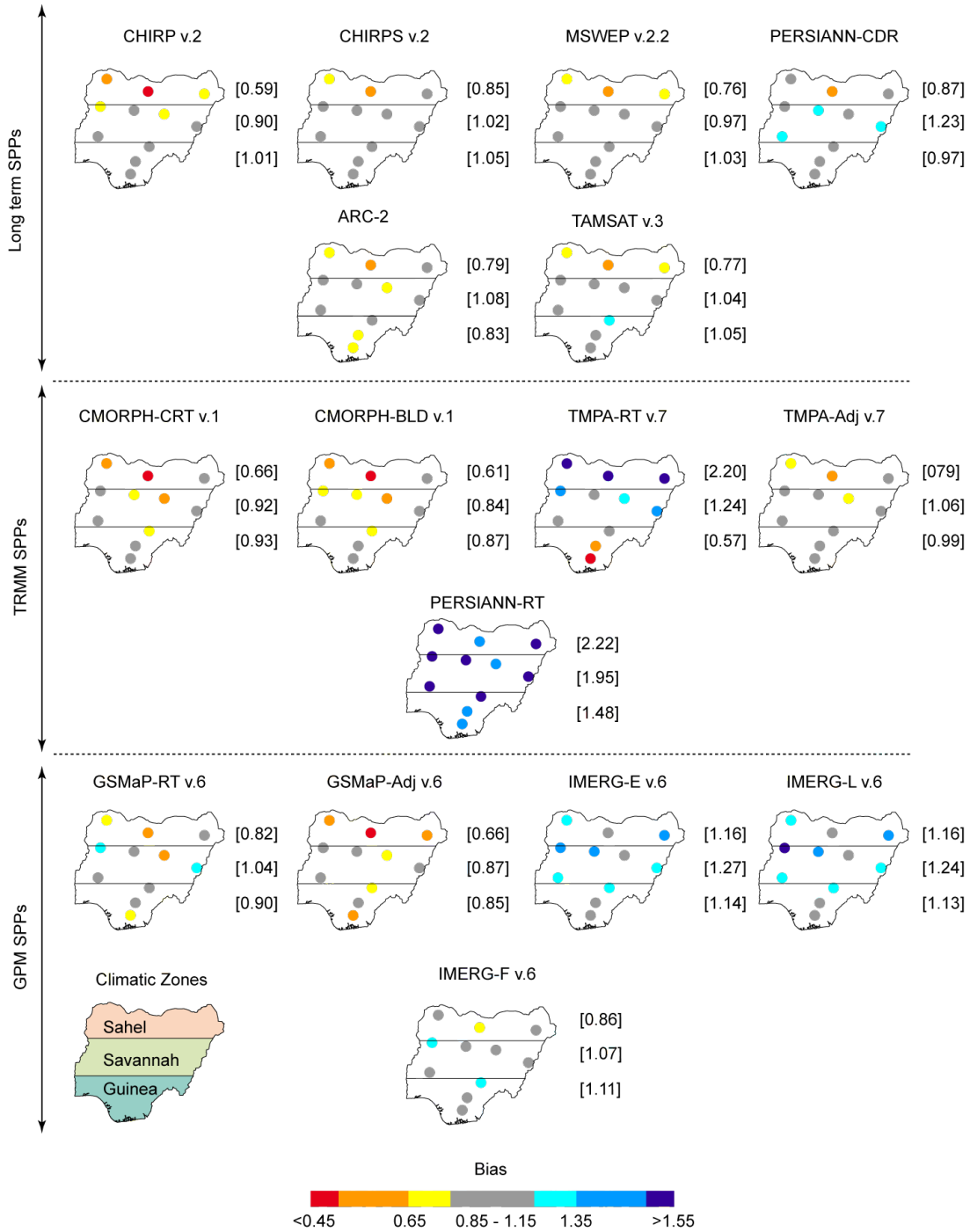


Figure 14: The β values obtained at the grid cell level for all SPPs over the 2000-2012 period. The SPPs are grouped according to their respective categories, and the gauges are separated by the country's ecological zones

correlation across the southern Guinea region. The southern part of Nigeria is a naturally cloudy region. The continuous presence of clouds, regardless of a rainy episode, might be challenging for SPP retrieval. On the contrary, the presence of cloud in the northern Savannah and Guinea regions are more related to rainy episodes, which minimizes potential mismatches between rain and no-rain clouds. This difference may partially explain the

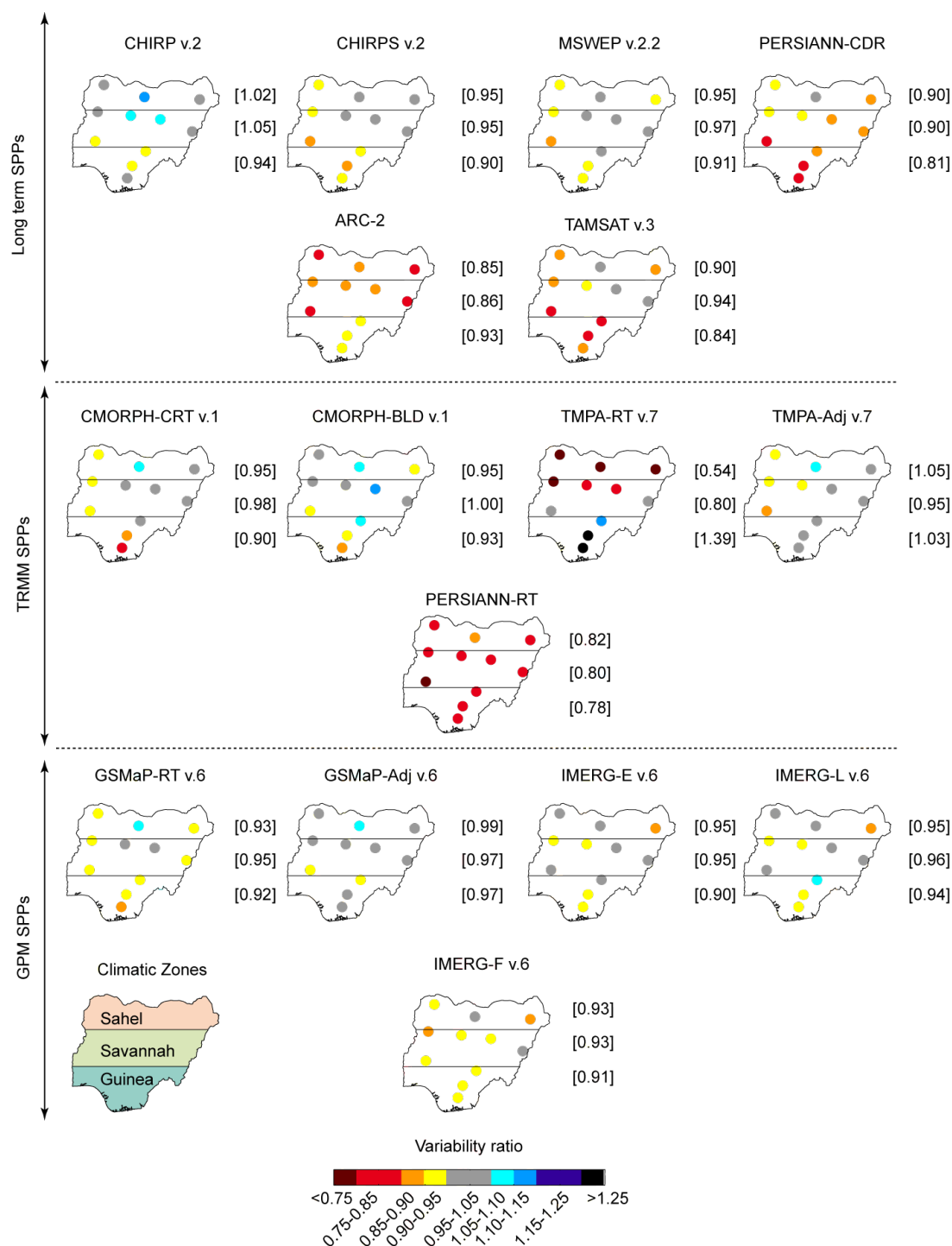


Figure 15: The Vr values obtained at the grid cell level for all SPPs over the 2000-2012 period. The SPPs are grouped according to their respective categories, and the gauges are separated by the country's ecological zones.

higher correlation observed from more gauge stations over the Sahel region.

In general, all SPPs underestimated precipitation in the northern Sahel region. As the correlation is generally higher for this region, it seems that the SPPs correctly cap-

tured the temporal occurrence of precipitation event but still underestimated the amount. This might come from specific short-term and light precipitation events occurring across the arid region, which is challenging for SPP retrieval methods Tian et al. (2009); Satgé et al. (2019b). However, it is worth mentioning here that an equivalent bias expressed in mm equals a different relative bias (Eq. 3) if considering high or low precipitation amounts. Therefore, the same bias (in mm) will result in higher relative bias over the Sahel than the Savannah or Guinea regions. The differences could partially explain the higher bias value observed over the Sahel region.

Finally, though that high discrepancy was observed in terms of SPP bias spatial distribution across Nigeria, over the Sahel region, IMERG-F v.6 and PERSIANN-CDR presented bias values closer to 1 (0.86 and 0.87, respectively). Whereas for the Savannah region, CHIRPS v.2 and MSWEP v.2.2 had 1.02 and 0.97, respectively. Finally, across the Guinea region, CHIRP v.2 and TMPA-Adj v.7 provided the less biased precipitation estimates, with a bias of 1.01 and 0.99, respectively.

Regarding the V_r values, all SPPs underestimated precipitation variability, particularly PERSIANN-RT and TMPA-RT v.7, and to a lesser extent ARC-2, TAMSAT v.3, and PERSIANN-CDR. The other SPPs presented reasonable V_r values. Interestingly, the gauge-based adjustment led to contradictory results depending on the considered SPPs. Indeed, IMERG-F v.6 had a lower V_r value than the non-adjusted version (IMERG-E and -L v.6), whereas both TMPA-Adj v.7 and GSMaP-Adj v.6 have V_r values closer to one compared to their non-adjusted versions (TMPA-RT v.7 and GSMaP-RT v.6).

As a general conclusion on gauge-based adjustment, despite an overall increase in KGE for TMPA and IMERG SPPs, the benefit shows more contrast when considering the KGE variables (r , (β) , and V_r) across the main Nigerian climatic regions (Sahel, Savannah, and Guinea). While all KGE variables (r , Bias and V_r) increased for TMPA across all climatic regions (Sahel, Savannah, and Guinea), a slight decrease was observed in terms of V_r for IMERG and all climatic regions. More interestingly, GSMaP V_r improved for all regions, whereas (β) (r) increased (decreased) for all regions (Savannah). Therefore, the adjustment process of GSMaP v.6 and IMERG-F v.6 should be optimised to avoid compromise in terms of precipitation feature optimisation (i.e., (β) , r , V_r).

5.6 Discussion

5.6.1 Long-Term SPPs for Precipitation Trend Analysis

This study aims to validate the usability and potency of long-term, TRMM, and GPM products for Nigeria using thirteen years of gauge observation data. However, the SPP reliability may exhibit temporal variation due to (i) different combinations of sensors over time, related to both ageing and newly released sensors, (ii) occasional technical issues, and (iii) variation in the available gauges (number and location) used to adjust some SPPs [Satgé et al. \(2019b\)](#). Variations in SPP reliability over time can influence SPP-based precipitation trend analysis. It is, therefore, crucial to report on SPP reliability over time. In this context, [figure 16](#) showed the KGE performance of the considered long-term SPPs (ARC-2, CHIRP v.2, CHIRPS v.2, MSWEP v.2.2, PERSIANN-CDR, and TAMSAT v.3) before 2000 (1985-1999) and after 2000 (2000-2012). Before 2000, the KGE is slightly better than after 2000 for all SPPs (except ARC-2). The highest difference between the KGE values obtained before and after 2000 was observed from CHIRP v.2 and CHIRPS v.2 ([figure 16](#)). A similar observation was made for CHIRPS v.2 over Nepal and was attributed to a decrease in available gauges for the adjustment process [Shrestha et al. \(2017\)](#). Similarly, the trend (KGE before 2000 higher than KGE after 2000) observed for MSWEP v.2.2, PERSIANN-CDR, and TAMSAT v.3 could be related to the gauge-based precipitation dataset (used in these particular SPPs) variation in terms of the number of gauges. In this context, TAMSAT v.3 uses consistent gauge-based information in space and time rather than continuously updated information to avoid adding any space or time discrepancy into the gauge network [Maidment et al. \(2017\)](#). Still, the KGE varies slightly in time, as other factors, such as ageing sensors and different sensor combinations, can influence SPP reliability over time.

Finally, with a median KGE value higher than 0.8 before and after 2000, MSWEP v.2.2 appears to be the best option for long-term precipitation needs over Nigeria. This is in line with the previous finding over the South American Andean Plateau [Satgé et al. \(2019b\)](#).

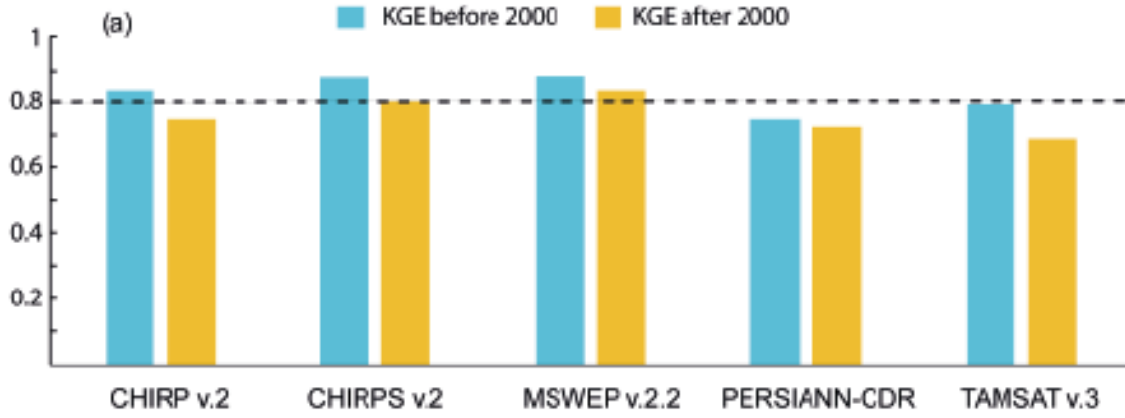


Figure 16: Median KGE values obtained from all the grid cell levels before and after 2000.

5.6.2 Enhancement from TRMM to GPM SPPs

The GPM came into existence to ensure the continuity of the TRMM. The expectations were high for GPM due to an increase in spatial (0.1°) and temporal (30 min) resolution. GPM SPPs (IMERG and GSMaP) are expected to provide an estimate of precipitation that is at least as accurate as that produced by the TRMM SPPs (TMPA-Adj and -RT v.7, CMORPH-CRT and -BLD v.1, PERSIANN-RT).

Figure 17 shows the difference in KGE values obtained at each grid cell between IMERG and TMPA SPPs. IMERG and TMPA datasets were compared, taking into account their available time latency. Therefore, IMERG-E and -L v.6 (time latency of 4 and 12 hours, respectively) were compared to TMPA-RT v.7 (1-day latency) (figure 17b, c), whereas IMERG-F v.6 (latency of 3 months) was compared to TMPA-Adj v.7 (3 months' latency) (figure 17a). Finally, IMERG-E and -L v.6 were also compared (figure 17d). GSMaP-RT v.6, GSMaP-Adj v.6, CMOPRH-CRT v.1, CMORPH-BLD v.1, and PERSIANN-RT were not considered for comparison because their overall reliability is lower than IMERG and TMPA datasets (figure 12). IMERG-F v.6 reaches higher KGE values than TMPA-Adj v.7 at nine out of 11 grid cell locations (figure 17a). The same was observed when comparing IMERG-E v.6 and -L v.6 to TMPA-RT v.7 (figure 17b, c). These results highlight a significant enhancement in precipitation estimates from TRMM to GPM SPPs. This finding is consistent with previous results reported in Bolivia Satgé et al. (2017b), Brazil Rozante et al. (2018); Salles et al. (2019), and Pakistan Satgé et al. (2018). Finally, IMERG-E v.6 and IMERG-F v.6 show a strong agreement with an abso-

lute difference inferior to 0.05 at 10 out of 12 gauge locations (figure 18b). Therefore, for real-time requirements, IMERG-E v.6 could be used instead of IMERG-L v.6 to obtain faster access to precipitation estimates across Nigeria (4 hours instead of 12 hours).

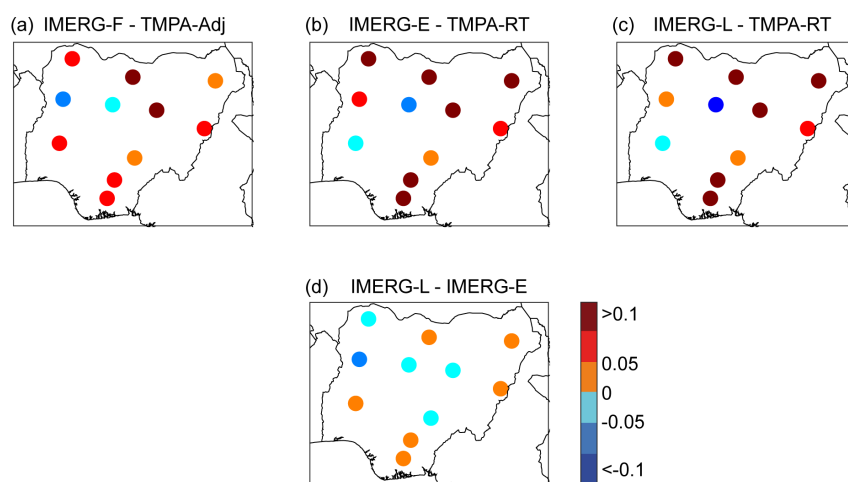


Figure 17: Comparative display of TRMM and GPM product performance at the gauge locations by comparing TRMM-TMPA vs. GPM-IMERG. (a) The performance of IMERG-F v.6 with TMPA-Adj v.7, (b) IMERG-E v.6 with TMPA-RT V.7, (c) IMERG-L v.6 with TMPA-RT v.7, (d) IMERG-L v.6 with IMERG-E v.6 at rain gauge points

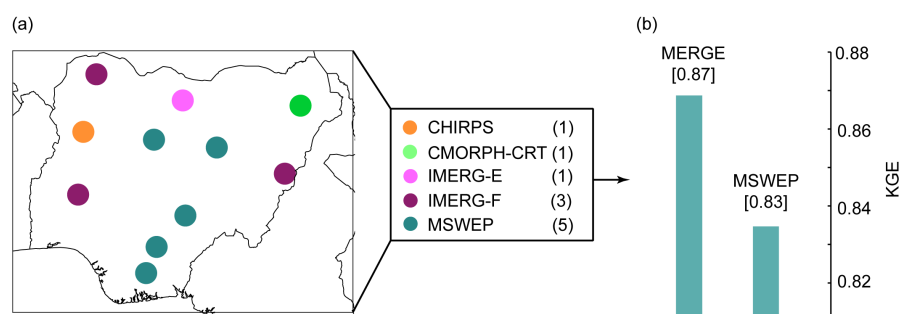


Figure 18: (a) Merging of the best product to each location's result revealed that MSWEP performed better in 5 out of 11 locations, (b) cumulative overall KGE score of MSWEP v.2.2 against the best performing products in other location

5.6.3 Towards an Enhanced Precipitation Dataset over Nigeria

As observed in [figure 13](#) to [figure 16](#), the SPP reliability varies in space, indicating that different SPPs should be considered depending on the region of interest within Nigeria. In this context, [figure 18](#) showed the SPPs with the highest KGE value at each considered grid cell. MSWEP v.2.2 showed the most robust performance in five gauge stations located in the central Nigeria region. IMERG-F v.6 reaches the highest KGE value at three grid cell locations, while CHIRPS v.2, IMERG-E v.6, and CMORPH-CRT v.1 are the best performers at a single grid location. To take advantage of all available SPPs, merging all SPPs to produce an enhanced precipitation dataset over the region should be a good option as shown in [figure 18](#). The potential benefit of such an improved precipitation dataset can be highlighted by the median KGE value of the most efficient SPP at each of the considered grid cell locations ([figure 18b](#)). The enhanced precipitation dataset reached a KGE value higher (0.87) than the most efficient SPP (MSWEP V.2.2, KGE = 0.83). Previous studies have reported on different merging approaches to retrieve a more realistic precipitation dataset from various SPPs over Pakistan [Muhammad et al. \(2018\)](#); [Rahman et al. \(2018\)](#), Tibet [Ma et al. \(2018\)](#), and different tropical complex terrains [Bhuiyan et al. \(2018\)](#). This method should be used as a guideline for Nigeria.

It is worth mentioning here that [figure 18](#) presents the best SPP in terms of KGE. However, as shown in the results section, the most efficient SPP changes according to the considered variables (i.e., KGE, r , (β) , and V_r). For instance, the most efficient SPPs in terms of bias are IMERG-F v.6 and PERSIANN-CDR across the Sahel region, CHIRPS v.2 and MSWEP v.2.2 across the Savannah region, and CHIRP v.2 and TMPA-Adj v.7 across the Guinea region. Therefore, interested users should select different SPPs in agreement with the foreseen use.

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Time Series Drought Assessment Across Nigeria

6.1 Overview

In this chapter, the study area's drought and wetness situation was assessed using the Standard Precipitation Index (SPI) and the Standard Precipitation and Evapotranspiration Index (SPEI) to evaluate the drought situation across Nigeria between 1981-2019 to determine the strength of drought in the country. The application of these two indices stemmed from the fact that SPI evaluates drought based solely on precipitation. SPEI, in contrast to SPI, considers both temperature and precipitation, partially accounting for the effects of global warming. Then, performances of both SPI and SPEI across the study area were compared for the two indices. The level of agreement between SPI and SPEI at various timescales, i.e. (3,6 and 12 months), revealed a high correlation of $r=0.94$. The assessment revealed that there were intense drought episodes between 1982 to 1984. Several drought types were present across the study area and in all the timescales. The highest intensity was determined to have occurred in 1983. However, the last extreme drought event was determined in 2016. As a result, we determined that the drought frequency has recently reduced. According to the results of this study, there is generally a satisfactory agreement between SPI and SPEI ratings in the study area. This chapter is being developed as a separate article. Currently, it is in an advanced stage towards submission to a journal.

6.2 Introduction

Drought is one of the consequences expected in the presence of a rapidly changing climate affecting every facet of human existence, especially the earth's hydro-ecological system. However, drought determination varies significantly due to factors such as magnitude and frequency. Consequently, what constitutes drought differs globally, depending on geographic location and prevailing seasons of the affected areas. Yevjevich (1967) asserted that any realistic drought definitions must be region and application-specific. Hence the reason for numerous definitions that have been created. Droughts are natural hazards having widespread and long-lasting impacts on society, the environment, and the economy (World Meteorological Organization, 2006), as cited in Apurv et al. (2017); Fang et al. (2020)

Generally, a drought occurs when there is an obvious deficit in precipitation supply over a period of time, indicating reasons for different drought types. A delay in the onset of the rainy season or a decrease in precipitation received over an extended period typically results in a drought Shukla et al. (2021); Christian et al. (2021). In many parts of the world, drought is frequently linked to humidity Dai (2011), which can considerably increase drought severity.

Historically, several attempts have been made to ascertain the conditions that lead to drought events appropriately. Although drought has been around for as long as human existence on earth, climate change has been the culprit of the recent increase in the intensity and duration of droughts globally. Humans have exacerbated the effects of drought through several activities such as land cover change, anthropogenic climate change, urbanisation, industrialisation and policy implementations have all impacted drought occurrences and progression. Zhou et al. (2016); Liu and Xia (2011) the hydrological cycle is anticipated to accelerate due to human-induced global warming

Continuous measurement and accurate information on the likelihood of drought is crucial for wholesome environmental planning, especially in agricultural, water resources, and energy production and distribution areas. However, despite the advanced technologies in monitoring water resources and drought events, there is still a limited dataset on droughts information.

Remote sensing approaches are an effective and better alternate method for detecting drought across wide areas. Different satellite-based indices have been created and are frequently used for drought monitoring [Alahacoon and Edirisinghe \(2022\)](#); [Alahacoon et al. \(2021\)](#), with the capabilities of providing drought information in a few meters across hundreds of kilometres. The temperature vegetation dryness index (TVDI), enhanced vegetation index (EVI), integrated drought severity index (IDSI) and normalised difference vegetation index (NDVI) are examples of water stress and drought monitoring estimates [Dutta \(2018\)](#); [Mbatha and Xulu \(2018\)](#); [Xie and Fan \(2021\)](#); [Liang et al. \(2014\)](#). Complex or multivariable indices contain a wide range of hydrological cycle components, including a combination of meteorological such elements as rainfall and evapotranspiration, [Yevjevich \(1967\)](#).

A different strategy for correctly identifying drought is to separate the individual variables responsible for the drought occurrence and analyse them as an interfering component, such as the inclusion of potential evapotranspiration in standard precipitation and evaporation index (SPEI) [Yevjevich \(1967\)](#).

Droughts have been classified into four categories; meteorological, agricultural, hydrological, and socioeconomic [Hisdal et al. \(2000\)](#); [Wilhite and Glantz \(1985\)](#). Drought classification such as meteorological, hydrological, agricultural and socio-economic droughts differs in intensity and duration [Wilhite \(2000\)](#). Anomalies in accumulated rainfall characterise meteorological droughts, agricultural droughts are characterised by decreased root-zone soil moisture and crop yields, hydrological droughts are measured by low stream flow, depleted groundwater, and reservoir level deficits and socio-economic droughts are characterised by the inability to meet societal water demands [Choi et al. \(2013\)](#); [Zarei \(2019\)](#).

Using various drought indices, numerous research has explored the causes of dryness and wetness variations in significant portions around the world. The Palmer drought severity index (PDSI) [Palmer \(1965\)](#), and the standardised precipitation evaporation index [Vicente-Serrano et al. \(2010\)](#), standardised precipitation index (SPI) [McKee et al. \(1993\)](#); [Edwards and McKee \(1997\)](#) are the assessment metrics that are most frequently employed.

Drought also results in severe human and economic catastrophes. Water shortages are frequently caused by the high geographical and temporal variability of water resources in different areas and periods. Given that climate change is predicted to increase droughts' frequency, duration, and severity, there are considerable worries about how these effects may affect our water security, socioeconomic development, and environmental sustainability.

Across the globe, various research focusing on droughts assessments, harmonisation of methods, validation of dataset, drought impacts on agriculture, and its role in climate change and global warming have all been conducted. For example, [Satgé et al. \(2019\)](#) impacts of droughts and agricultural intensification on the Altiplano water resources of Bolivia, using satellite products and SPI. [Barker et al. \(2019\)](#) evaluated the historic hydrological droughts 1891–2015: systematic characterisation for a diverse set of catchments across the UK using a standardised streamflow index (SSI). [Domínguez-Castro et al. \(2019\)](#) characterised the climatology of drought events over mainland Spain and the Balearic Islands using high-resolution (1.21 km²) meteorological data from 1961 to 2014. [Rascón et al. \(2021\)](#) assessed dry and wet events from 1981 to 2019 that have taken place in Chachapoyas, by applying the SPI and the SPEI. Finally, [Nam et al. \(2015\)](#) assessed drought hazard in the context of climate change for South Korea.

Across Africa, several methods and datasets have been used to assess droughts [Polong et al. \(2019\)](#); [Mwangi et al. \(2014\)](#); [Rouault and Richard \(2005\)](#); [Gebrechorkos et al. \(2020\)](#); [Rieckmann et al. \(2018\)](#). The majority of these studies have raised the concern that incessant droughts in the Sahelian region are the primary cause of diseases, crop failure, insecurity and ethnic conflicts, and mass emigration from the region [Boubacar \(2010\)](#); [De Rouw \(2004\)](#); [Abiodun et al. \(2020\)](#); [Harmon \(2016\)](#); [Nyong \(2006\)](#); [Thébaud and Batterbury \(2001\)](#); [Ajaero et al. \(2015\)](#).

In Nigeria, few researchers have looked at the performance of drought occurrence using various indices at various spatial scales and approaches. Notable among them are [Adedeji et al. \(2020\)](#) preferred to monitor drought using remote sensing data such as NDVI and EVI due to limitations of SPI and PDSI. [Oloruntade et al. \(2017\)](#) assessed meteorological and hydrological drought across Nigeria, [Abaje et al. \(2013\)](#) used normalised rainfall index (NRI) to assess drought, and [Shiru et al. \(2019\)](#) used only SPEI for a long

time drought assessment. Despite all these, information on the effectiveness of drought, mitigating strategies, and drought prediction are still lacking, resulting in severe drought disasters overwhelming the country, especially in the northern axis.

Nigeria is the most populous nation in West Africa. Nigeria's primary food source is agriculture. Most of this food is produced in the regions where droughts are hitting the nation frequently and repeatedly. Most Nigerian farmers are dependent on rain for crop survival and bountiful yield. The herders-farmers crisis in Nigeria is fuelled in parts by drought conditions that have exacerbated the water scarcity in Nigeria's northern axis. In addition, displacing farmers and herders who have lost their means of sustenance has resulted in forced migration across the Sahel region.

The aim of this study is to use SPEI and SPI to evaluate droughts detrimental to the ecological status across Nigeria and monitor drought severity and environmental conditions. SPI makes it possible to detect water or moisture deficit over a short or long period. Whereas SPEI makes it suitable to study drought and identify climate change's impact. As well as project the likely drought situation in the future.

6.3 Materials & Methods

6.3.1 Dataset

A monthly climatic dataset on evapotranspiration was chosen for this assessment and downloaded from the TerraClimate WorldClim website. While the precipitation dataset from the Multi-Source Weighted Ensemble Precipitation version.2.2 (MSWEP v.2.2) was also downloaded from the MSWEP website (personal communicated link). The temperature dataset was a reanalysis dataset downloaded from the 5th generation of the European Centre for Medium-Range Weather Forecasts (ECMWF, ERA-5 land) website.

Although the ET dataset from the TerraClimate dataset is updated weekly, it is available on monthly averages with a 4 km spatial resolution (1/24th degree). TerraClimate employs climatically assisted interpolation, which combines high-spatial resolution climatological normal from the WorldClim dataset with poorer spatial resolution,

but time-varying data from Climate Research Unit (CRU) Ts4.0 and the Japanese 55-year Reanalysis (JRA55). According to [Abatzoglou et al. \(2018\)](#), the Annual reference evapotranspiration fields from TerraClimate were well related to station-based reference evapotranspiration from FLUXNET stations.

The temperature dataset from ERA-5 covers global lands at 9 km spatial resolution, while the WorldClim dataset covers the global land at 4 km spatial resolution. Several authors have validated the ERA-5 dataset and the estimates were found to correlate well with in-situ stations [Liu et al. \(2021\)](#)[Valeriano et al. \(2019\)](#)[Martens et al. \(2020\)](#).

MSWEP, on the other hand, has a spatial resolution of 0.1° (11.1 km), and it merges gauge, satellite, and reanalysis data to obtain the highest quality precipitation estimates at every location [Beck et al. \(2019\)](#). At the datasets covered the study area spatially and temporally and have been validated within the study area and were found to have a reasonable correlation with gauge estimates within the study area. [Nwachukwu et al. \(2020\)](#); [Liu et al. \(2021\)](#); [Valeriano et al. \(2019\)](#); [Martens et al. \(2020\)](#); [Abatzoglou et al. \(2018\)](#).

Image-to-image interpolation using the coordinates of the dataset with the least spatial resolution (in this case, the 4km spatial resolution WorldClim dataset) was applied to transform the other climatic datasets with spatial resolutions more than 4km using nearest neighbours methods. This method translation and alignment two images with similar geometry and of the same geographic area such that matching elements of the same ground area appear in the same place on the registered images. This is to avoid biases due to overlap when comparing the pixels of two variables with different spatial resolutions resulting from spatial mismatch during analysis.

Data of El Niño events using Monthly El Niño-3.4 index data from the National Weather Service (NSW) was used to compare detected drought intensity so as to identify if El Niño had an influence on drought in Nigeria.

6.3.2 Detecting Precipitation Trend

In assessing the precipitation trend, precipitation from MSWEP was extracted from nine city stations spread across the ecological zones (Sahel, Sudan and Guinea/Rainforest) (Figure stations). This study of long-term precipitation records is critically important in understanding a country's surface and groundwater rechargeability, whose food security and economy rely on the timely availability of water. The Mann–Kendall test and Sen's slope model were used to identify the trend and the magnitude of the change, respectively, for all the stations [figure 3](#) computed as follows;

$$\beta = \frac{x_j - x_i}{j - i} \quad (6.1)$$

In order to identify the presence of a trend in the data sets, slope estimator β is also used from the equations. Here, β is the median of all possible combinations of pairs for the whole dataset. A positive of β indicates an increasing trend (values that increase with time), while a negative value indicates a 'downward trend' (decreasing values) [Mavromatis and Stathis \(2011\)](#). The Mann-Kendall (MK) trend test is regarded as one of the best techniques for identifying trends in time series (cite). Applying the MK test to find monotonic (either growing or decreasing) trends. Mk is efficient because the nonparametric MK test's statistic is based on (+ or -) signs rather than the values of the random variable. The identified trends are less affected by outliers even though there is a likelihood that outliers will be present owing to extreme precipitation occurrences [Helsel and Hirsch \(1992\)](#). The MK statistic S is defined as follows to detect a trend in the rainfall time series, assuming that the time series is independent;

$$S = \sum_{i=1}^{n-1} \sum_{j=1+1}^n \text{sgn}(x_i - x_j) \quad (6.2)$$

where x_i and x_j are sequential data for the i th and j th terms; n is the sample size; and

$$\text{sign}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j - x_i > 1 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 1 \end{cases} \quad (6.3)$$

The statistics S is approximately Gaussian when $n = 18$ with the mean $E(s)$ and the variance $\text{Var}(S)$ of the statistics S given by the expression;

$$E(s) = 0, \text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (6.4)$$

If there are ties in the data set, the equation for $\text{Var}(S)$ must be changed and is now:

$$\text{Var}(S) = \frac{\{n(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5)\}}{18} \quad (6.5)$$

6.5 variables, q and tp , represent the number of tied groups and the quantity of data values in the p th group. For a one-tailed test of the statistic S , the standardised statistic (Z) is as follows:

$$Z_{mk} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (6.6)$$

An increasing trend is observed if Z_{mk} is positive, and vice versa.

6.3.3 SPI and SPEI drought indices

6.3.3.1 Standardised Precipitation Index (SPI)

The standardised precipitation index (SPI) [McKee et al. \(1993\)](#) is one of the most widely used meteorological drought indexes. The SPI was created by normalizing the probability of precipitation. It describes the precipitation shortfall and enables drought monitoring

on various timescales. SPI can be calculated on daily or weekly data. However, monthly analysis is preferred. SPI has been well reviewed and recommended by the World Meteorological Organization (WMO) as the most important drought index that is mandatory in all nations due to the implicit nature of SPI and its applications. observing the effects of the drought on the weather.

The SPI calculation begins by fitting the gamma probability distribution which is then transformed to the normal distribution so that the mean SPI value for the locations is zero and the standard deviation is one. As a result, the SPI values correspond to the fitted distribution's Z scores. Various percentiles of the chosen distribution correspond to various categories of precipitation situations. The intensity of the drought increases as the SPI decreases. A time-invariant probability distribution, typically the gamma distribution, is utilized in traditional SPI calculations to fit observed rainfall series. Fitting a time-varying gamma distribution to a trending rainfall series leads to nonstationary SPI series [Shiau \(2020\)](#). The density probability function for the gamma distribution is presented as follows (as partly explained in [Singh et al. \(2019\)](#));

$$g(x) = \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad \text{For } x > 0 \quad (6.7)$$

where $\alpha(> 0)$, $\beta(> 0)$ are two parameters(shape and scale); x is precipitation amount; $\Gamma(\alpha)$ = gamma function.is the gamma function expression. Where the precipitation distribution, especially for short timescales, may contain some zero values, and the gamma distribution is undefined at $x = 0$, the cumulative probability $H(x)$ is corrected as;

$$H(x) = q + (1 - q)G(x) \quad (6.8)$$

where q = probability of zero precipitation. Finally, $H(x)$ is transformed into the standardized variable, with a mean of zero and a variance of one, which is the value of the SPI. The fundamental benefit of SPI is that it allows for regional comparisons of drought [Cerp Reyes et al. \(2022\)](#).

6.3.4 Standardised precipitation evaporation index (SPEI)

The SPEI was developed by [Vicente-Serrano et al. \(2010\)](#). The SPEI is based on precipitation and temperature data, and it has the benefit of being multiscalar while also being able to account for the effects of temperature fluctuation on drought assessment. A climatic water balance, the accumulation of deficit/surplus at different time scales, and correction to a log-logistic probability distribution are all part of the technique for calculating the index. The SPEI is calculated based on a water balance equation, using the difference between precipitation and potential evapotranspiration at a predefined time scale such as monthly or weekly. In the absence of the ET_p dataset, ET_p can be estimated using the Thornthwaite method [Thornthwaite \(1948\)](#). [Guttman \(1998\)](#) noted that the interpretation of drought at different time scales using SPI has also provided better than superior to the Palmer Drought Severity Index. This method evades entanglements involved in the popular Penman-Montieth method which requires a lot of parameters that are sometimes not readily available. However, in Thornthwaite, temperature and precipitation are all the parameters need. Hence, the Thornthwaite method requires only temperature as the input variable as follows;

$$F(x) = \frac{\beta}{\alpha} \left(\frac{x - \gamma}{\alpha} \right)^{\beta-1} \left[1 + \left(\frac{x - \gamma}{\alpha} \right)^{\beta} \right]^{-2} \quad (6.9)$$

where α , β and γ are scale, shape and location parameters, respectively. Then, standardization of the cumulative distribution function to standard normal form having mean zero and standard deviation one is done to obtain the SPEI index. The SPEI's multi-scalar properties, however, make it possible to distinguish between various drought types and their effects in the context of global warming, giving it a significant advantage over the most popular drought indices that take the effect of ETo on drought severity into account [Vicente-Serrano et al. \(2010\)](#)..

The Pearson correlation coefficient, r , which assesses the strength of the statistical association between the SPI and SPEI, is used to determine if both indices depict the same pattern (regardless of magnitude). At the *95percent* confidence level, this coefficient determines if the indices have a linear relationship. The connection coefficient (R)

ranges from $+1$ to -1 , with $+1$ indicating a perfect positive relationship, 0 indicating no relationship, and -1 indicating a perfect negative relationship. The magnitude of the correlation indicates the relationship's strength, and a R value of ≥ 0.5 is considered a high correlation (Taylor, 1990). The following is how R is calculated:

$$R_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (6.10)$$

Where:

n = number of observations, and for this study x and y represent the SPI and SPEI values respectively.

R = correlation coefficient

x_i = values of the x-variable in a sample

$\bar{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\bar{y}$ = mean of the values of the y-variable

6.3.4.1 Drought Identification

According to Guo et al. (2017); McKee et al. (1993), a drought event is defined by a period with at least two consecutive months with negative SPI values and at least one month with an SPI lower than -1 . The SPI scale is used to characterize droughts for both SPI and SPEI (McKee et al., 1993). The SPI scale is utilized since both indices are calculated using the same concepts. Extreme drought (≤ -2), severe drought from $(-2$ to $-1.5)$, and moderate drought from $(-1.5$ to $-1)$ are the SPI/SPEI index scales used in this study. A drought ends when the SPI/SPEI approaches zero and advances to a positive number. We used the method described by Yevjevich (1967) to define the drought characteristics (severity, duration, and intensity). The duration of the drought is defined in this study as the number of months during which the drought has occurred, while the magnitude of the indices represents the severity of the drought.

A drought event is described in this study as a period expressed in months (t)

Table 6.1: SPI and SPEI classification and categories

Sn	Categorization	SPEI values
1.	Extremely wet	≥ 2.0
2.	Severely wet	$\geq 1.5 \text{ to } < 1.99$
3.	Moderately wet	$\geq 1.0 \text{ to } 1.49$
4.	Near Normal	$\geq -0.99 \text{ to } 0.99$
5.	Moderate drought	$\geq -1.0 \text{ to } < -1.49$
6.	Severe drought	$\geq -1.5 \text{ to } < -1.99$
7.	Extreme drought	< -2.0

having a drought index value, $DI(t)$, less than the defined threshold, DI_0 . These thresholds are the SPEI and SPI drought classifications such as extreme drought (SPEI/SPI < -2.0), severe drought (SPEI/SPI < -2.0 , to ≤ -1.5), and moderate drought (SPEI/SPI < -1.5 , to ≤ -1.0). This approach was to distinguish between a drought and a non-drought. Near normal (SPEI/SPI $-0.99 \text{ to } 0.99$) was not considered a serious drought situation in this study. Drought can be characterized by duration (D), magnitude (M), or severity (S) which are also dependent on magnitude.

The term drought frequency refers to the number of droughts that occur within a given period [Zhang et al. \(2015\)](#); [McKee et al. \(1993\)](#). The duration of a drought is the amount of time (for example, the number of months) from its onset until its conclusion. It is calculated by dividing the total number of drought events by the sum of their duration. The accumulated shortfall with the SPEI or SPI values continually lower than 0 can be used to determine drought intensity, which measures the severity of the drought during the drought event. The drought characterisation calculated as magnitude and severity is presented as follows;

$$M = \sum_{t=1}^D \{DI_0 - DI(t)\} \quad (6.11)$$

$$S = \frac{M}{D} \quad (6.12)$$

Drought magnitude is the time-integrated deficit below the threshold level, and drought severity is calculated as the mean magnitude across the period of the drought.

6.4 Results

The results of the MK test, SPEI and SPI assessment to determine the occurrence and magnitude of droughts are presented here. SPEI and SPI drought analyses were done at different time scales for three (3), six (6) and twelve (12) months periods over 1981-2019. Accordingly, SPI and SPEI were compared in order to establish whether potential evapotranspiration has an effect on the drought index. Both indices were calculated at different time scales (3, 6 and 12-months) to represent different droughts such as meteorological, agricultural, and hydrological droughts, respectively. The two indices showed a strong correlation in their ability to detect drought events within the study area. However, they differ in magnitude and duration. This disagreement in magnitude highlights the impact of temperature and ET_p inclusion for the SPEI calculation, inverse to SPI calculation.

6.4.1 MK Trend

The precipitation trend analysis showed an increasing trend in two stations across the Sahel and two stations across the Guinea/Rainforest ecological zone. One station (Yola) in Sudan showed a decreasing trend. Elsewhere, the MK trend test applied to the historical precipitation presented a no-trend situation [figure 19](#).

Across the study area, the increasing trend observed in the Guinea/Rainforest zone (Enugu and Port Harcourt) showed a p-value of 4.451 & 1.4, at the rate of 0.04 and 1.01 mm/year of precipitation. Similarly, the significance level increasing trend observed in the Sahel region (Sokoto & Kano) were 5.7 and 0.00, respectively, where the trend analysis from precipitation in Kano showed a significant p-value. Yola (a region within the Sudan Savannah) revealed decreasing trend with a p-value of 2.19.

6.4.2 Temporal Variation Between the SPI and SPEI

From the results, we observed that the frequency and severity of droughts in Nigeria have been inconsistent. The drought situation can be characterized by mainly moderate to

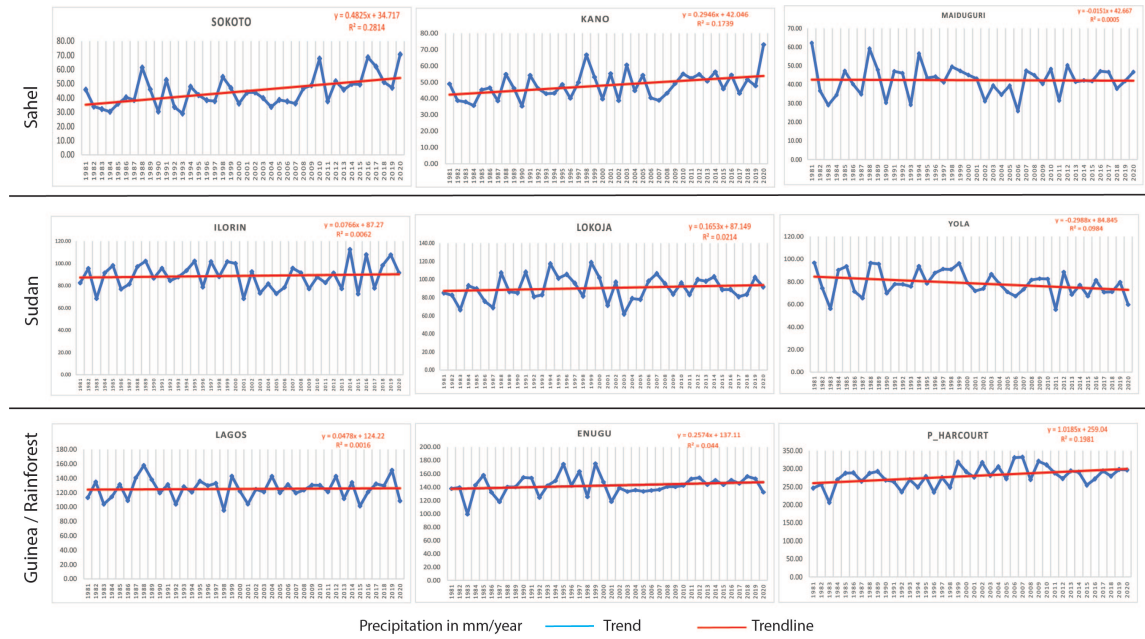


Figure 19: Annual average precipitation of 9 stations in annual spread across the ecological zones (Sahel, Sudan and Guinea/Rainforest) of the study area within the period 1981–2020.

extremely dry ($SPEI \leq 2.0$) based on the SPEI index. Both the SPI and SPEI changed frequently and widely, mostly around -1.0 to -1.5 (figure 20 & figure 21).

Within the period considered by this assessment (1981-2019), the result showed the effects of short-term climatic change on the subtle shift in water gain and loss at 3-months, 6-month and 12-month timescales. Additionally, as timescales were extended, the SPI and SPEI showed obvious variations in the duration of absence of adequate water and apparent interannual and inter-decadal changes. This may have reflected the long-term minor influence of climate change on drought magnitude.

In general, the SPI and SPEI variations exhibited agreeable patterns over a range of timescales, but there were still minor differences in the oscillations, which meant that they displayed different patterns of drought frequency and intensity. For instance, SPEI and SPI detected extensive extreme drought (drought < 2.0) between 1983-1984 and 2015. However, the 12-month SPI could not detect the intensity in the 2015 drought but replicated the pattern observed in the 1983-1984 drought (figure 20 & figure 21). In order words, as the timeline was extended, the indices' variances increased. An indication of SPI-SPEI difference in relation to the influence of the parameters used in the calculation. Thus, SPI (Standardized Precipitation Index) monitors water supply through pre-

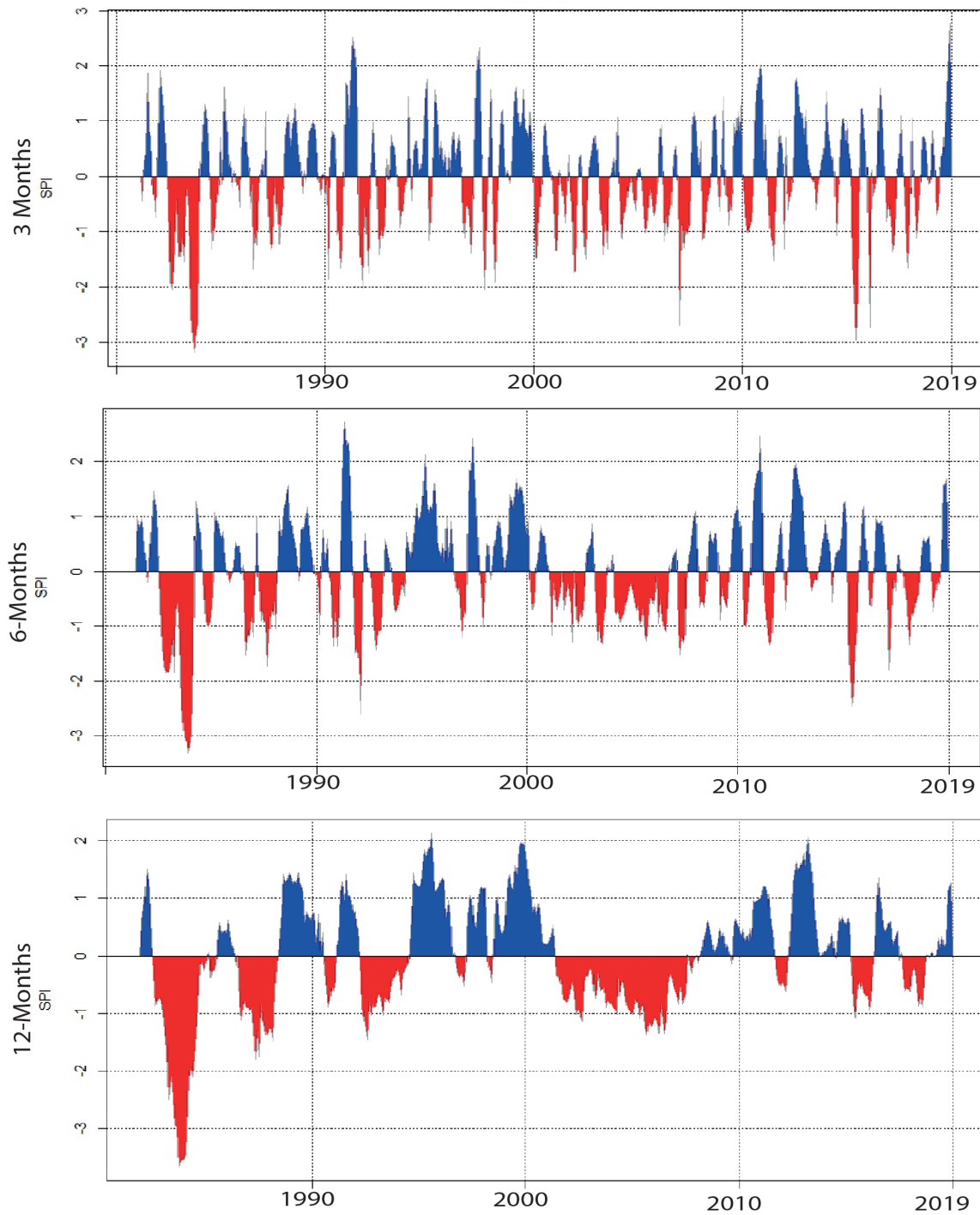


Figure 20: SPI plots showing the duration and magnitude of drought across Nigeria

cipitation. In contrast, the SPEI (Standardized Precipitation Evapotranspiration Index) measures both water supply (precipitation) and captures the main impact of increased temperatures on water demand (evaporation+transpiration=evapotranspiration). The variation in the observed pattern could be because warmer temperatures increase the evapotranspiration rate, thereby increasing droughts' severity.

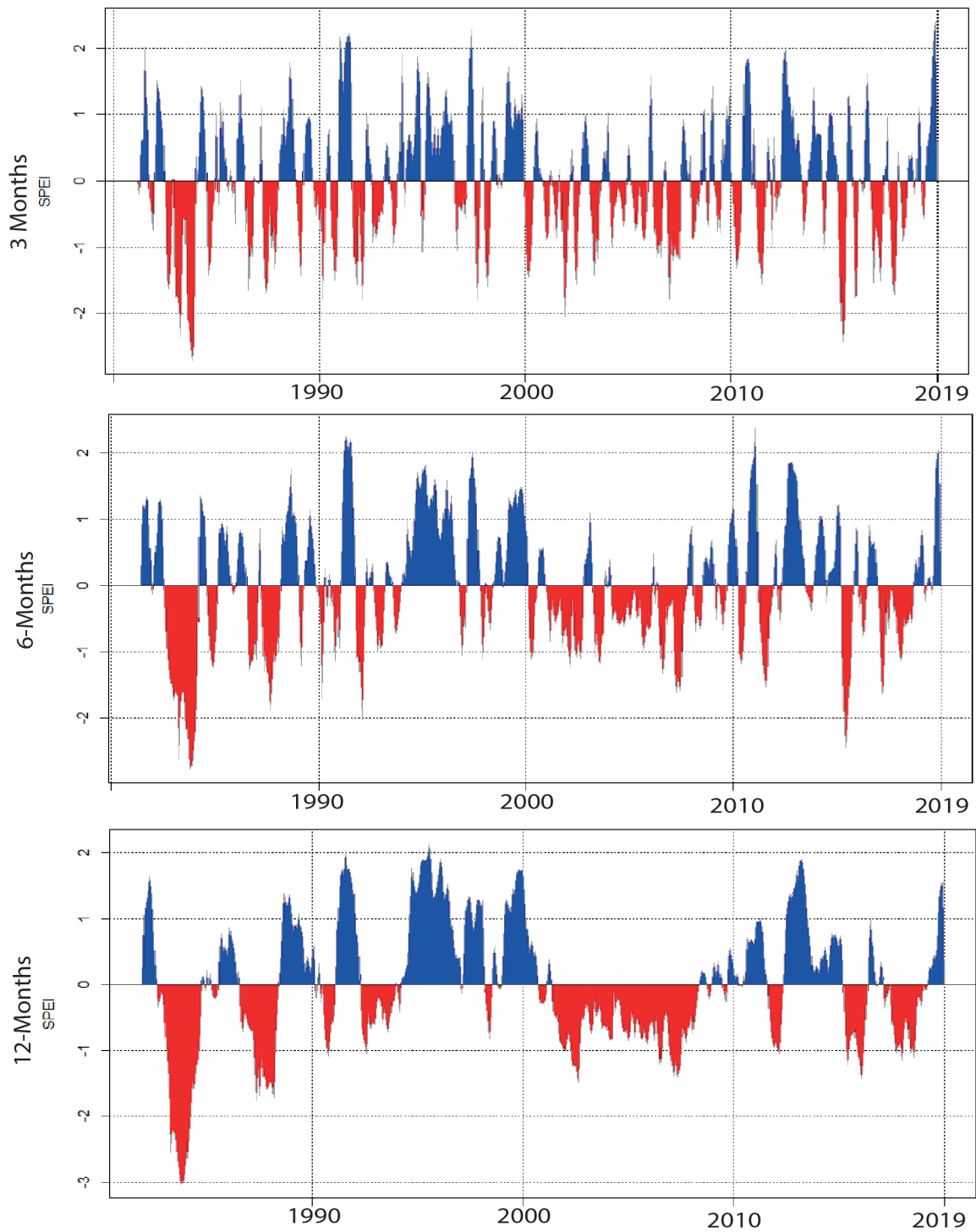


Figure 21: SPEI plots showing the duration and magnitude of drought across Nigeria

Both SPI and SPEI showed high-frequency fluctuation in 3-months given the little period of time during which the variables are considered. The 6-month and 12-month revealed increase in the duration of dryness. The highest drought recorded in 3-months was (SPEI=-2.7 and SPI=-2.9). On a 6-month time scale, the SPI and SPEI values fluctuate between 2.73 and -3.31 (figure 20 & figure 21). Comparing the 12-month

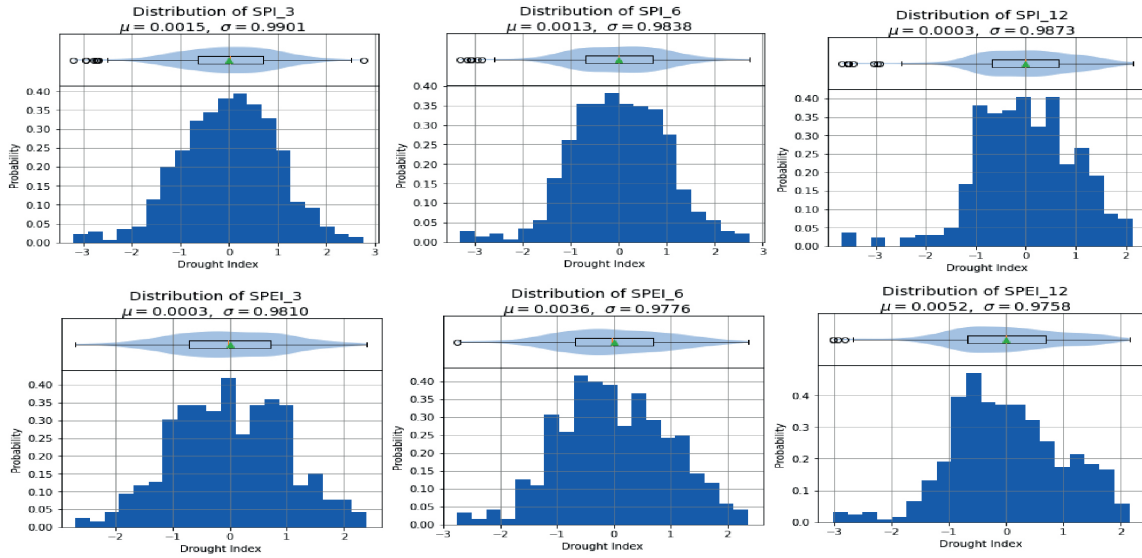


Figure 22: Statistical description of SPEI and SPI distribution. σ =standard deviation; μ = mean

SPI and SPEI 3-month, the results of the index support the assertion that When the temporal scale is enlarged, both dry and wet occurrences displayed lower intensities and lasted longer [Vicente-Serrano et al. \(2010\)](#).

In contrast, the index values of the 12-month timescale revolve around 2.15 and -3.6. SPI and SPEI indices for the 12-months are more steady due to dry and wet episodes occurring less frequently but lasting longer. The 12-month classifies the identical droughts as high magnitude and intensity droughts. [Issaharou-Matchi et al. \(2021\)](#) also observed drought increasing with an increase in SPEI timescale

In assessing the reliability of SPEI and SPI performance across Nigeria, the correlation coefficient of different timescales, e.g. 3, 6 and 12-months, to examine the consistency of the SPI and SPEI. It is evident that there were variations in each timescale based on the different indices correlation coefficients. The SPI and SPEI were remarkably high at 0.94 for all the timescales and rose 0.31,0.32, and 0.33 for 3,6 and 12-months timescales, respectively. The high correlation has also been observed in other locations by other authors [Ojha et al. \(2021\)](#); [Bera et al. \(2021\)](#); [Stojanovic et al. \(2018\)](#); [Zhang et al. \(2019\)](#); [Ajayi and Ilori \(2020\)](#).

6.4.3 Monthly Variations in the SPI and SPEI

The SPI maps show how moisture conditions changed naturally during the years, both in terms of time and space, depending on the prevailing season. The SPI and SPEI's monthly variation features were discernible at various timescales, which amply depicts changes in the dry and wet degree of each month in the study area, particularly from 1983 to the early part of 1984 and again in 2015. The intensity of droughts in these months grew evidently (figure 24 to figure 27).

It is important to report severe and extreme droughts (drought = -1.5 to <-2) due to their impact on the hydro-ecological systems and agricultural production. These two types of drought were prominent in most of the study areas, on 3 and 6-month timescales assessments and in both SPI and SPEI. Severe droughts occurred more frequently in 3-months and 6-months in both SPEI and SPI but appeared less frequent in the 12-month SPI and SPEI. In comparison, SPI detected more extreme droughts than SPEI (Table 6.2). The 12-month SPI presented extreme droughts in the dry months with increased intensity (Table 6.2), which varies with SPEI in the same timescale. Subsequently, extreme droughts were only detected in the study area in the 3 and 6-months in recent times (Table 6.2). However, the 2015 drought episode was in wet months.

The result from the (figure 20 & figure 21) showed that on a 1- to 3-month time period, dry weather could be seen in the drought trend, identifying the magnitude and trend. Similarly, the 6-month assessment of both the SPI and SPEI revealed a synonymous trend that differs slightly in magnitude. However, at 12-months, both indices suggested that most parts of the country would have witnessed devastating drought events. The various timescales considered in the assessment showed that the most intense periods of drought were from August to December 1983 and May -July 2015. Based on SPI 12-months, there was an obvious water deficit that started in April 1982 and ended in April 1984. This is worrisome because it encompassed both dry and wet season

Furthermore, both indices detected simultaneous extreme events in 3, 6 and 12-months, such as in 1983 (SPI and SPEI detected extreme drought in October, November and December). This particular event was recorded by the indices in all the assessment periods (table 6.1). It is not a coincidence that these droughts were detected during the

Table 6.2: Extreme droughts and their date as identified by the defined temporal scales of both the SPEI and SPI as identified. The index values are expressed in months

Year	SPEI_3	SPEI_6	SPEI_12	SPI_3	SPI_6	SPI_12
9/1/1982				-2.05		
4/1/1983	-2.34	-2.61	-2.54			-2.49
5/1/1983			-2.29			-2.35
6/1/1983			-2.2			-2.1
7/1/1983			-2.26			-2.47
8/1/1983	-2.07	-2.18	-2.64	-2.51	-2.44	-2.93
9/1/1983	-2.14	-2.17	-2.82	-2.94	-2.86	-2.97
10/1/1983	-2.52	-2.76	-3.03	-3.2	-3.08	-3.67
11/1/1983	-2.7	-2.69	-3.02	-2.79	-3.1	-3.57
12/1/1983	-2.45	-2.71	-2.95	-2.68	-3.31	-3.54
1/1/1984		-2.41	-2.69		-3.18	-3.53
2/1/1984		-2.14	-2.5		-2.96	-3.45
3/1/1984		-2.29				-3.03
4/1/1984						-2.12
6/1/1984						-2.11
11/1/1991				-2.02		
2/1/1992		-2.01			-2.6	
9/1/1997				-2.06		
12/1/2001	-2.04					
1/1/2007				-2.7		
5/1/2015	-2.02			-2.09		
6/1/2015	-2.42	-2.43		-2.95	-2.46	
7/1/2015	-2.01	-2.09		-2.07	-2.23	
2/1/2016				-2.73		

onset of the dry season in Nigeria. This is an indication of the role of solar radiation and extreme temperature in drought intensity.

6.4.4 Extreme Droughts at Point Locations

Table 6.3: Means of extreme and severe droughts from the indices at the point locations

Index Timescale	Guinea/Rainforest	Sudan Savannah	Sahel
SPEI 3-months	-1.79	-1.82	-1.83
SPEI 6-months	-1.85	-1.83	-1.80
SPEI 12-months	-1.82	-1.78	-1.76
SPI 3-months	-1.88	-1.94	-1.94
SPI 6-months	-1.98	-1.98	-1.84
SPI 12-months	-1.95	-1.87	-1.79

The mean SPEI and SPI droughts analysis for the selected stations across the

ecological zones are shown in [table 6.3](#). At those locations, the results are similar to the wide area pixel drought detected by the indices. The majority of the droughts occurred between 1982-1984. The 6 and 12-month droughts are important due to their implication on hydrological components, which can impact hydrologic features such as surface and groundwater level rechargeability. The drought severity in those selected locations indicated that the highest mean value was detected in the Guinea/Rainforest ecological zones based on 6-months in both indices. Values from the SPEI and SPI showed that there were more high droughts based on the SPI, which is unsurprising based on the input data for SPI calculated, which requires only precipitation as input. Therefore, three-month precipitation cessation, especially in the Guinea/Rainforest zones, would have tipped off the index. On account of the duration of these droughts, the results from the 12-month assessments were lesser than the 3 and 6-month. Therefore these results indicated that mostly climatological and agricultural droughts were more prevalent for the period this assessment covered. This would have affected agricultural practices, leading to crop failures, food shortages, and forced migration.

When the SPEI and SPI results were compared with El Niño events using Monthly Niño-3.4 index data from the National Weather Service (NSW) for the period under consideration, there were no apparent similarities in trend. This suggests that the El Niño event had influenced drought propagation in Nigeria.

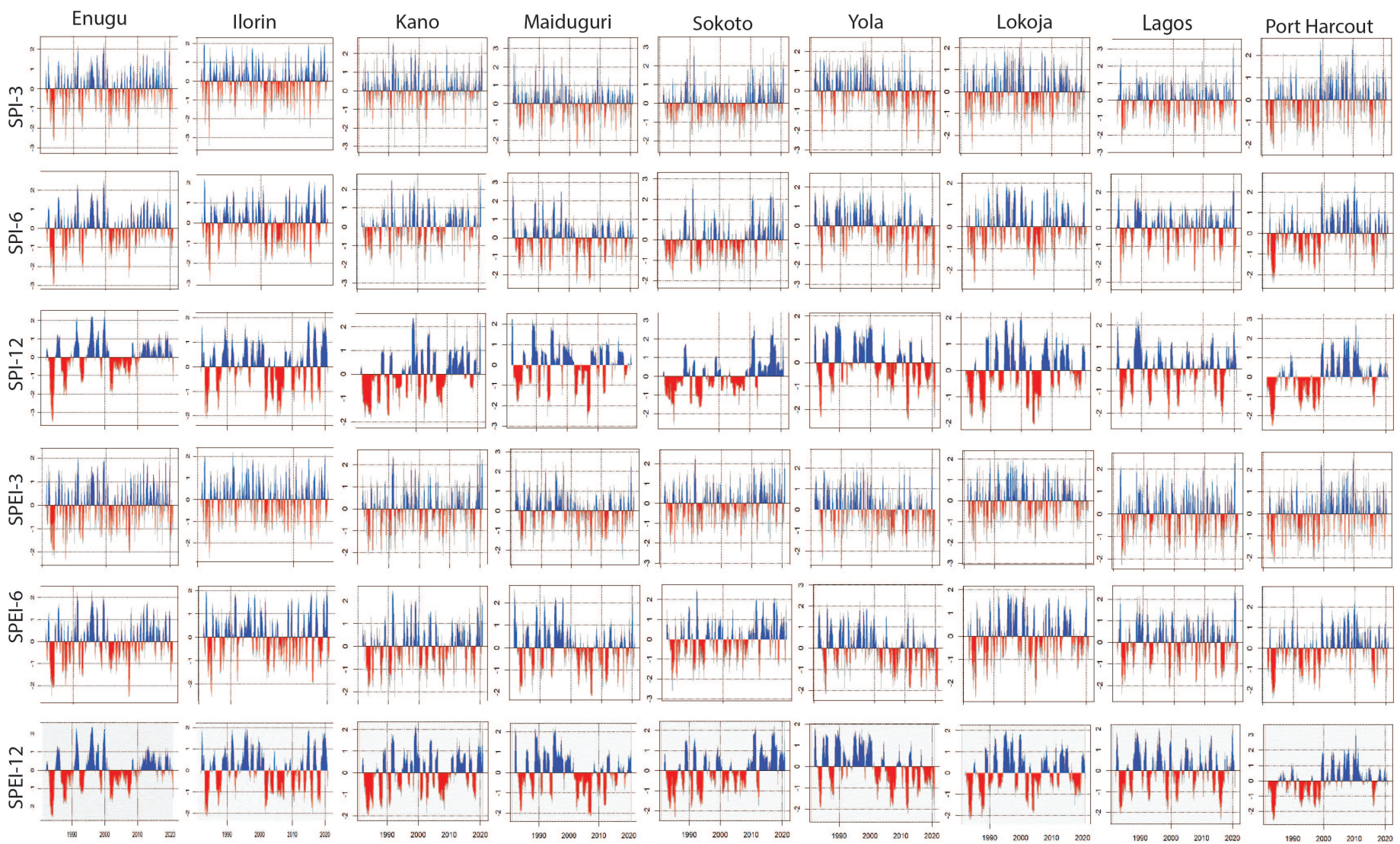


Figure 23: Forty-year SPEI & SPI analysis from 9 locations selected according to different latitudes and longitudes, as well as the ecological zones covering Nigeria.

6.4.5 Spatial Distribution of the SPI and SPEI Trends

Figure 24 to figure 27 depicts the distribution of the SPI and SPEI trends over different months across Nigeria. For the purpose of clarity, we would present the result where various drought types had been detected in unison (ie 1982 to 1983). 1984 will be mentioned in reference also due to the intensity of drought detected during that period when both indices detected all drought types in high degree within the study area.

6.4.5.1 SPI

Regarding the 3-month SPI during 1982, moderate, severe and extreme droughts occurred in far northern Nigeria (Sahel region). Elsewhere, a near normal (drought ≥ -0.99 to < 0.99) situation was witnessed.

Similarly, there were extreme drought episodes in the Sahel, Sudan and the Guinea/Rainforest ecological zones during at 6-months SPI calculation. In addition, a near-normal situation was observed across the study area. However, severe and extreme droughts were present in the Sahel for 12-months. The 12-month drought episodes occurred during the second half of the year. In addition, the 12-month SPI showed extreme and severe wetness in the Sahel (northeast). Consequently, in 1983, the 3-month SPI sustained the drought observed in the previous year. Although, there were periods of moderate wetness. The 6-month SPI revealed a further increase in the severity and magnitude of the drought episodes, extending to the Guinea/Rainforest. Finally, the 12-month SPI revealed an obvious moisture shortage across the country.

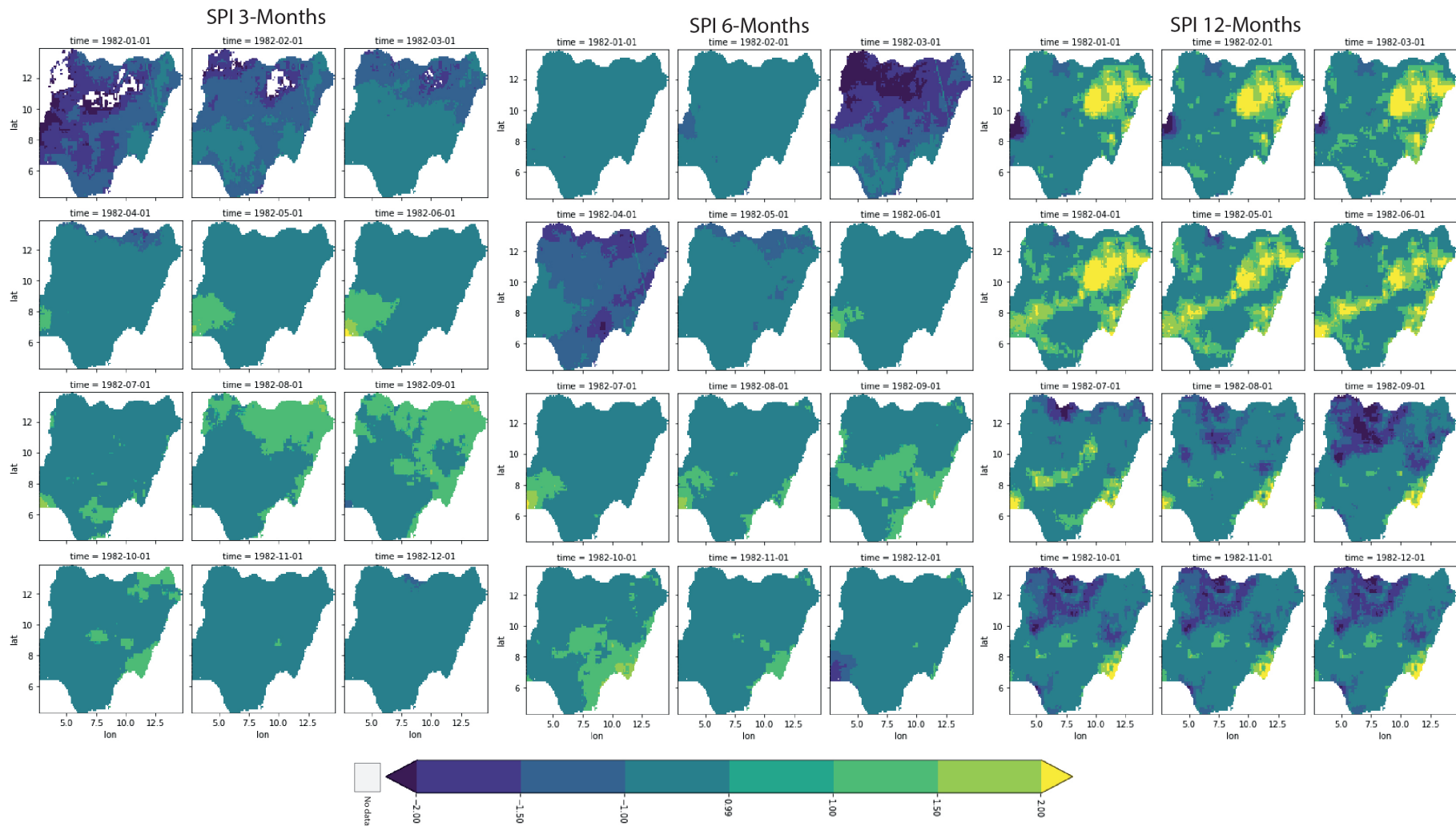


Figure 24: Nigeria's SPI distribution on 3-, 6-and 12-months timescale in 1982

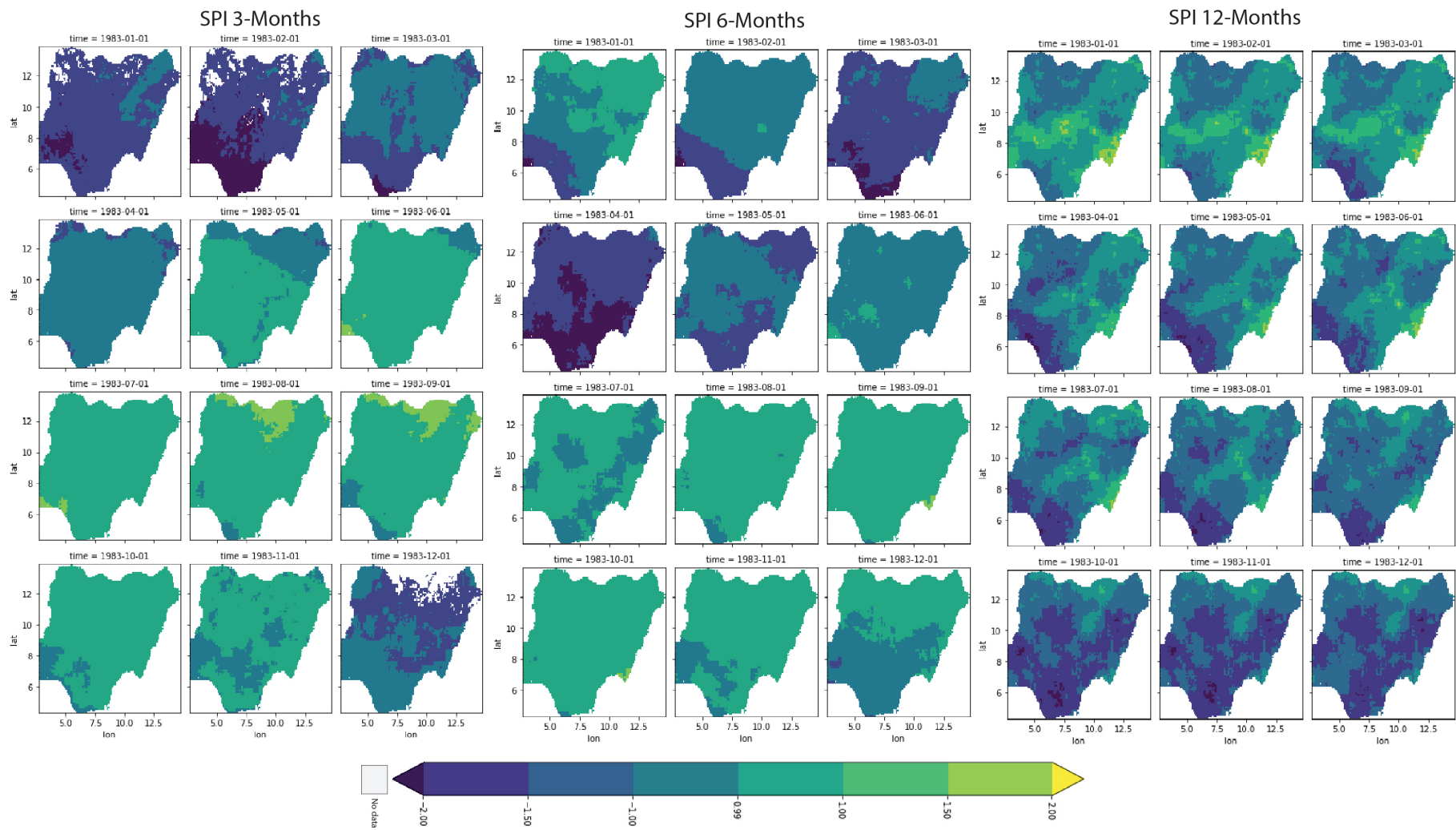


Figure 25: Nigeria's SPI distribution on 3-, 6-and 12-months timescale in 1983

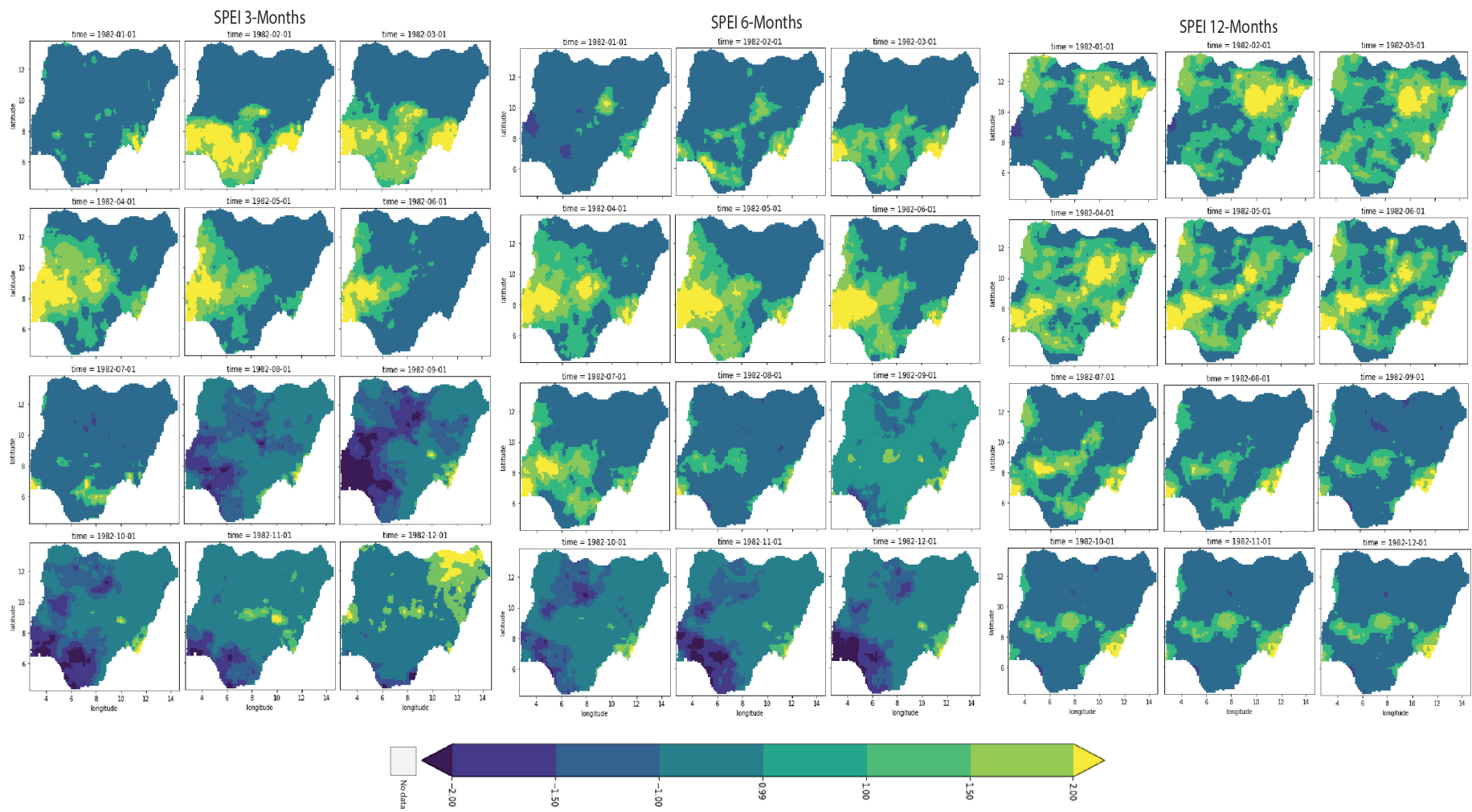


Figure 26: Nigeria's SPEI distribution on 3-, 6-and 12-months timescale in 1982

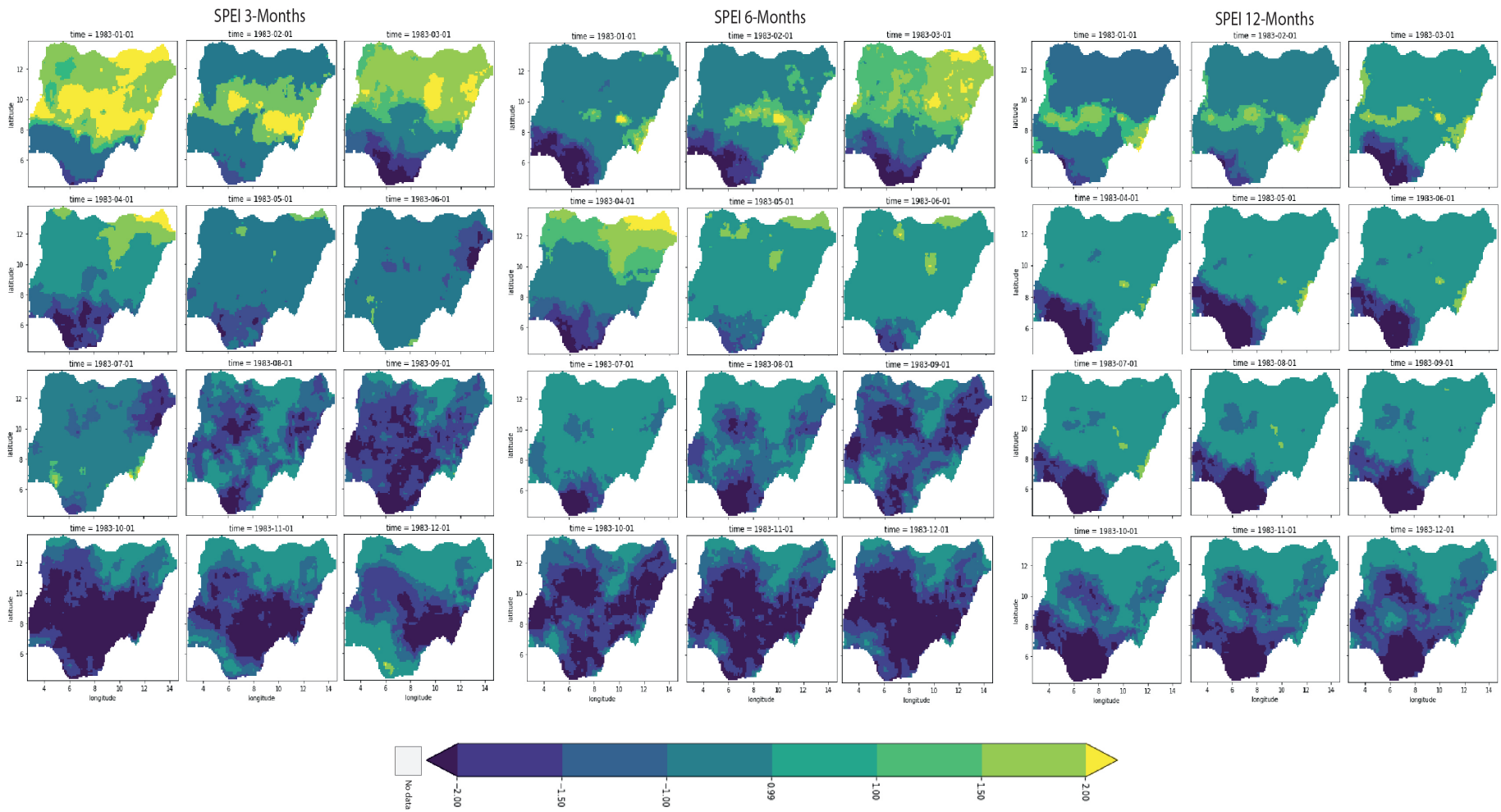


Figure 27: Nigeria's SPEI distribution on 3-, 6-and 12-months timescale in 1983

6.4.5.2 SPEI

In contrast, the 1982 SPEI 3 and 6-months revealed more wet episodes in the first half of the year. Even the severe and extreme droughts witnessed occurred mainly in the Guinea/Rainforest zone during the wet season. Elsewhere, near normal, moderate wet, severe wet, and extreme wet across the study area. The 12-months in 1982 followed the pattern observed in the 3 and 6-months. Characterize by early onset of moisture and moisture deficit as the year progresses.

Results from the [figure 27](#) showed that the study area witnessed extreme, severe and moderate droughts in 1983, exacerbating the moisture deficit that started in the previous year, 1982. More episodes of all drought types can be seen in all the ecological zones (Sahel, Sudan and Guinea/Rainforest). The 3 and 12-month SPEI droughts were mainly detected in southern Nigeria. The 6-months again was well detected across the Guinea/Rainforest.

6.5 Discussion

6.5.1 Characterisation of Drought severity

Accordingly, the longest drought occurrences varied ([figure 28](#)). However, the longest event between 1982-1984 stood out as the most extreme drought recorded within that period. [Oloruntade et al. \(2017\)](#) also reported extreme drought in part of the study area between 1982-1988. Additionally, the 3 and 6-month timescale of both SPEI and SPI detected extreme drought in (May-July) 2015. It is also important to note that drought frequency and accumulation time have decreased in recent years, as there are less severe and extreme droughts. Thus, incessant meteorological droughts have been reported in the study area by [Shiru et al. \(2019\)](#). The dry season in the Sahel induced by high temperature is the dominating factor for drought in the region [Shiru et al. \(2019\)](#). Elsewhere, [Noureldeen et al. \(2020\)](#) has reported that drought occasioned by an increase in temperature over the Sahel had impacted agriculture.

Again, the 12-month assessment is less frequent when compared with the 3, and 6-months in both SPEI and SPI. Particularly from March to August 1993 when all the timescale detected water deficit. This period is interesting because these droughts occurred in the wet season, usually characterised by abundant precipitation. March to September is the wet season period in Nigeria [Nwachukwu et al. \(2020\)](#), although this time may vary depending on the latitudinal location. Similarly, a short-time SPI with high frequency and extensive duration could result from the dry season. In most of Nigeria, the dry season lasts for seven months. It is also estimated that 580,841 km^2 , about 63.83% of Nigeria's landmass, is under desertification [Olagunju \(2015\)](#), as a result of gradual and persistent droughts that have turned into an ecological disaster. Even make lakes and rivers are drying up [Dioha and Emodi \(2018\)](#)



Figure 28: Heat map showing the concentration and severity of extreme drought events

Accordingly, events with maximum negative intensities (i.e., extreme droughts) were detected in both timescales by SPEI, with severe episodes occurring in April 1983. Similarly, the most intense extreme droughts were present from August 1983 to March February 1984 on all timescale and extended to June 1984 on 12-months SPI. Additionally,

SPEI and SPI detected extreme droughts in 2015 during the wet season (May to July). However, these droughts occurred on a short timescale (3 and 6-months).

6.5.2 SPI and SPEI distribution cross the ecological zones

Based on the spatial distribution of drought episodes, it was observed from the SPI that the extensive drought detected by SPI would have been devastating to agriculture and food production. Considering that the index is calculated based on the availability of water. The drought lasted so long that it extended over two years from the Sahel to the Guinea/Rainforest in the south, covering the entire study area. [Barker et al. \(2016\)](#); [Bevacqua et al. \(2021\)](#) have all reported agricultural and hydrological droughts due to such extensive dryness. In addition, about 5 million metric tonnes of grains valued at over 4 billion Naira (US\$400 million) in 1987 were reportedly lost in Nigeria at that time to drought (New Nigerian, 12 January 1988 as cited in) [Olukayode Oladipo \(1993\)](#)

[figure 28](#) provides a wide-scale result of drought occurrence, intensity and duration. The extracted drought events and their characteristics are shown in SPEI and SPI across the defined timescale. The analysis here proved that the SPI and SPEI are both interesting indices for drought assessment [Tefera et al. \(2019\)](#); [Hoffmann et al. \(2020\)](#). Substantiating the WMO position that SP-1 and SPI-1 months to SPI 6-months can be used to represent meteorological and agricultural drought, respectively [Guide \(2012\)](#). At the same time, SPI-6 and SPI-12 are suggested for describing hydrological drought that affects surface and groundwater resources. SPI-6 is better suited for observing seasonal trends, whereas SPI-12 is better for measuring stream flows, reservoir levels, and groundwater levels.

Likewise, the SPEI detected an enormous amount of drought in various ecological zones of the study area, especially in the wet months as revealed in [figure 23](#) and [figure 21](#). This is most alarming because over 80% of the annual precipitation in the study area occurs within the wet months. Furthermore, the coherency in the drought pattern across the entire timescale showed a pattern suggesting an early onset of precipitation that abruptly stopped, followed by an extended period of moisture deficit. It is also interesting that SPEI detected extreme wetness in the Sahel and Sudan ecological zones in some years.

Similar wetness in the midst of below-average precipitation was observed by [Nicholson et al. \(2000\)](#)

In general, SPI and SPEI varied slightly in drought severity and across space and time. For example, while 3-month SPI detected drought in the early parts of the year, SPEI detected extreme wet episodes. These results highlight the significance of ET_p inclusion in calculating SPEI. This finding is consistent with previous results reported by [Domínguez-Castro et al. \(2019\)](#); [Li et al. \(2020\)](#); [Lee et al. \(2017\)](#). The same pattern was observed for 6-months. However, the 12-month SPI and SPEI could pick drought episodes simultaneously. Although they differ slightly in intensity. Generally, SPEI detected more drought across Nigeria in the wet months than SPI. This is because SPI replicated the moisture deficit observed within the dry season across Nigeria.

In terms of the SPEI, the pattern suggests several types of droughts in the wet season. This pattern proved that the Guinea/Rainforest zone leaned toward drought at the 3-month and 6-month timescale, respectively, during the onset of the wet season (March and April) and across the entire study area ([figure 27](#) & 6-months). Therefore, SPEI could be used in drought assessment that focuses on the impact of climate change drought events.

For the SPEI, the drought trends across Nigeria in 1983 were evident at 3-month and 6-month timescales. The northeastern trend suggests a heavy alteration in surface moisture within the study area due to an increase in the wetness index that abruptly ended in April 1983.

Conversely, the 3-months SPI revealed the presence of extreme dryness in the dry season across Nigeria in the first three months of 1983. In addition, it revealed intense droughts across southern Nigeria within the same period. These drought events are synonymous with dry months. However, the 6-month SPI revealed a slight shift, detecting droughts during the onset of dry months (March and April) ([figure 25](#) 6-months).

In total, there were 157 drought events detected by SPEI and SPI across timescales in 39 years. There were 23 extreme drought events, 53 severe droughts, and 139 moderate droughts. The highest intensity was presented thus; SPEI_3 (-2.7), SPEI_6 (-2.76), SPEI_12 (-3.03), SPI_12 (-3.67), SPI_6 (-3.31), SPI_3 (-3.2). Extreme drought 15.28

%, severe drought 36.30% and moderate drought 89.91%.

Based on different drought classification in [Hisdal et al. \(2000\)](#), It is also evident that meteorological drought events abound in the study area, with the 3-month timescale detecting droughts during the wet seasons, a season that is characterised by intense precipitation. Specifically in Nigeria, drought in the wet season is a concern for farmers and overall food production due to the reliance on rain-fed agriculture. Drought detected in the 6 months would present negative agricultural impacts. There are similar reports in the Czech Republic [Potop et al. \(2012\)](#), and in Hungary, [Mohammed et al. \(2022\)](#). Drought in the 12-month SPEI and SPI leads to deficiencies in surface, or underground water supply signifies hydrological drought. [KO and Tarhule \(1994\)](#); [Abubakar et al. \(2018\)](#); [Gana et al. \(2019\)](#) have all reported drying of the surface water and wells in some parts of the study area. The primary concern should be the frequency and severity of hydrological drought. Remarkably, high intensity hydrological droughts have reduced in recent years. Only one hydrological drought event has been recorded since September (2006) in the SPEI category. While SPI revealed intermittent hydrological drought events even as recently as (2016).

6.6 Conclusion

This drought evaluation was started due to the previous history of drought occurrences and the resulting ecological situation in Nigeria. Four meteorological drought indexes were created using lengthy temperature and precipitation datasets. In this work, we compared and examined the temporal and spatial variations' effects on the SPI and SPEI's performance in drought monitoring. We also talked about the consistency and application of the SPI and SPEI in Nigeria. From 1981 to 2019, physical drought parameters (highest drought magnitude, maximum duration, and frequency of occurrence) were estimated for the SPI and SPEI at 3, 6, and 12-month timescales. In addition, spatial maps of the physical parameters of the driest years were created. The main conclusions were as follows:

The temporal evolution of the SPI and SPEI was comparable across timeframes.

However, there were still slight variations in fluctuation value and continuity, which decreased as the timescale extended. With increasing time series, the SPEI's reflection of the drought in some months was stronger than the SPI's, while SPI detection of the drought was more robust in a short timescale.

The SPI and SPEI drought characteristics were significantly variable depending on the zones and timescale. The severe and extreme droughts in Nigeria appeared to commence in the Sahel and spread to other zones in the south as time passed. An illustration of the spatial distributions of drought trends anticipated by the SPI and SPEI as well as overall precipitation deficits at different time scale points.

The SPI and SPEI differed in some ways regarding tracking the Nigerian drought. At the 12-month timescale, the two indices showed the most significant variances and most frequent variations. The SPI and SPEI swing highly frequently over the shortest timescales.

An analysis of the SPI and SPEI's applicability in Nigeria shows that both indices have advantages and can frequently follow local drought. Due to high temperatures in several parts of Nigeria, the SPEI may be more relevant than the SPI for monitoring drought in Nigeria compared to typical drought occurrences and vegetation indices. It is worth noting that the overall increase in trend across the Sahel is likely the reason for the decrease in drought frequency as observed by the indices, especially in the 12-month timescales.

The study gave a guide for choosing and evaluating drought indexes in drought monitoring and gave more insight into the peculiarities of the drought in Nigeria. According to the study, the significant variance in temperature and the ET record are the leading causes of the SPEI and SPI disagreement in some locations. Due to Nigeria's enormous area and variety of natural features. Therefore, when a uniform ecological zone is considered, each of the indices may be improved. This is because natural factors such as seasonality may significantly impact the drought index's capacity. Hence drought was exacerbated by drying tendencies.

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Sensitivity of Evapotranspiration to Changes in Climatic Variables Across Nigeria

7.1 Overview

In this chapter, Evapotranspiration (ET), a critical climate indicator in studying climate change impacts on hydro-ecological system due to its contribution to the hydrologic cycle and the energy balance, was assessed. The assessment was done by investigating the influence of other climatic variables such as temperature, precipitation, solar radiation, and wind against evapotranspiration. This is to determine their impacts on ET across Nigeria using descriptive spatial statistics and the Mann–Kendall (MK) trend test estimator for trend detection. The trend impact on land use and land cover was assessed using overlay operation on data from the sentinel-2 (10 meters spatial resolution). The Mann-Kendall results indicated remarkable differences across the study area, having significant or non-significant positive and negative trends. Comparing ET's relationship with the other climatic variables using statistical regression showed a correlation (r) with temperature ($r=0.69$), precipitation ($r=0.68$), solar radiation ($r=0.88$) and wind speed ($r=0.31$). The statistical results showed that solar radiation and temperature had more influence on the ET of the study area in terms of their correlation and magnitude. The results from the assessment suggest that the baseline climate substantially impacts overall ET sensitivity. This chapter is being developed as a separate article. Currently, it is in an advanced stage

towards submission to a journal.

7.2 Introduction

Assessing changes in evapotranspiration (ET) is essential for understanding a particular region's hydrological system and water balance. ET is the sum of water evaporation from the sea, snow, land and transpiration from plants and animals [Hanson \(1991\)](#); [Gaur and Squires \(2018\)](#). ET is a significant component of the hydrologic cycle after precipitation and determines the crop water requirement. It represents the dominant global surface water loss and accounts for over 60% of global rain [Mishra et al. \(2017\)](#); [Jing et al. \(2019\)](#). However, ET is impacted by several factors such as percentage of soil cover, temperature, humidity, solar radiation and wind speed [Adnan et al. \(2020\)](#); [Tyagi et al. \(2019\)](#); [Karimi et al. \(2020\)](#). Other factors that significantly affect ET under climate change include land use and land cover changes. ET is an objective variable for measuring water changes. The scale of ET variability makes its study important for understanding the role of the climatic variables that impact ET across space and time.

Any change in climatic parameters due to climate change will affect ET. Solar radiation is absorbed by the atmosphere, and in exchange, the heat radiated by the earth increases air temperature within the environment. In fact, evapotranspiration rates increase with higher temperatures [Swelam et al. \(2010\)](#); [Davarzani et al. \(2014\)](#). The physical heat of the air transmits energy to plants and controls the evapotranspiration rate [Gad and El-Gayar \(2010\)](#); [Luo et al. \(2021\)](#). This phenomenon leads to increased transpiration to the atmosphere when there is sufficient water and significantly reduced transpiration on a cool, cloudy day. This condition is exacerbated by the immediate local wind of a specific area. The wind transports the available surface moisture from the ground to its direction and above the surface to another layer. When this layer becomes saturated, evapotranspiration stops, and condensation begins. The action of wind, much like temperature, determines whether the ET will increase or decrease. A drier air mass increases the potential for evapotranspiration [Basara et al. \(2019\)](#); [Ehsani et al. \(2020\)](#), as does the wind speed.

In recent times, climate change impacts on ET are prevailing, rise in surface temperature that boosts intense ET events, and change in precipitation patterns observed around the globe, to mention but a few. Climate change and anthropogenic activities on land have severe impacts on hydro-ecological changes that continue to deteriorate, causing adverse environmental and socio-economic problems. For instance, in sub-Saharan Africa, where most farmers rely on rain-fed agriculture, changing rainfall pattern and elongated dryness is already impacting agricultural yields and food security. Furthermore, in Nigeria, climate change has been blamed for the destruction of biodiversity, desert encroachment, large-scale flooding, and land degradation. Further impacts felt in low agricultural productivity, increase in agricultural pests and diseases [Okoli and Ifeakor \(2014\)](#); [Ebele and Emodi \(2016\)](#); [Onafeso et al. \(2017\)](#). This has also driven most pastoralists in some parts of Nigeria, resulting in farmers-herders conflicts [Amusan et al. \(2017\)](#); [Olajide et al. \(2018\)](#); [Egbuta \(2018\)](#). In addition, other forms of socio-economic activities, such as fishing, have been impacted by high temperatures, such as the drying up of Lake Chad [Okpara et al. \(2016\)](#); [Magrin \(2016\)](#); [Onamuti et al. \(2017\)](#), aquatic death, scarcity and migration of fish species [Ayinde et al. \(2020\)](#).

The scale and locations of climate change impacts on ET vary spatially due to the high temporal variability of ET. Therefore, most of the research on ET has focused mainly on two different aspects. One is its temporal variations across space, and the other is the influence of other climatic elements on ET. The former has adopted several methods and algorithms for ET estimation to derive ET datasets. This has also led to technological advancement in terms of sensors and satellites that can detect measures ET in near real-time. Whereas the latter has led to advances in the models used in ET estimation that incorporate other climatic elements such as the Penman-Monteith equation and the inclusion of ET parameters in some climate Models such as the Coupled Model Intercomparison Project (CMIP5) of the World Climate Research Programme (WCRP).

Nevertheless, climate impact studies that investigate the influence of climate forcing on ET at both catchment and regional levels, based on projections for the variables mentioned above, abound. [Tabari and Talaei \(2014\)](#) studied the sensitivity of ET to four climate types (humid, cold semi-arid, warm semi-arid and arid). Across South America, [Satgé et al. \(2017\)](#) used monthly satellite products to assess ET losses over

the Altiplano for the period 2000–2014. They pointed at the ET increase from cropland as one of the causes of Lake Poopó's decline. In Asia, Wang et al. (2017) assessed the Spatiotemporal variability of reference evapotranspiration and contributing climatic factors in China during 1961–2013 and concluded that wind speed was the most influential parameter. Ghiami-Shomami et al. (2019) assessed the sensitivity of potential evapotranspiration to climate factors in forested and mountainous watersheds. They observed that temperature and solar radiation are responsible for the current ET status in those watersheds. Guo et al. (2017) assessed the sensitivity of potential evapotranspiration to changes in climate variables for different Australian climatic zones. In Africa, Blakeley et al. (2020) study Evapotranspiration Trends in West Africa to Support Drought Insurance. They suggested that evaporative demand and precipitation could serve as the basis for index insurance design. Kwesi et al. (2019) Nooni et al. (2019) linked ET's response in different regions of the basin to the availability of precipitation.

In Nigeria, few studies focusing on climatic variables' impact on ET due to climate change have been conducted. However, each has a specific purpose. For instance, Ashaolu and Iroye (2018) examined the climatic water balance and aridity in Nigeria's Western Littoral hydrological zone using gauge data from only southwestern Nigeria. In addition, Isikwue et al. (2015) assessed the correlation between ET and other climatic parameters in some selected cities in Nigeria. They also evaluated the seasonal and annual variations of ET with climatic parameters in Ibadan, Nigeria. Consequently, the assessment of climatic influence on one major component of atmospheric moisture across Nigeria is limited in terms of a holistic assessment of spatial coverage of ET within Nigeria. Therefore, this study's main goal is to first evaluate the influence of temperature, precipitation, solar radiation and wind speed on the ET over Nigeria between 1981-2020. This study will specifically address the impact of changing climatic variables and the contribution of each on the ET status in the study area.

The main goal of this study is to unravel the influence of climatic variables such as temperature, precipitation, solar radiation and wind speed on evapotranspiration across Nigeria in forty (40) years. In addition, this study aims to provide useful information to climate change modellers, socio-economic planners, water resources managers, and potential climate change researchers in their choice of datasets for their research.

7.3 Study Area, Materials & Methods

7.3.1 Data Description & Methodology

7.3.1.1 Climate dataset

In this study, we considered monthly reanalysis datasets from the 5th generation of the European Centre for Medium-Range Weather Forecasts (ECMWF, ERA-5 land), the TerraClimate from the WorldClim datasets and the Multi-Source Weighted Ensemble Precipitation version 2.2 (MSWEP v.2.2). Parameters from the ERA-5 datasets are solar radiation, temperature and wind speed. The choice of MSWEP v.2.2 for precipitation is based on earlier validation of sixteen (16) satellite precipitation products for the study area by the authors [Nwachukwu et al. \(2020\)](#), which MSWEP v.2.2 had the best performance when compared with gauge observation, hence fit for precipitation and hydrological analysis within the study area. For the purpose of this study, WorldClim evapotranspiration data was preferred due to its extensive coverage and close correlation with evapotranspiration estimates from the study area.

ERA-5 covers global lands at 9 km spatial resolution, while the WorldClim dataset covers the global land at 4 km spatial resolution. Several authors have validated the ERA-5 dataset and the estimates were found to correlate well with in-situ stations [Liu et al. \(2021\)](#)[Valeriano et al. \(2019\)](#)[Martens et al. \(2020\)](#). MSWEP on the other hand has a spatial resolution of 0.1° (11.1 km), and it merges gauge, satellite, and reanalysis data to obtain the highest quality precipitation estimates at every location [Beck et al. \(2019\)](#). ET was downloaded from TerraClimate WorldClim datasets. Although the TerraClimate dataset is updated weekly, it is available on monthly averages on a 4 km spatial resolution (1/24th degree). TerraClimate employs climatically assisted interpolation, which combines high-spatial-resolution climatological normals from the WorldClim dataset with poorer spatial resolution, but time-varying data from Climate Research Unit (CRU) Ts4.0 and the Japanese 55-year Reanalysis (JRA55). According to [Abatzoglou et al. \(2018\)](#), the Annual reference evapotranspiration fields from TerraClimate were well related to station-based reference evapotranspiration from FLUXNET stations [Abatzoglou et al. \(2018\)](#). The ET trend is further examined by finding the ET difference which is

computed by subtracting the initial state dataset (ET 1981) from the final state dataset (ET 2020). In this work, the difference was done for ten-year periods each. These datasets augment the high cost of climate data acquisition in this study area. Additionally, the choice of regular grid datasets also augments the low density of the gauge observation network in the study area.

The temporal resolution, spatial resolution and availability of these datasets substitute in areas without adequate climate data measurement and data paucity. The full description of the datasets is provided in [table 7.1](#).

Table 7.1: Summary of main characteristics and references of the climatic datasets

SN	Variable Name	Product Name	Spatial Resolution	Temporal Coverage	SpatialCoverage	Temporal Resolution	Link	Reference
1	Precipitation	MSWEP v.2.2	0.1° (11.1 km)	1983-Present	Global	3 hourly	http://www.gloh2o.org/	Beck et al. (2019)
2	Evapotranspiration	WorldClim	4km	1981 – <i>Present</i>	Global lands	daily	http://thredds.northwestknowledge.net:8080/thredds/terraclimate/atolog.html	Abatzoglou et al. (2018)
3	Solar radiation	ERA-5	9Km	1979– <i>Present</i>	Global lands	Daily	https://cds.climate.copernicus.eu/	Muñoz-Sabater (2019)
4	Temperature	ERA-5	9Km	1979–Present	Global lands	Daily	https://cds.climate.copernicus.eu/	Muñoz-Sabater (2019)
5	Wind Components	ERA-5	9Km	1979–Present	Global lands	Daily	https://cds.climate.copernicus.eu/	Muñoz-Sabater (2019)
6	Land use and land cover imagery	Sentinel-2 Land Cover	10 meters	2017-2021	Global lands	Yearly	https://livingatlas.arcgis.com/landcover/	Karra et al. (2021)

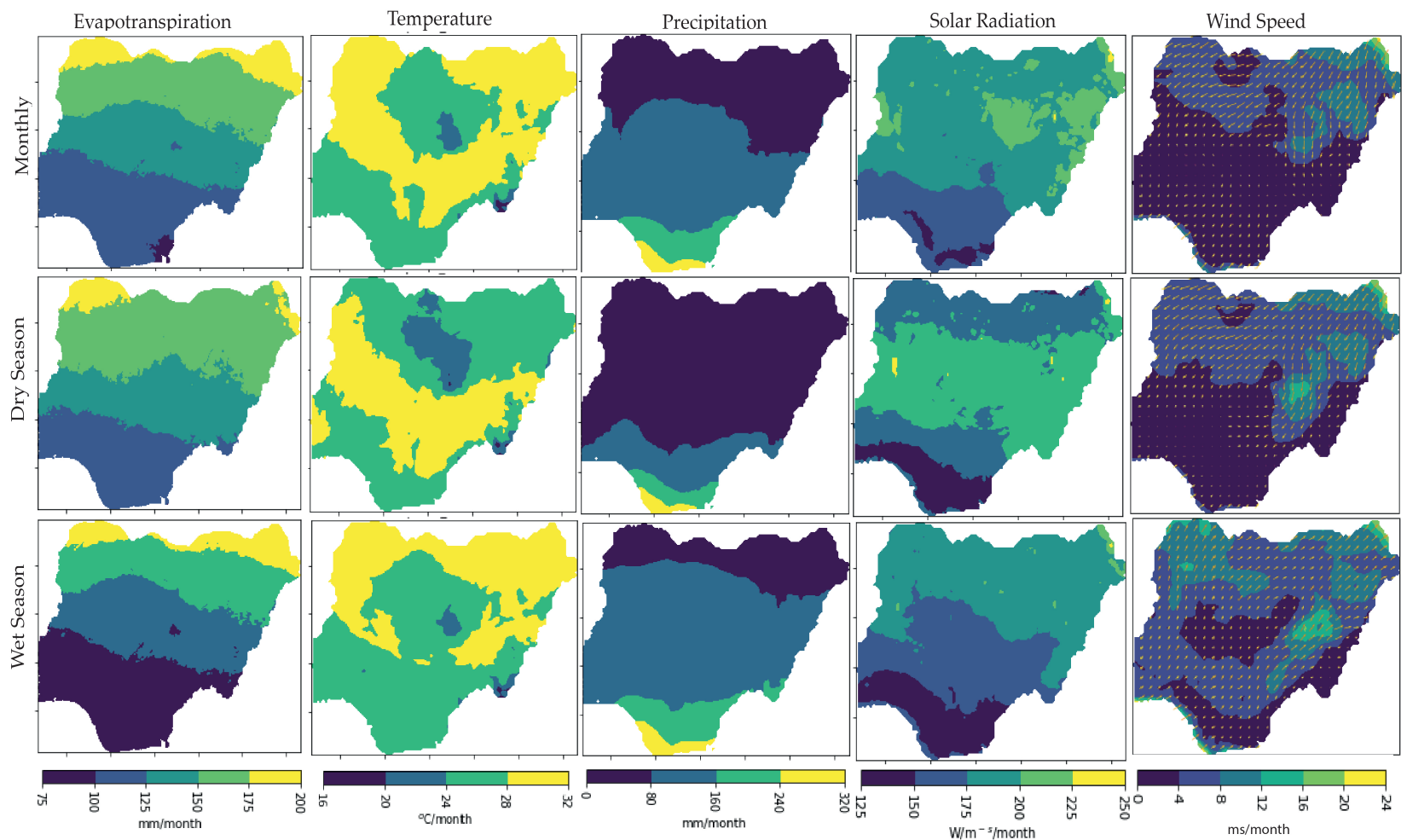


Figure 29: Spatial pattern of the mean monthly and seasonal ET, temperature, precipitation, solar radiation and wind speed during the period (1981-2020).

7.3.2 Data Processing

Each dataset was masked spatially using a Nigerian shapefile that defined the aerial extent with the exact bounding latitude and longitude values to precisely extract values that correspond to Nigeria and define the time scale of this work, which is 1981-2020. Furthermore, specific variables were extracted, especially from the ERA-5 netCDF file containing variables such as solar radiation, temperature and wind components (u and v components indicating wind speed and direction, respectively). The magnitude of wind is derived by the square roots of u and v components of the wind as follows;

$$ws = \sqrt{u^2 + v^2} \quad (7.1)$$

Image-to-image interpolation using the coordinates of the dataset with the least spatial resolution (in this case, the 4km spatial resolution WorldClim dataset) was applied to transform the other climatic datasets with spatial resolutions more than 4km using nearest neighbours methods. This method translation and alignment two images with similar geometry and of the same geographic area such that matching elements of the same ground area appear in the same place on the registered images. This is to avoid biases due to overlap when comparing the pixels of two variables with different spatial resolutions resulting from spatial mismatch during analysis.

Where annual assessment was required, the variables were aggregated to annual means for each pixel by averaging each of the 12 months of the year starting in January 1981 and ending in December 2020. Annual cycles of the statistical analysis carried out were computed in the same way.

The study area is relatively large, with uneven meteorological zones that differ significantly. Therefore, the sensitivity of ET to other climate variables in the entire study area would be assessed using the datasets. Then the Mann-Kendall trend test would be applied to each pixel of each variable in order to determine whether there was an increase or decrease in the climatic variabilities within the period considered.

Global land use and land cover (LULC) map of 2020 derived from ESA Sentinel-

2 imagery at 10 meters spatial resolution was downloaded from ESRI¹. This dataset will provide information such as the location and quantities of each LULC class found within the study area.

The aerial extent of the positive trend location of each variable was converted into a shape file. The resulting shape file was used to extract the LULC classes occurring within areas of positive Mann-Kendall trends within the study area. This is to enable accurate extraction assessment of increasing Mann-Kendall trend on the LULC classes.

7.3.3 Trends Analysis & Statistical Test

Trends in ET and its components were calculated using the Mann–Kendall non-parametric technique Hussain and Mamhud (2019). This approach is widely used to detect trends in hydro-meteorological time series Mavromatis and Stathis (2011). The tests were calculated based on Yue and Wang’s modified Equation, a machine learning method that considered variance correction (Yue and Wang, 2004).

$$S = \sum_{i=1}^{n-1} \sum_{j=1+1}^n \text{sgn}(x_i - x_j) \quad (7.2)$$

Where S is the rating score (called the Mann–Kendall sum), x is the data value, i and j are counters, n represents the number of data values in the series, and sgn is a function shown in Equation (1). A positive value of S indicates an increasing trend, and a negative value indicates a decreasing trend. The variance is calculated as;

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (7.3)$$

S is standardised as shown in Equation (1) by subtracting its expectation (zero) divided by its standard deviation σ_S

¹More information on <https://livingatlas.arcgis.com/landcover/>

$$Z_S = \begin{cases} \frac{S-1}{\sigma} & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ \frac{S+1}{\sigma} & \text{if } x < 0 \end{cases} \quad (7.4)$$

Where the trend can be identified by the value of S . A positive (negative) S value denotes a significant increasing (decreasing) trend. We set the significance level to 0.05, corresponding to $Z_{\alpha/2} = 1.96$.

7.3.3.1 Theil-Sen Formula Slope

Then Theil-Sen equation was applied to estimate and characterise the linear trend of slopes of annual ET and its components. This approach is popular and unaffected by outliers or extreme values and shows the direction and magnitude of the trend in time series (Equation (3)).

$$\Delta\sigma = \text{media} \left(\frac{x_j - x_k}{j - k} \right) \quad (7.5)$$

where $\Delta\sigma$ is the slope between two data points in the time series, the median is a function, and x_j and x_k are the data values for time points j and k ($j > k$), respectively. If $\Delta\sigma > 0$, the trend is increasing; if $\Delta\sigma < 0$, the trend is decreasing.

7.4 Results and Discussion

7.4.1 (Overview of Nigerian Climate Pattern

As shown in [figure 29](#), the interannual ET rates are considerably higher in the northern region (the Sahel and Sudan Savannah) with 200mm/month and middle-belt regions of the study area. Seasonally, the high ET rates were maintained in the North during dry and wet seasons. On the other hand, the southern edges maintained monthly and seasonal low ET rates, especially in the wet season, reaching only about 75 mm/month in some

locations. Similar to ET rates, the interannual highest temperature $\geq 30^{\circ}\text{C}$ was recorded in the northern region (northwest and Northeast). The temperature during the wet season showed a pattern of high-temperature values along the watersheds of River Niger and River Benue (figure 29). It maintained these high-temperature values along the far northern edges during the wet season. The temperature during the dry season reflected the impact of the North-East trade winds that set out earlier in the northern part of Nigeria. The northern region (Sahel, Sudan Savannah) experiences hot days (afternoon especially) and cold nights during the onset of the dry season characterized by dusty harmattan wind. This phenomenon is intense around the highlands (Jos Plateau and Adamawa highlands) figure mean plot.

The highest mean precipitation values $\geq 320\text{mm/month}$ were recorded in the wet season along the coastlines across southern Nigeria. Elsewhere within the study area, precipitation varied latitudinally and seasonally, getting as low as 0.0 mm/month in the dry months figure 29. Also, the number of months in the dry season varies depending on the latitudinal location. Values from solar radiation were also highest (250 W/m-s month) in the northern region. Again, during the dry season, the middle belt witnessed more energy, while at the same time, the far northern region had more solar radiation in the wet season.

The interannual and seasonal wind speeds showed a uniform pattern with the highest values of $25\text{ m}^2/\text{s}$ coming from the Northeast and northwest. Apart from 1991, the wind speed had not significantly increased and remained relatively static.

7.4.2 Climatic Trend on the National Scale

Climatic factors, especially temperature, precipitation, solar radiation and wind speed which determine the overall inputs of water and energy, are the dominant factors controlling ET. The climatic trends showed that warming and wetting were apparent during the last 40 years figure 30. From the interannual time series, both the increasing and decreasing trends were observed for the ET time series across Nigeria, reaching its peak in 1984 and then, lowest in 1992, making a gradual and consistent increase between (1991-2011). The seasonal influence in both dry and wet greatly influenced the result. During the pe-

riod assessed, ET significantly increased during the monthly and wet seasons; however, it declined in the dry season. This is due to the cessation of precipitation in the dry season, which creates moisture scarcity and reduced evapotranspiration. Consequently, it can be seen that there was a period of increase in ET during the dry season that occurred in 2015 [figure 30 \(b\)](#). Although, that event was followed by a sharp decline that continued into 2020.

Similarly, the interannual and seasonal temperature revealed an annual fluctuating pattern that has been consistently increasing since 1996 ([figure 30](#)). Temperature witnessed a remarkable consistent increasing trend both monthly and seasonally, with change rates of 0.451%. Despite seasonal variations observed between the interannual and seasonal temperatures, a familiar pattern was present, which showed that constant temperature increase continues in both seasons. Indicating the alarming situation resulting from anthropogenic and natural global warming.

On an annual basis, precipitation across Nigeria increased from 1985-2000 and 2003. After that, a period characterized by low precipitation occurred between 2001-2010, followed by another period characterized mainly by increasing and decreasing precipitation. The same pattern was observed during the wet season, while the dry season did not show any increasing pattern until after 2015 when both the interannual and seasonal assessments began to increase.

Solar radiation showed a noticeable trend from 1981 to 2020, with an annual change rate of 3.864%. The interannual time series of solar radiation showed a static pattern that recently increased above the long-term mean since 2005. Although there was a decrease in 2013, even so, it was followed by another period of increase. The trend began to increase again in 2005. Although, the monthly and wet seasons maintained a consistent slightly increasing trend. Conversely, the dry season had maintained a slight decline since 1985.

Wind speed slightly increased from 2007 to 2020 with change rates of 11.944% [figure 30 \(e\)](#).

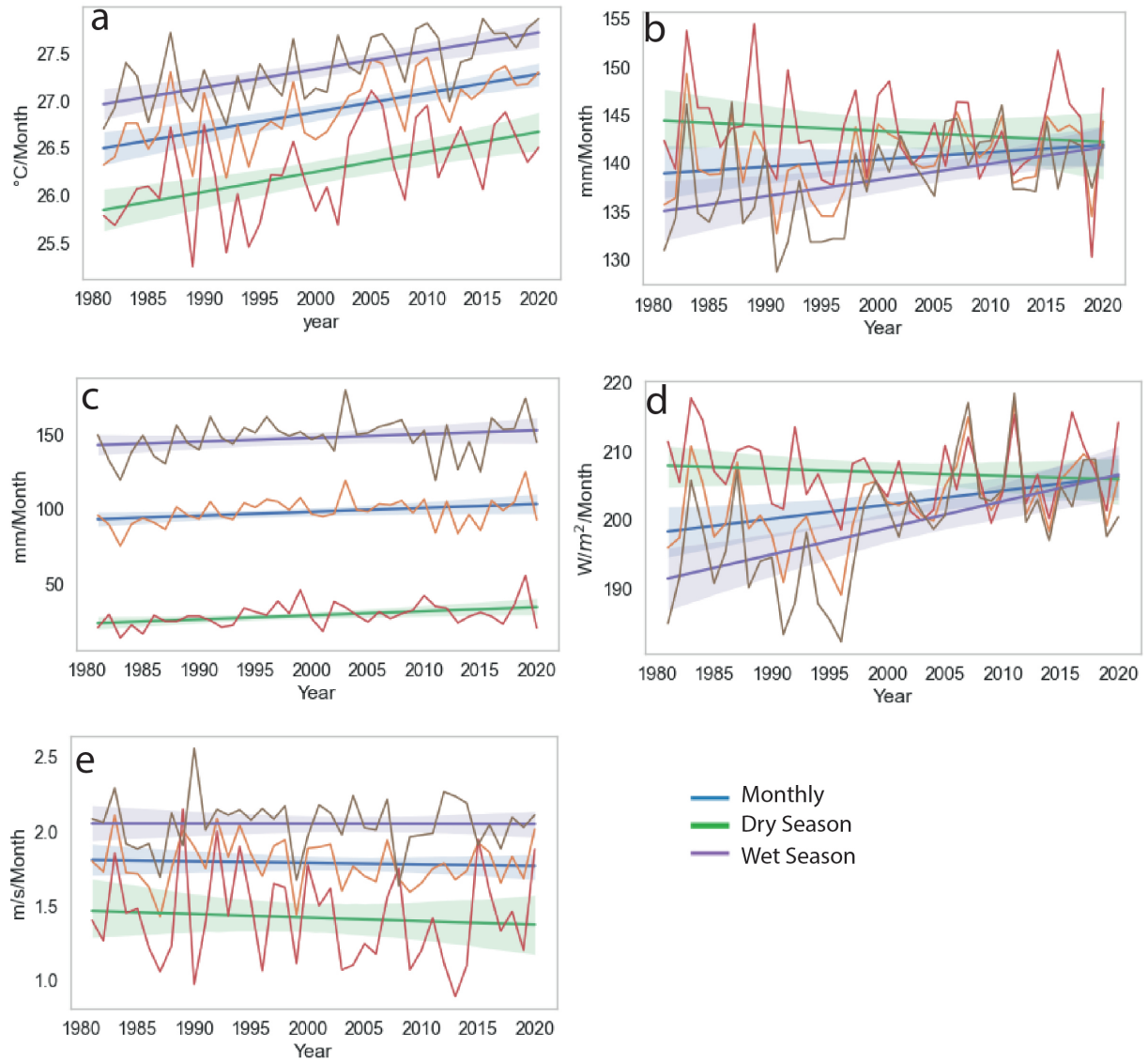


Figure 30: Monthly and seasonal hydroclimatic variability. (a) Temperature (b) Evapotranspiration; (c) Precipitation (d) Solar radiation & (e) Wind speed. The blue trend lines and confidence interval represents the monthly trend, while the green and purple indicates Dry and Wet season, respectively

7.4.3 Climate Trend at the Pixel Level

The overall Mann-Kendall trend test and Sen Slope statistic confirmed a significant increasing trend in several magnitudes in the data series. Applying the Mann-Kendall trend to the monthly and seasonal datasets revealed large differences and seasonal influence due to variations in seasonal quantities. Positive, negative and undetected trends were recorded from the result of the Mann-Kendall test. However, In this study, the pixel values with significant trends (i.e., where statistically significant positive trends have

been detected) were considered and used for further analysis, such as shown in Sen slope magnitude [figure 31](#). Therefore, from the Mann-Kendall test indicator, the monthly ET demonstrates a statistically significant positive trend in most parts of the Northeast and north-central parts of Nigeria. The Mann-Kendall showed the highest magnitude (0.30) in the Northeast. The dry season witnessed a drop, with a small portion of significant positive trends in the Northeast [figure 31\(b\)](#). Whereas the magnitude of the Mann-Kendall trend during the wet season showed a high ET magnitude (0.30) across the Northeast, Northcentral and parts of Southwest [figure 31 \(c\)](#).

Temperature exhibited a positive trend with a high magnitude (0.03) in most parts of the study area in monthly and seasonal analysis [figure 31](#). The interannual test showed increasing magnitude in the far North and Northcentral. This trend was also experienced during the wet season, while the dry season showed increasing trends in the far North and the South lines.

Precipitation's significant increasing trends were detected along the South-south coastlines during the monthly and dry season. There was also a significant trend with slight magnitude in some parts of the Northwest and Northeast during the wet season [figure 31 \(c\)](#). However, the magnitude of the detected trend was insignificant during the dry season.

Mann-Kendall test from solar radiation showed a significant increasing trend along the Northeast, Northcentral and North and Southwest parts of Nigeria in the monthly and wet season's test. The dry season trends are concentrated in the Southwest, with a handful of positive trends in the Northeast. The test revealed high magnitude in the Southwest in all the timescales considered ([figure 31 a & b](#)). In addition, high magnitudes were observed in the Northcentral and Northeast during the wet season [figure 31 \(c\)](#).

Wind speed revealed a positive trend in most parts of the South (Southwest, Southeast and South-south) in the monthly and wet season assessment. There was also a significantly increasing magnitude on the edge of the Northeast (in which the Sahel and) during the wet season [figure 31 \(c\)](#). The wind speed's increasing trends during the dry season occurred along the coastal fronts and towards the hinterlands of the Northcentral.

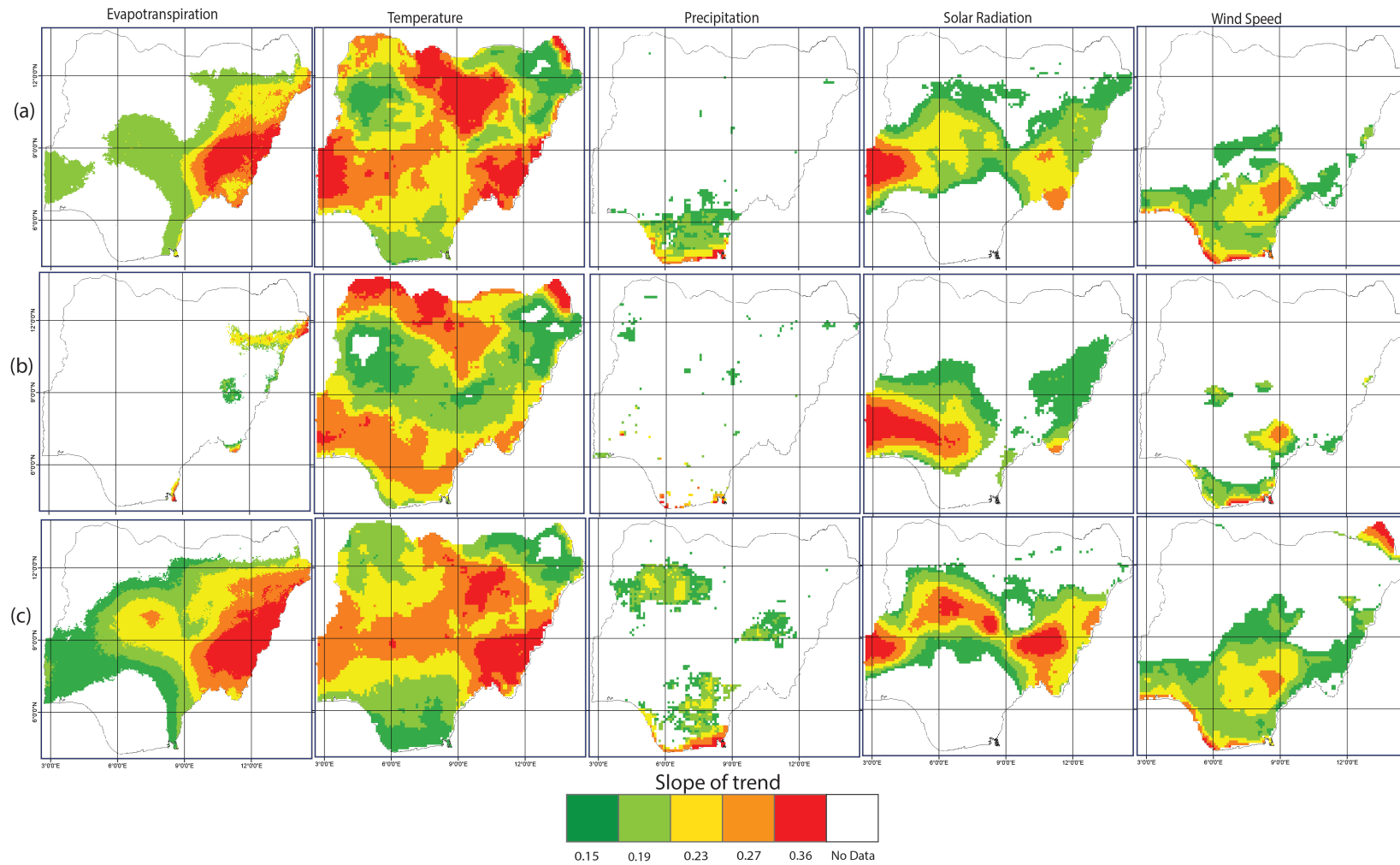


Figure 31: Mann-Kendall Trend result showing the magnitude of positive trends in slope. Row (a) is the interannual magnitude of the variables; (b) is the magnitude of positive trends in the dry season; (c) is the magnitude of the trends in the wet season

Except for the temperature, which showed a trend across the study area in all the considered timescales, significant increasing trends with high magnitudes (slope=0.30) observed from the other variables occurred in the Sudan and Guinea savannah region of the study area. The eastern parts of all the ecological regions (Sahel, Sudan & Guinea Savannah) witnessed the majority of the significant ET increasing trends in all the considered timescales. A pattern which was almost identical to the trend observed with solar radiation. However, the magnitudes of ET and solar radiation trends differ in location. This is because the higher magnitudes in ET trends were detected mainly in the eastern parts of the ecological regions. In contrast, the higher magnitudes in solar trends were detected mainly in the western parts of the ecological regions. Although seasonally, higher magnitudes of increasing trends were prominent during the wet season, maintaining high magnitude in the Northeast. The insignificant trend observed during the dry season is evidence of the reduced and sometimes absence of precipitation during the dry season.

Regarding the spatial pattern observed from the seasonal precipitation trend, there is an indication that the study area witnessed an increasing trend in the wet season in the Sudan Savannah and Guinea/Rain forest zones. However, there is no clear trend pattern, such as in ET and solar radiation, where the Eastern part of the study area revealed simultaneous higher magnitude in both monthly and seasonal assessments. Interestingly, a slight similarity exists between precipitation and wind speed in terms of location and magnitude of the monthly and seasonal trends. The Mann-Kendall trend types in the study area represent the outcome of the dominant underlying intra-processes operating within the hydroclimatic system. Notably, all the variables show that a strong seasonal influence is evident. Hence, massive differences between seasonal events observed in the wet and dry seasons exist.

In the Mann-Kendall test discussed in [figure 31](#), most locations showed a trend pattern that corresponds to negative or positive, whereas some places could not show a trend. A result showing a similar trend has been observed in a previous study. Abiye et al. (2019) also observed this mixed trend across West Africa [Abiye et al. \(2019\)](#) and highlighted the sharp differences observed in ET_p across West Africa. Finally, it is worth mentioning that the positive slope values correspond with locations where positive trends have been detected.

7.4.4 ET sensitivity to other climate variables

ET is inextricably linked with other climatic variables considering the feedback loops connecting the atmosphere and biosphere. ET sensitivity to climate change is discussed here using statistical approaches to link climatic variables such as temperature, precipitation, solar radiation and wind speed to ET production. From the result, it is crucial to report ET variations across Nigeria, linking its performance over time and space with the responses from the climatic variables that showed statistical significance.

The interannual variability showed that ET's magnitude and temporal variation followed a seasonal cycle, reaching its maximum in the dry season ([figure 30](#)). At the same time, the most diminutive ET occurred in the south during the wet season. During the wet season, these least ET values in the south demonstrate an intricate interplay between precipitation abundance and feedback from solar radiation and cloud interaction.

Despite precipitation providing the required moisture to enhance ET, incessant clouds and other atmospheric constituents such as aerosols in the southern region limit solar radiation's ability to drive an intensification of ET. Aerosols in the atmosphere impact solar radiation by absorbing and dispersing it, thereby deviating the radiation balance of the atmosphere [Kaufman et al. \(2002\)](#); [Rosenfeld et al. \(2019\)](#).

Thus, the correlation matrix to determine the variation and influence of the climate variables assessed and determined a fit pattern between ET and the climatic variables. ET with temperature and solar radiation had a positive relationship during the studied periods with $r=0.69$ and 0.88 , respectively. ET and wind speed had a weak positive relationship in the study area $r=0.31$. Precipitation had a relatively strong negative relationship $r=-0.68$, indicating that the rate of ET declined while the precipitation amount increased. This would have been the case in Southern Nigeria, with cloudy and rainy conditions obscuring solar radiation for most of the year. This phenomenon leads to a decline in the ET rate due to cloudy conditions that precede precipitation.

The event discussed in the above paragraph directly impacts high temperature on ET intensification. In the principle of climate alteration, a warmer atmosphere escalates the evaporation rate from land [Girma et al. \(2020\)](#), causing more moisture to circulate

all over the troposphere.

7.4.5 Mann-Kendall Trend Severity on Land Use Classes

Assessing the Mann-Kendall trend on the land use and land cover (LULC) of the study area reveals the influence climatic variables such as temperature and precipitation had on evapotranspiration variability (decrease increase) trends observed from the study area's LULC. [figure 32](#) showed the positive MK trends on LULC results at the 95% significance level. In addition, our analysis showed that the increasing MK-trend in temperature encompasses all the land cover types found within the study area ([figure 32](#) & [table 7.2](#)). Furthermore, the most common land use in the study is shrub/scrub, coinciding where most of the significant increasing trend of each climatic variable was detected. A significant positive trend of ET occurred on 65% of shrub/scrub, temperature 62% and solar radiation 60% all occurring on shrub/scrub. In general, a positive trend in temperature occurred significantly across all LULC classes in the study area.

Additionally, 62 % of the precipitation's increasing trend occurred mainly in locations corresponding to Tree/Forest land cover types, indicating the importance of precipitation and surface and soil moisture in sustainable vegetation regeneration.

Table 7.2: Summary of positive Mann-Kendall Trend on land use and land cover classification

SN	Class	Overall class (%)
1	No Data	
2	Water bodies	0.99
3	Trees/Forest	23.93
4	Grass	0.28
5	Flooded Vegetation/ Wetland	0.93
6	Crop	9.26
7	Scrub/Shrubs	65.01
8	Built Area	2.48
9	Bare Surface	0.12

7.4.6 ET Pattern with Major Influencing Variables

ET's behaviour in the annual time series reveals a conspicuous pattern that corresponds with the patterns observed in temperature and solar radiation, indicating ET's relationship with the annual variability of temperature and solar radiation. ET anomalies show an increasing trend that reached 5.0mm in recent years. The seasonal variability agrees

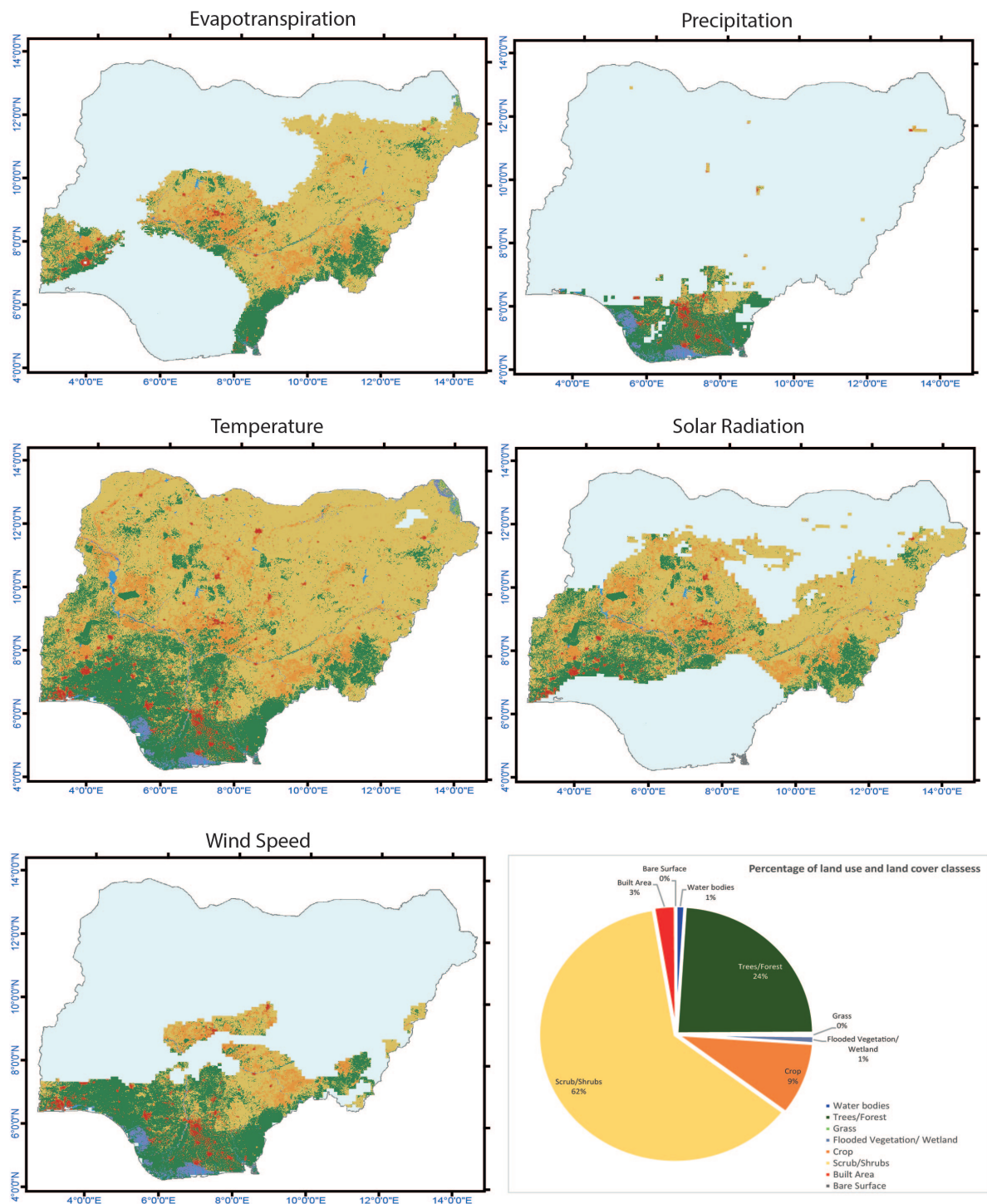


Figure 32: Percentage of the positive trends from the climatic variables on different land use classes

with previous studies by [Ghiami-Shomami et al. \(2019\)](#) in Japan and by [Fan et al. \(2016\)](#) in China.

The interannual ET show a significant increase in ET anomalies, except from 1991 to 1999, with a variation that reached 8.5mm in 1984. Solar radiation increased and decreased in the same period, following a similar trend to ET. These results indicated that ET's spatial patterns and temporal variations were closely related to solar radiation. The ET increment's consistency in the last two decades matched the pattern observed from temperature and solar radiation. A similar observation was made on ET in studies over Australia, which was attributed to baseline climate [Guo et al. \(2017\)](#), in Senegal river basin [Ndiaye et al. \(2021\)](#) and specifically of temperature in Southern China [Liu et al. \(2019\)](#).

Temperature anomalies show a gradual and consistent increasing pattern, with an increasing difference of 0.5% in 2001 and 2011. In addition, a ten-year cycle in temperature pattern was observed to have started in 1991. This period marks the period climate change became a global issue [Moser \(2010\)](#); [Liu et al. \(2008\)](#); [Hulme and Turnpenny \(2004\)](#); [Palm et al. \(2017\)](#).

All the variables show spatially distinct increases in their mean annual and seasonal values (figure line plot). The yearly cycle anomalies revealed that apart from wind speed, all other variables increased, especially since 2000, with the temperature reaching a 10.2 % increase within this period. Temperature showed substantial warming over recent decades, with precipitation reaching 27mm, solar radiation 0.4 W/m² and wind speed 0.3 in the recent decade.

Most indications indicated that the highest ET increase would have occurred between 2005-2008. This finding further reveals that the increase in the wet season precipitation in the last decade was substantial from 2012, reaching a high peak in 2019. ET comparison with the time series anomalies of temperature, precipitation, solar radiation, and wind speed reveals that in the recent decades, the maximum increase observed in ET anomaly peak from 2011 coincided with the increase in temperature, precipitation and solar radiation within the same period. The finding corroborates the results of [Sun et al. \(2019\)](#) [Sun et al. \(2019\)](#) and [Guo et al. \(2017\)](#) [Guo et al. \(2017\)](#), [Ghiami-Shomami et al.](#)

(2019) Ghiami-Shomami et al. (2019).

Consequently, the ET process causes the transpired water vapour to be held in the atmosphere, which contributes to warming the atmosphere and encouraging increased loss of surface water through ET. This event stretches plants' bane of tolerance, leaving them vulnerable. Meanwhile higher increasing trend was observed from only temperature than in any other variable assessed [figure 30](#). The last high value occurred in 2000 before a ten-year decline ending in 2010. However, there has been a gradual increase since 2011, reaching 0.5% in 2020. Solar radiation anomaly exceeded 4% in 2000. Notably, an increase and decrease pattern was detected with the recent increase in 2018. Wind speed anomaly reached 0.5% in 1984 and has since declined. Only to increase to 0.3% in 2016. Most climatic variables presented a positive anomaly, indicating that the observed variable increased more than the baseline mean.

7.5 Conclusion

The aim of this study was to assess the hydroclimate responses to prevalent climate change impact through the assessment of evapotranspiration across Nigeria and their implication for climate adaptation in the water resources and freshwater biodiversity sectors. The datasets were acquired independently downloaded and processed using the Mann-Kendall trend test and linear regression to investigate the trend and spatial connotations. Results of long-term data analysis showed mixed trends in the variables assessed, with ET specifically showing positive trends in the northeast and central of Nigeria. The regression analysis shows from the plots that solar radiation has more influence on ET across the country. Furthermore, mean ET rose from the coast to the interior north, reflecting latitudinal differences in cloudiness, land use and land cover as well as solar radiation. Monthly mean ET varied significantly across different regions, with wet season months having greater ET than dry season months. In fact, all the assessed variables are greatly influenced by dry and wet seasons. This is due to the relationship between the variables and the oscillation of the Inter-Tropical Discontinuity's (ITD) seasonal migration across West Africa that determines annual precipitation inception, temperature distribution and variations as well as the cloudiness of the study area. The increase in observed tempera-

ture and precipitation across Nigeria was attributed to these phenomena. The influence of temperature can further be revealed by the temperature values obtained during the wet season around the banks of river Niger and river Benue. The temperature warms the surface, which causes the surface and plants to evaporate and transpire. This results in the atmosphere holding much moisture trapped in the atmosphere. The implication is that areas having more moisture experience higher rainfall and such a trend will continue due to a rapid increase in surface temperature. In addition, ET showed significant variations between the periods 1981–2000 and 2001–2020 in both seasons, rising up to 7.5mm in the southwest and falling with the same margin in the northeast parts of Nigeria. Despite the fact that there were both negative and positive changes in ET between the four decades reference periods, its reduction in low values in the southern region was largely due to increased cloud cover and precipitation events. Nevertheless, the result shows that there is more precipitation in southern Nigeria, especially along the Atlantic fronts than in any other part of the country. Finally, the most significant contributor was discovered to be solar radiation. However, A catchment-wide study of the study area is needed to isolate the diverse climate condition as well as the topography as a constituent geophysical unit. This will remove the biases introduced by mixed climate conditions when carrying out this type of study.

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General Conclusions

8.1 Overviews

This chapter discusses the conclusions reached in this thesis based on the overall view of the thesis and the results from the data analysis conducted during this thesis. Then, future perspectives are also presented. Observation from this thesis showed that meteorological data is inconsistent in the study area, only a few of the stations across the country are operational. Nevertheless, researchers and students nationwide are constantly asking for precipitation measurement data. Hence the decision to evaluate the performances of several satellite precipitation datasets to recommend the best product(s), which will act as an alternative to gauge measurements for researchers and water resources managers.

Similarly, this thesis looked at the role of climatic variables in ET, which significantly determine climate change and energy balance. The statistical trend analysis showed that temperature and solar radiation were responsible for changes in ET production in the country. Furthermore, results from the drought assessment showed that on a broad scale, extreme droughts have reduced in recent years compared to the situation in the 1980s. However, meteorological drought persists. This information is necessary for farmers and planners in the region.

8.1.1 Remote Sensing Capabilities

In general, the analysis conducted in this thesis has shown that drought studies and their effects on ecosystems can be conducted using only satellite remote sensing observations. This promising unique collection of techniques provides platforms and data to investigate droughts and their effects on ecosystems through satellite remote sensing observations. Interestingly, the advancement of remote sensing technology for Earth observation continues to break new opportunities. In the distant past, just a few techniques were available for using numerous satellite sensors to derive long-term climate data records. Similarly, other satellites, such as Gravity Recovery and Climate Experiment (GRACE) and Atmospheric infrared sounder (AIRS), only provide data for a short period. Making them unsuitable for studies on climate when evaluating climate change from a historical perspective. Although many satellite data sets, like GRACE and AIRS, only contain observations going back ten years, which is insufficient for assessing an event in past climatic conditions. Alternatively, combining a variety of satellite sensors to produce long-term climate data records would be beneficial. This limitation might make it more challenging to analyse satellite data-based metrics. Reanalyses are attractive new meteorological data sources for the expanding scientific community, as discovered by the performances of reanalysed data used in this thesis. Combining these data sets can be coupled with those from other remote sensing methods or the outcomes of reanalysis to generate long-term climate data records. For this strategy to advance, reliable statistical methods for merging data records from various sensors must be created.

Interestingly, since the launch of satellites with improved spatial, spectral, and temporal resolutions created to monitor and detect changes on the Earth's surface, remote sensing for monitoring drought and surface water resources has gained popularity. But unfortunately, it is not being used to its full potential, especially in areas lacking data. This presents a barrier to incorporating data from remote sensing into operational applications and decision-making processes. To compensate for this, some data types can be combined with additional remote sensing data sets or reanalysis results to obtain long-term climate data records. Also, developing reliable statistical methods for combining data records from various sensors is necessary for progress in this approach. Significant improvements in climate feedback monitoring, notably in drought regional early warning,

can result from more research in this area.

The application of remote sensing for hydrological monitoring in this thesis has shown the potential to be employed in data-scarce regions, such as Africa, where there are few physical monitoring stations. Future research is encouraged to explore further utilisation of satellite data indices to enhance drought early warning systems and preparedness and support proactive decision-making. Furthermore, engaging decision-makers in model and indicator creation is essential to disseminating remotely sensed drought information. Therefore, the approach should include community engagement and converting remote sensing data into information translatable into a policy. This is a crucial step in providing the public with pertinent and worthwhile information on remote sensing. Additional studies on uncertainty quantification will significantly improve the utility of satellite drought information. Presently direct satellite observations are not currently used for drought monitoring. Instead, there are many satellites capable of monitoring precipitation and soil moisture, increasing early drought detection (e.g., satellite near-surface air relative humidity and water vapour data) will be possible.

Again, modelling climate interaction and responses requires large-scale, long-term experiments and observations. It is necessary to collect the data needed for generalisation. For example, the perception of dwellers in a particular location should be integrated into model prediction. Most coarse satellites used for Earth observation lack the capabilities to detect small details. Thereby resulting in ignoring minute details that could have aided model prediction or estimating impacts. Details such as the initial re-forestation condition may not convey anything meaningful when seen on satellite imagery. However, at that stage of re-forestation, there is already a contribution to the climate hosting the re-forestation. Microwave brightness temperature is sensitive to land surface factors, such as temperature and land cover. It offers valuable information regarding drought, such as land cover, vegetation structure, temperature, soil moisture, and snow cover. A constellation of satellites currently provides access to the diurnal cycle of the microwave brightness temperature on a worldwide scale.

The developments in microwave land emissivity remote sensing show the potential to quantitatively evaluate surface soil moisture and vegetation water content. Therefore data on microwave emissivity could be used to create a tool that measures soil water

content and mixed vegetation. Another potential is to expand the analytical framework for producing multi-index or composited rainfall information based on various satellite measurements, such as precipitation, soil moisture, and relative humidity. There are many satellite-based drought indicators, but they all lack a quantitative way to express uncertainty.

The routine retrieval of rainfall using satellite data acquired in various wavelengths of the electromagnetic spectrum (EMS) has led to the development of several approaches. One of the benefactors is the dual-frequency precipitation radar on the global precipitation measurement (GPM DPR) mission. This is an improvement that helps the satellite algorithm detect light precipitation. It is possible to translate cloud top temperature correlations from satellite infrared (IR) and visible satellite imagery (VIS) images into a precipitation rate, as shown in our analysis of satellite products based on cold cloud detection algorithms.

8.1.2 From Climate Change Perspective

Without a doubt, effective climate mitigation measures are still essential to prevent the worst effects of climate change. Still, we are past the stage when mitigation measures are sufficient to address the issues that climate change is causing. For example, climate heat puts extra pressure on higher water demand brought on by agricultural expansion or intensification. Naturally, this could reduce the water supply through increased soil moisture deficits. Therefore, socioeconomic factors, particularly at the local level, including adaptive capability, knowledge, and coping mechanisms, influence drought vulnerability. The flexible methods that enable a group's geographical and temporal awareness of risk and opportunity might be crucial in tying research and land use policy with adaptive management for agriculture and other sectors where future conditions may grow more diverse.

Nevertheless, most estimates of future land capabilities have not provided a successfully assumed perfect adaptation. For instance, the climate change effect on ET analysed in this thesis pointed to natural climate change (solar radiation and temperature). The anthropogenic contribution is insignificant, considering that GHG emissions

from heavy processing industries are non-existence. However, natural contribution consistency and quantification remain varied between years and seasons. Therefore constant evaluation of climate change impacts in Nigeria is advocated.

Recent developments have seen the Climate Change Initiative (CCI) for Soil Moisture start to provide worldwide satellite-based soil moisture data gathered from several sensors. It is expected that developing these techniques integrates climatological and hydro-ecosystem perspectives evaluation of precipitation variations resulting in drought. Recent satellite missions have supplied data on atmospheric CO₂ and present a chance to create indicators for evaluating the connections between water deficits and the nutrient cycle. It is possible to create new markers that quantify how drought affects the carbon and nitrogen cycle. Without these technologies, assessing the effects of drought and climatic variability on ecological and biogeochemical processes would be impossible.

From all indications, microwave-based vegetation monitoring is an innovative method for analysing the effects of drought on plant dynamics and canopy density. Combining the information provided by optical and microwave vegetation monitoring techniques helps better understand how ecosystems react to climate variability. Future studies in this field may help us comprehend the effects of drought on ecosystems, including modifications to phenology, biomass, and carbon cycling.

Hydro-climate indicators for determining the combined water content of vegetation and soil and vertical profiles of vegetation moisture have also improved. Recent improvements in measuring microwave land emissivity from a distance suggest that it is possible to quantify surface soil moisture and vegetation water content. Therefore data on microwave emissivity can be used to create an indicator of the combined water content of the soil and vegetation.

The level and magnitude of studies on climate change and drought impact in the Sahel region have helped clarify the biophysics of the drought phenomenon in the region. Interestingly, it is possible to create new metrics that quantify how drought affects the cycling of carbon and nitrate. It is now possible to create indicators for evaluating the connections between water deficits and nutrient cycling thanks to some recently launched satellite missions that provide information on atmospheric CO₂. Eco-hydrologic reaction

to climatic change may help us comprehend the effects of drought on ecosystems, including modifications to phenology, biomass, and carbon cycling.

8.1.3 Drought Propagation

Monitoring and detecting droughts and surface water resources have improved thanks to improvements in indices, techniques, and the accessibility of multi-temporal and multi-spectral images. However, these indices still need improvement to address factors such as cloud contamination. In addition, drought is more likely to occur due to climate change. Hence it is essential to study the effects of droughts based on historical, present, and future scenarios, especially in the Sahel, a region with little data. Furthermore, different climatological and hydrological characteristics that define a drought must be understood and effectively monitored in order to minimise the effects of droughts and climate variability.

Changes in drought risk impacting water resource management, ecosystems, and land use systems, should necessitate the development of new institutional structures, regulatory frameworks, and planning tools. This will make it possible to quickly identify droughts, which is crucial for regions like the Sahel prone to incessant drought and aid in water resource planning. It can also assist decision-makers in determining the best course of action to prevent future drought disasters. Early understanding of the adaptation process is essential to necessitate closer examination of practices exacerbating drought and evaluate what is known and what is unknown. Better monitoring and synthesis of drought stress data, including field observations and remote sensing approaches, are also necessary towards drought risk assessment.

Land surface variables like soil moisture and temperature are also crucial for assessing drought. In addition, satellite observations of precipitation are essential in evaluating hydrologic conditions. Particularly in ecosystems with limited water resources, soil moisture is an essential part of the water cycle and is crucial for monitoring and predicting droughts. Since soil moisture impacts plant development and productivity, it is frequently used to gauge agricultural drought, land use, and land cover. For practical drought monitoring, a set of near-real-time satellite-based precipitation data such as IMERG-E and

TMPA-RT can be essential, as provided in the precipitation data comparison treated in this thesis. Most satellite soil moisture algorithms are based on either passive MW or a combination of data from various sensors. There are empirical correlations between the volumetric water content of the soil and passive MW brightness temperature and active MW backscattering. Accordingly, measuring agricultural or ecological drought using the diurnal fluctuation of the microwave brightness temperature as a proxy for available combined soil moisture and vegetation water content is possible.

8.2 Challenges, Future Work & Perspectives

Although the idea of including streamflow in this thesis was dropped due to data and time issues, a review of existing literature and concepts showed that remotely sensed cloud depth and precipitation rate estimates in various land surface and hydrological models improve streamflow estimates. As a result, streamflow can be used to monitor hydrological drought events. Future research on drought trends and patterns in Nigeria should leverage this research and the data it generated, combined with streamflow, to evaluate the increasing drying and flooding at watershed levels of North and Southern Nigeria. Unfortunately, this combination has not yet been wholly explored for monitoring and assessing droughts in Nigeria.

Again, it will be necessary for the future to compare the results obtained in this research historical and projected climate outputs of GHGs such as carbon dioxide (Co₂), methane (CH₄) and nitrous oxide (N₂O) from the CMIP6 model. This will reveal the GHG's concentration pattern within the period considered, helping to establish whether GHGs influenced precipitation cessation and fluctuations leading to drought..

Periodic systematic evaluations of land use and land cover in Nigeria should be encouraged, with a level of spatial resolution that enables studying human-induced changes and a frequency that allows monitoring of long-term trends and interannual variability.

List of Abbreviations

AED: Atmospheric Evaporative Demand.

AIRS: Atmospheric infrared sounder.

AMSR-*E*: Advanced Microwave Scanning Radiometer for EOS.

ARIMA: Auto-Regressive Integrated Moving Average.

ARC-2: African Rainfall Climatology.

AVHRR: Advanced Very High-Resolution Radiometer.

CCI: Climate Change Initiative.

CH₄: Methane.

CO₂: Carbon Dioxide.

CHIRP: Climate Hazards Group Infrared Precipitation.

CHIRPS V.2: Climate Hazards Group Infrared Precipitation with Stations.

CMIP: Coupled Model Intercomparison Project.

CMORPH-BLD: Climate Prediction Centre Morphing Technique (Bias Corrected).

CMORPH-CRT V.1: Climate Prediction Centre Morphing Technique.

CRU: Climate Research Unit.

DEM: Digital Elevation Model.

DPR: Dual-frequency Precipitation Radar.

EBBR: Energy Balance Bowen Ratio.

EC: Eddy Covariance.

ECMWF-ERA5: Fifth Generation European Centre for Medium-Range Weather Forecasts.

EMS: Electromagnetic Spectrum.

EOS: NASA's Earth Observing System.

ET: Evapotranspiration.

ET_p: Potential Evapotranspiration.

ET_o: Reference Evapotranspiration.

ET_{P pan}: Pan Evaporation.

ERTS-1: Earth Resources Technology Satellite.

fES: Freshwater Ecosystem Service.

GCM: General Circulation Model.

GHG: Greenhouse Gase.

GIS: Geographic Information Systems.

GPS: Global Positioning Systems.

GPM: Global Precipitation Measurement.

GSMaP-RT: Global Satellite Mapping of Precipitation.

GSMaP-Adj: Global Satellite Mapping of Precipitation (Adjusted).

IDSi: Integrated Drought Severity Index.

GRACE: Gravity Recovery and Climate Experiment.

IMERG-E: Integrated Multi-Satellite Retrievals for GPM Early Run.

IMERG-F: Integrated Multi-Satellite Retrievals for GPM Final Run.

IMERG-L: Integrated Multi-Satellite Retrievals for GPM Later Run.

IPCC: Intergovernmental Panel on Climate Change.

IR: Infrared.

ITD: Inter-Tropical Discontinuity.

JAXA: Japan Aerospace Exploration Agency.

JRA55: Japanese 55-year Reanalysis.

KGE: Kling-Gupta Efficiency.

LEO: Low Earth-orbital.

LULC: Land Use and Land Cover.

LULCC: Land Use and Land Cover Change.

LSM: Land Surface Models.

MDI: Microwave Integrated Drought Index.

MK: Mann–Kendall.

MSI: Satellites’ MultiSpectral Instrument.

MSWEP: Multi-Source Weighted-Ensemble Precipitation.

MNDWI: Modified Normalised Difference Water Index.

NASA: National Aeronautics and Space Administration.

NDVI: Normalised Difference Vegetation Index.

NDWI: Normalised Difference Water Index.

NIMET: Nigerian Meteorological Agency.

NOAA: National Oceanic and Atmospheric Administration.

NPC: National Population Commission.

NRI: Normalised Rainfall Index.

NSW: National Weather Service.

MODIS: Moderate Resolution Imaging Spectroradiometer.

N₂O: Nitrous Oxide.

PDSI: Palmer Drought Severity Index.

PHDI: Palmer Hydrological Drought Index.

PERSIANN-RT: Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks.

PERSIANN-CDR: Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climate Data Record.

PMW: Passive & Active Microwaves.

RCP: Representative Concentration Pathways.

RS: Remote Sensing.

SMAP: Soil Moisture Active Passive.

SMOP: Soil Moisture and Ocean Salinity.

SPEI: Standard Precipitation and Evaporation Index.

SPI: Standard Precipitation Index.

SPP: Satellite Precipitation Product.

SSI: Standardised Streamflow Index.

SSP: Shared Socio-economic Pathways.

SAR: Synthetic Aperture Radar.

SVM: Support Vector Machine.

SWAT: Soil & Water Assessment Tool.

TAMSAT: Tropical Applications of Meteorology using Satellite Data and Ground-Based Observations.

TIR: Thermal Infrared.

TMPA-Adj: TRMM Multi-Satellite Precipitation Analysis.

TMPA-RT: TRMM Multi-Satellite Precipitation Analysis.

TRMM: Tropical Rainfall Measuring Mission.

TVDI: temperature vegetation Dryness Index.

UNFCCC: United Nations Framework Convention on Climate Change.

USA: United States of America.

VCI: Vegetation Condition Index.

VIS: Visible Satellite Imagery.