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THEME:

Assessing the potential of biochar to enhance maize productivity and soil organic carbon sequestration under future climate scenarios in Togo

A THESIS

IN THE RURAL POLYTECHNIC INSTITUTE OF TRAINING AND APPLIED RESEARCH IN PARTNERSHIP WITH THE WEST AFRICAN SCIENCE SERVICE CENTRE ON CLIMATE CHANGE AND ADAPTED LAND USE (WASCAL), SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN CLIMATE CHANGE AND AGRICULTURE OF THE UNIVERSITY OF SCIENCES, TECHNIQUES AND TECHNOLOGIES OF BAMAKO (USTTB)

Presented and defended on:

By Dodji Komlan AZIANDEKE

JURY

President	:	Mr. Chiaka DIALLO	Associate Professor	IPR/IFRA
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Director	:	Prof Alou COULIBALY	Full Professor	IPR/IFRA
Co-Directors	:	Prof Gbénonchi MAWUSSI	Full Professor	Université de Lomé
		Dr Ekpetsi Chantal BOUKA-GOTO	Senior Researcher	ITRA
Advisor	:	Dr. Murilo dos Santos Vianna	Associate Researcher	Agrosphere Institute, Jülich, Germany

Assessing the potential of biochar to enhance maize productivity and soil organic carbon sequestration under future climate scenarios in Togo

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by

Dodji Komlan Aziandeke

Certification

a) By the student

This work has not been presented elsewhere for the award of a degree, or any other purpose.

Candidate's name: **Dodji Komlan AZIANDEKE**

Signature……………………………. **Date………………….**

b) By the supervisor

I certify that this work has been carried out by Dodji Komlan Aziandeke under my supervision and that, to the best of my knowledge, it has not been submitted elsewhere for the award of a degree

Major Supervisor **Prof. Alou COULIBALY**

Signature…………………..… **Date……………….**

Co-Supervisor **Prof. Gbénonchi MAWUSSI**

Signature…………………..… **Date……………….**

Co-Supervisor **Dr. Chantal Ekpetsi BOUKA-GOTO**

Signature…………………..… **Date……………….**

Postgraduate School **Prof. Amagana DOLO**

Director of EDSTM

Signature…………………..… **Date……………….**

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Dedication

To the loving memory of my beloved mother, SOGLO Ami ("Rosa"), whose unwavering strength, sacrifices, and silent prayers continue to guide my path, this work is a tribute to all that you were and will always be to me.

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List of acronyms

ANAMet	:	National Meteorological Agency
ANOVA	:	Analysis Of Variance
APSIM	:	Agricultural Production Systems sIMulator
CEC	:	Cation Exchange Capacity
CERES	:	Crop Environment Resource Synthesis
CMIP	:	Coupled Model Intercomparison Project
CRAL	:	Agronomic Research Center of the Littoral
CSM	:	Cropping Systems Models
DOC	:	Dissolved Organic Carbon
DSSAT	:	Decision Support System for Agricultural Technology Transfer
EPIC	:	Environmental Policy Impact Climate
FAO	:	Food and Agriculture Organisation
GCM	:	General Circulation Model
GHG	:	Greenhouse Gas
HI	:	Harvest Index
INRES	:	Institute of Crop Science and Resource Conservation
IPCC	:	Intergovernmental Panel on Climate Change
ITRA	:	Togolese Institute for Agronomic Research
LAI	:	Leaf Area Index
LSD	:	Least Significant Difference
POC	:	Particulate Organic Carbon
POM	:	Particulate Organic Matter
ROC	:	Readily Oxidized organic Carbon
RothC	:	Rothamsted Carbon Model
RRMSE	:	Relative Root Mean Square
SDG	:	Sustainable Development Goal
SIC	:	Soil Inorgnic Carbon
SIMPLACE	:	Scientific Impact assessment and Modeling Platform for Advanced Crop and Ecosystem management

SOC	**:**	Soil Orgnic Carbon
SSP	**:**	Shared Socioeconomiaue Pathways
WRB	**:**	World Reference Base

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Abstract

Ensuring food security has become a major challenge in the face of climate change impacts on agricultural systems, leading to soil fertility decline and reduced crop yields. To investigate the potential of biochar, three field experiments were conducted from July 2022 to January 2024 at the research station of the Togolese Institute for Agronomic Research, the Center of Agronomic Research of the Littoral (ITRA/CRAL) based in Davié across three growing seasons. To leverage our analysis, we used the data to calibrate and evaluate a process-based crop model (DSSAT-Ceres) and applied it to estimate the implications of biochar use under future climate projections. The application of 20 t ha^{-1} of biochar (B20) significantly increased SOC concentration by 2.20 g kg^{-1}. Meanwhile, B10 and C1 did not significantly influence SOC. The effect on soil total nitrogen from different treatments was not significant. Grain yield increased significantly with biochar application at a rate of 20 t ha^{-1} during the second season, while the positive effect was marginal in the third growing season. After calibration, the DSSAT-Ceres model showed an RMSE of 0.16% and 0.09%for biomass and SOC, respectively. The future projections at the Davié site showed an increase in temperature of 1.27°C equivalent to 4.58% under the optimistic scenario (SSP126) and 2.05°C which is equivalent to 7.38% under the pessimistic scenario (SSP585) across almost all the 5 GCMs selected in this study, but a +6.67 mm increase under the SSP126 scenario and -12.99 mm decrease in rainfall. If crop management remains the same, maize yields are projected to decrease by 0.84% to 13.03% under the optimistic and 9.05% to 24.11% under the pessimistic scenarios for the years 2040-2070. However, this was not statistically significant. Similarly, the SOC is projected to decrease by 0.11% to 3.47% under the optimistic scenario (SSP126) and decrease by 0.89% to 5.26% under the pessimistic scenario (SSP585). When biochar is integrated as management practice (C0F0B20), the yields and SOC could be increased by 374.38 % and 73.38 %, respectively, as compared to low-input practice (e.g., C0F0B0) in average for historical and future scenarios. If combined with compost and mineral fertilizers, the increase in yield and SOC is higher (483.98 and 80.82%) as compared to low-input, but when compared to C1F1B0 the effect on yields is small (12.83%) whereas SOC increases considerably (20.54%). The model should be improved to capture the management practices and residual effects of soil organic amendments to give a representation close to reality.

Keywords: Maize, Biochar, Soil organic carbon, crop modelling, Climate Change.

Résumé

Assurer la sécurité alimentaire est devenu un défi majeur face aux impacts du changement climatique sur les systèmes agricoles, entraînant une baisse de la fertilité des sols et des rendements agricoles. Afin d'évaluer le potentiel du biochar, des expérimentations de terrain ont été menées de juillet 2022 à janvier 2024 à la station de recherche de l'Institut Togolais de Recherche Agronomique, au Centre de Recherche Agronomique du Littoral (ITRA/CRAL) basé à Davié, couvrant trois saisons culturales. Pour approfondir notre analyse, les données ont été utilisées pour calibrer et évaluer le modèle DSSAT, qui a ensuite été appliqué pour estimer les implications de l'utilisation du biochar dans le cadre de projections climatiques futures. L'application de 20 t/ha de biochar (B20) a significativement augmenté la concentration en carbone organique du sol de 2,20 g/kg. En revanche, les traitements B10 et C1 n'ont pas eu d'effet significatif sur le carbone organique du sol. L'effet des différents traitements sur l'azote total du sol n'était pas significatif. Le rendement en grains a augmenté de manière significative avec l'application de biochar à une dose de 20 t ha^{-1} durant la deuxième saison, tandis que l'effet positif était marginal lors de la troisième saison culturale. Après calibration, le modèle DSSAT a montré une RRMSE de 0,16 % pour la biomasse et de 0,09 % pour le carbone organique du sol. Les projections futures sur le site de Davié indiquent une augmentation de la température de 1,27 °C (soit +4,58 %) dans le scénario optimiste (SSP126) et de 2,05 °C (soit +7,38 %) dans le scénario pessimiste (SSP585), à travers presque tous les 5 modèles climatiques globaux (GCM) retenus dans cette étude, mais aussi une augmentation des précipitations de +6,67 mm sous le scénario SSP126 et une diminution de -12,99 mm sous le SSP585. Si la gestion des cultures reste inchangée, les rendements en maïs devraient diminuer de 0,84 % à 13,03 % dans le scénario optimiste et de 9,05 % à 24,11 % dans le scénario pessimiste pour la période 2040-2070. Toutefois, ces diminutions ne sont pas statistiquement significatives. De même, le carbone organique du sol devrait diminuer de 0,11 % à 3,47 % dans le scénario SSP126 et de 0,89 % à 5,26 % dans le scénario SSP585. Lorsque le biochar est intégré (C0F0B20), les rendements et le carbone organique du sol pourraient augmenter respectivement de 374,38 % et 73,38 % en moyenne par rapport à une pratique à faibles intrants (par exemple, C0F0B0), tant dans les scénarios historiques que futurs. En cas de combinaison avec du compost et des engrais minéraux, l'augmentation des rendements et du carbone organique du sol est encore plus élevée (483,98 % et 80,82 %), comparée à la gestion à faibles intrants. Toutefois, lorsqu'on compare cette combinaison à C1F1B0, l'effet sur les rendements est plus modeste (12,83 %), tandis que le carbone organique du sol augmente considérablement (20,54 %). Le modèle devrait être amélioré pour mieux représenter les pratiques de gestion et les effets résiduels des amendements organiques afin de refléter plus fidèlement la réalité.

Mots-clés : Maïs, Biochar, Carbone organique du sol, Modélisation des cultures, Changement climatique.

CHAPTER ONE: INTRODUCTION

1.1 Problem or Justification

Climate change is one of the world's most significant challenges, threatening food security, particularly in countries with limited economic resources. The impacts of climate change are unevenly distributed, with significant variations across and within regions. This disparity stems from varying levels of vulnerability driven by intersecting environmental, social, and economic factors (Clissold et al., 2020). The annual average temperature increases and a succession of extreme events, such as droughts, floods, storms, etc., have harmful impacts on agricultural production and the food supply chain (Rosenzweig et al., 2014; Hong et al., 2024). The agriculture sector is considered as the most affected by climate change (Rosenzweig et al., 2014). In Africa and developing countries, climate change and variability pose the most significant threat to food security, particularly given their heavy reliance on labor-intensive and rain-fed agricultural production systems (Antwi, 2013).

The situation doesn't change for Togo where the agriculture sector is also rainfed-based (Dossa & Miassi, 2023; Affoh et al., 2024). Climate change significantly impacts food security through various pathways. Rising temperatures and altered precipitation patterns directly affect crop development and growth, leading to yield variability and increased food insecurity (Foley et al., 2011; Lobell & Gourdji, 2012). Furthermore, these impacts extend beyond agriculture, cascading through economic, environmental, social, and political systems, with profound consequences for livelihoods and community well-being (Yang et al., 2024).

The agriculture sector is not only subjected to the impacts of climate change but also plays a major role in contributing to it (Tubiello et al., 2022; Luo & Dou, 2024). The sector is a great emitter of greenhouse gases (GHG) contributing to climate change as it accounted for 38% of GHG in the four sectors of Agriculture, Energy, Waste, Industrial Processes and Product Use (Luo & Dou, 2024). Its significant contribution arises from activities such as livestock production (methane emissions from enteric fermentation), fertilizer application (nitrous oxide emissions), rice cultivation (methane emissions from flooded fields), and land-use changes (carbon dioxide emissions from deforestation) (FAO, 2018).

Soil management practices are the primary drivers of changes in soil organic carbon (SOC) stocks and greenhouse gas (GHG) emissions in agricultural ecosystems (Smith, 2012). In Sub-Saharan Africa, intensive agricultural practices, including both crop production and livestock rearing, are major drivers of soil degradation (Ng'ang'a et al., 2020) as it contributes to soil erosion, nutrient depletion, and loss of organic matter, significantly reduces soil fertility. Consequently, agricultural productivity declines, leading to decreased incomes for farmers and contributing to food insecurity within the region (Shiferaw et al., 2009; Ng'ang'a et al., 2020). Unsustainable management practices have resulted in the degradation of approximately half of all global soils, characterized by a significant decline in soil organic carbon (SOC) stocks (FAO, 2015). One concrete pathway to address global crises, aligned with the 17 Sustainable Development Goals (SDGs), is to prioritize soil health by enhancing organic matter content and simultaneously increasing soil carbon sequestration (Rumpel et al., 2022). Carbon sequestration which is a crucial ecosystem service, is primarily driven by photosynthesis, whereby plants remove CO_2 from the atmosphere and contribute to carbon storage in soils (Blanfort & Stahl, 2013; Idrissou et al., 2024).

Among the various strategies for enhancing soil carbon (C) sequestration, biochar application has gained considerable attention (Mason et al., 2023). Biochar, produced through the pyrolysis of organic matter, is recognized for its potential to mitigate climate change by sequestering carbon in the soil (Woolf et al., 2010) while simultaneously improving soil fertility (Majumder et al., 2019). The effect of biochar on soil can vary significantly depending on several factors, such as the type of feedstock used for biochar production, the pyrolysis temperature, and the rate of biochar application, as revealed by a series of meta-analyses (Wu et al., 2014; He et al., 2018). The effect of biochar on soil fractions has received significant scientific attention. Studies focused on the effects of biochar on soil readily oxidized organic carbon (ROC), particulate organic carbon (POC), and dissolved organic carbon (DOC) (Li et al., 2018; Wang et al., 2018; Zhang et al., 2023).

Compost is another soil amendment, which is stable, decomposed organic material produced through the accelerated biological breakdown of organic matter under controlled aerobic conditions. It is created from plant and animal remains with the goal of recycling these materials for crop production (Kelbesa, 2021). Compost serves as an effective strategy for managing organic waste by significantly reducing its volume, degradability, and phytotoxicity, resulting in biologically stable products that are safe and suitable for agricultural use (Grigatti et al., 2024).

Numerous research has been conducted worldwide, on biochar and compost in agricultural systems, but there is still a lack of information with regard to Togolese context particularly in the coastal southern agroecological zone, also known as the Maritim region, which includes the cities Lomé, Davié, Tabligbo, among others. Additionally, most studies focused on the individual impact of biochar and compost on soil fertility and crop yields while the synergistic effect with mineral fertilizers is still underexplored. Furthermore, there is a need to understand the long-term carbon sequestration potential of biochar and compost in the context of climate change using process-based crop models.

In Togo, maize is the most widely consumed cereal and serves as a primary staple crop, playing a crucial role in ensuring food security and sustaining the livelihoods of rural communities. Enhancing its productivity therefore requires concerted efforts to improve soil fertility.

1.2 State of the knowledge

In sub-Saharan Africa, climate change continues to threaten agricultural productivity and soil health in a region where agriculture is primarily rainfed and soils have low fertility (Ongoma et al., 2025). Maize (*Zea mays* L.), a staple crop in Togo, is a source of food for families and among crops that generate incomes for smallholder farmers (Gadedjisso-Tossou et al., 2019). The decline of soil fertility and the adverse effects of changing climate variables, including increased average temperatures and irregular rainfall patterns, threatened its productivity.

Nature-based solutions, including biochar and compost, have gained attention for their ability to enhance soil health, crop yields and climate change mitigation (Pandian et al., 2024). Biochar is a carbon-rich material obtained from the pyrolysis of organic biomass in anaerobic conditions (Pandian et al., 2024). Its benefits when applied to soil include the improvement of soil properties such as nutrient retention, water-holding capacity, cation exchange capacity (Singh et al., 2022). Biochar characteristics, including porous structure, large surface area confer upon it a stable structure and contributes to long-terms soil organic carbon sequestration and thus, contributes to climate change mitigation (Hematimatin et al., 2024).

The performance of biochar is context-dependent and is influenced by soil type, climate, crop species, production condition, type and applied rate even though several studies highlight its numerous benefits (Khan et al., 2024). To date, global literature on biochar's great agronomic and environmental impacts is evolving in West Africa, but in Togo, information is still limited. Several studies conducted in West Africa on different soil types, different crops and different biochar feedstock revealed the great advantages of biochar to enhance crop yield and soil health (Amoakwah et al., 2017; Phares & Akaba, 2022; Frimpong et al., 2025). Many of the studies conducted investigated the integrated management by combining biochar with compost and mineral fertilizers, reaching to the results that such combination could enhance nitrogen uptake (Ullah et al., 2020; Peng et al., 2021).

Compost serves as a valuable soil amendment that enhances organic matter content while promoting long-term soil fertility. Beyond supplying essential plant nutrients such as nitrogen, it significantly improves the soil's physical, chemical, and biological characteristics (Adugna, 2016). Composting is an eco-friendly way to handle organic material in soil, boosting its quality and stimulating microbial growth. It lessens reliance on damaging synthetic fertilizers while increasing agricultural productivity (Sebahire et al., 2024).

Because biochar contains relatively low levels of nutrients, its effectiveness in promoting plant growth is significantly improved when it is combined with nutrient sources such as mineral fertilizers, compost, or plant growth-promoting microorganisms (Abbott et al., 2018). Conversely, while compost supplies nutrients readily, it decomposes quickly once applied to the soil, which limits its long-term carbon sequestration potential (Barthod et al., 2018). However, combining compost with biochar or other organic and inorganic inputs can enhance its stability. As a result, using a mixture of biochar and compost may offer a more effective soil amendment strategy than using either component alone (Aubertin et al., 2021).

Crop models are mathematical representations of plant-environment interactions, designed to simulate growth stages, physiological processes, and final yields based on genetic, climatic, and agronomic inputs (Wimalasiri et al., 2023). Various process-based crop models exist, each exhibiting distinct levels of complexity, functionality, and requirements for input data, processing methods, and output formats (Wimalasiri et al., 2021). Among these, the Decision Support System for Agrotechnology Transfer (DSSAT) stands out as one of the most prominent and extensively utilized modeling frameworks in agricultural research (Hoogenboom et al., 2019).

Recognizing this situation, a significant knowledge gap remains in understanding the long-term agronomic and ecological impacts of biochar in southern Togo. This PhD research seeks to address this lack of information by investigating how biochar, compost, and synthetic fertilizers together influence maize yields and soil organic carbon dynamics, considering both present and future climate scenarios. Through field trials and crop modeling, this work intends to provide reliable data for developing climate-smart agricultural practices in Togo.

1.3 Research hypothesis

Our study aimed to test four hypotheses corresponding to our specific objectives:

- Biochar applied alone or in combination with compost and/or synthetic fertilizers (NPK and Urea) may improve soil physicochemical properties
- Combined application of biochar, compost, and synthetic fertilizers may increase maize yields

- Climate variability may affect maize yields in southern Togo
- Future climate change scenarios may impact maize yields and enhance soil organic carbon sequestration in southern Togo under long-term climate projections

1.4 Objectives

1.4.1 Overall objective

The overall objective of this thesis was to understand how soil organic carbon sequestration and maize productivity could be enhanced through biochar application for the current and future climate.

1.4.2 Specific objectives

The specific objectives are listed below:

1. Determine the effect of biochar applied alone or in combination with compost and/or mineral fertilizers (NPK and urea) on soil physicochemical properties;
2. Assess the effect of biochar, compost in association with mineral fertilizers on maize yields across different cropping seasons;
3. Assess the climate variability impact on maize yields in southern Togo;
4. Modelling the impact of integrated management on maize yields and soil organic carbon stock under climate change.

CHAPTER TWO: LITERATURE REVIEW

2.1 Biochar: Description and production

Biochar (or bio-charcoal) is a type of charcoal produced from organic materials such as woods, crop residues, animal manure, wastes that are heated under low oxygen through a process that is known as pyrolysis (Duku et al., 2011). Pyrolysis is a thermal degradation process that occurs in the absence of oxygen, transforming low-energy biomass into a range of valuable products: synthesis gas (a medium-calorific value gas), bio-oil (a high-density liquid), and biochar (a high-density solid) (Bridgwater et al., 1999). Biochar utilization is a way for soil conditioning and to sequester carbon. Its application into the soil may results in good soil fertility and increases crop yields (Wakudkar & Jain, 2022). Three stages are generated by the pyrolysis during the degradation of the biomass. There is a solid part known as biochar, a liquid part known as bio-oil and a gas part. The quantity of each part depends on the pyrolysis method (Brewer et al., 2011). Depending on the operating condition, there are several methods of pyrolysis among which slow pyrolysis and fast pyrolysis are mainly used (Wakudkar & Jain, 2022). In the fast pyrolysis system, the dry biomass is heated very quickly (above 1000°C S^{-1}) in the absence of oxygen with a residence time of about 2 seconds. Its purpose is to maximize the production of bio-oil. In the conventional system (slow pyrolysis system), the dry biomass is heated slowly in the absence of oxygen (1°C – 20°C min^{-1}) and with a residence time varying from a few hours to a few days. A maximum temperature of 350 °C during slow pyrolysis results in the highest porosity of the produced biochar (Dutta et al., 2012). Pyrolysis significantly alters the physical and chemical properties of biomass. Increasing pyrolysis temperatures lead to an enrichment of carbon content in the resulting biochar. Concurrently, the process can influence the recovery of other elements, such as nitrogen and phosphorus, due to the release of volatile compounds and the dehydration of the initial biomass (Enders et al., 2012). Additionally, pyrolysis also enhances physical properties, including porosity and specific surface area, and chemical properties like cation exchange capacity (CEC) and pH. Pyrolysis typically yields biochar, constituting approximately 50% of the pyrolyzed biomass, which can be subsequently returned to the soil (Figure 1) (Lehmann, 2007).

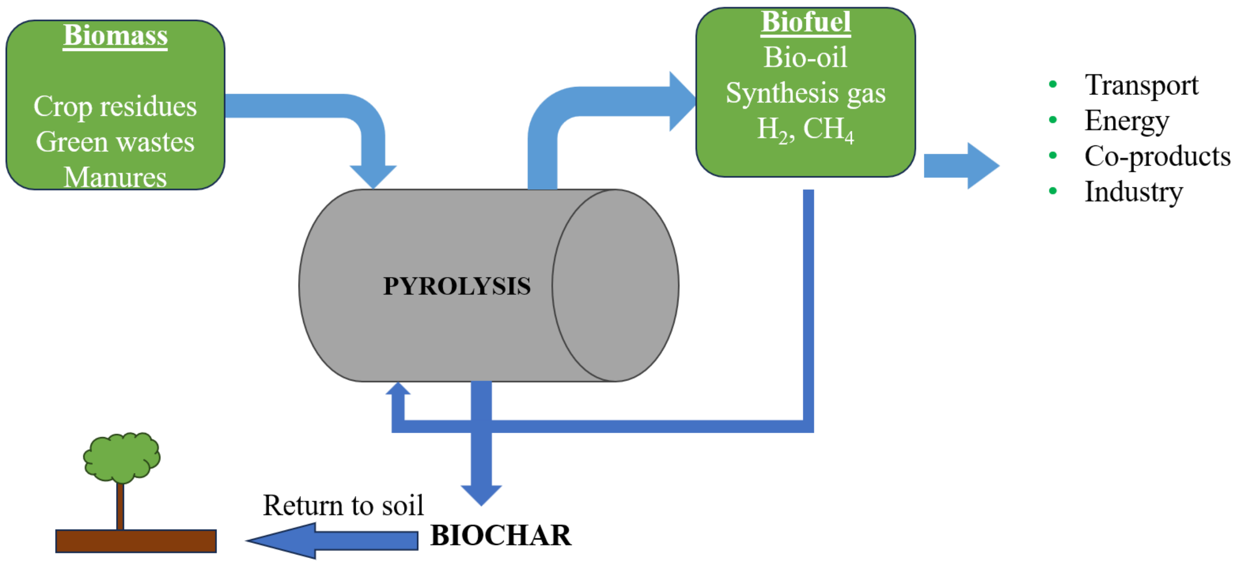

Figure 1: Low-temperature pyrolysis with biochar sequestration (Adapted from Lehmann, 2007).

2.2 Soil organic carbon sequestration

2.2.1 Definition

Soil organic carbon plays various roles in the climate system and climate change adaptation and mitigation. Not only the increase of SOC stock allows to reduce GHG emissions, but also it is crucial for soil health by improving water holding capacity that helps plants to access water, food production potential and their resilience to drought (FAO, 2017). There are various factors that influence the quantity of SOC in agricultural ecosystems. These factors include: climate, soil conditions, crops and field management practices (Koga & Tsuji, 2009).

Carbon sequestration is defined according to Olson et al. (2014) as "the process of transferring CO_2 from the atmosphere into the soil of a land unit, through plants, plant residues and other organic solids which are stored or retained in the unit as part of the soil organic matter (humus). Retention time of sequestered carbon in the soil (terrestrial pool) can range from short-term (not immediately released back to atmosphere) to long-term (millennia) storage." It is simply defined as "the increase and long-term (> 20 years) storage of carbon stocks in soil as stable forms of soil organic matter" (Chenu et al., 2019; FAO & ITPS, 2022). Most often, it is easy to use carbon sequestration and carbon storage in an equivalent way, but there is a need to differentiate these two terms. According to Chenu et al. (2019), carbon storage is defined as "the increase in SOC stocks over time in the soils of a given land unit, not necessarily associated with a net removal of CO_2 from the atmosphere".

There are several ways by which soil can store carbon. Through the process of photosynthesis, when plants grow, they absorb CO_2 from the atmosphere and convert it into simple sugars or structural compounds like fiber and cellulose that plants use for energy and growth. When a plant's roots die, or when a part of the plant is incorporated into the soil, soil-dwelling insects, earthworms, and microbes "eat" sugars and other compounds by breaking them down. It is released into the atmosphere as carbon dioxide (CO_2). Some remains in the ground. A part of the plant becomes difficult to decompose and becomes part of the soil organic matter.

2.2.2 Soil management practices that foster SOC sequestration

The literature identified several practices that aim to manage sustainably soils. For an assessment purposes of a sustainable soil management practice, there are a set of indicators that are generally recommended such as: soil productivity, soil organic carbon, soil physical properties, soil biological activity (FAO & ITPS, 2020). Soil carbon sequestration can be enhanced through diverse management practices. These practices include among others: organic amendments (compost, biochar…), minimum soil disturbance, cover-cropping, crop rotation, incorporation of residue, water harvesting and conservation, terraces, agroforestry. These processes result in the stabilization of carbon, thereby preventing its release into the atmosphere (Dignac et al., 2017). Furthermore, these practices lead to increase yields and increase soil carbon sequestration depending on the agroclimatic conditions (Branca et al., 2013). Organic amendments as compost and biochar enhance soil fertility, increase the soil water holding capacity, soil microbiology that are crucial for its health.

Application of these practices enhance soil quality and fertility, reduce erosion, increase biomass production and allow good humification of carbon in crops residues and to soil organic carbon sequestration. Additionally, they contribute to a reduction in GHG emissions, thereby fostering the development of sustainable agricultural systems that are more resilient to the impacts of climate change (Nazir et al., 2024). Likewise, in agroforestry systems, the carbon of the aboveground biomass is usually higher than in the land use without trees (Branca et al., 2013).

2.3 Effect of biochar on soil organic carbon sequestration

Biochar as carbon rich material, which has porous characteristics and high surface area that are known to promote soil moisture accumulation, increase soil porosity, reduce density and bulk density, and promote soil aggregation formation (Wu et al., 2014). Likewise, biochar addition to soil tends to influence plants growth due to its crucial effect on soil ecological processes such as organic matter accumulation and nutrient conversion (MA et al., 2019; Gong et al., 2021). There are several options for soil organic carbon sequestration, but biochar is recognized to be the most promising option to sequester carbon in biomass for the long term (Gupta et al., 2020). It is revealed that the high potential of biochar for carbon sequestration is mainly due to its high carbon content in a very stable form. Gupta et al. (2020) identified three major properties of biochar that are responsible for its high potential for long-term carbon storage:

- Biochar is a rich and stable form of carbon
- Biochar leads to a relatively higher rate of carbon sequestration
- Leads to agricultural and forest waste management

This ability of biochar to improve soil organic carbon sequestration lead to consider it as one of the most promising field management techniques for mitigating global warming (Koga et al., 2017). Biochar production itself does not sequester carbon from the atmosphere, but converts carbon sequestered in biomass to a more stable form, and helps improve the sequestration of organic carbon in the soil. Studies conducted worldwide have demonstrated the real impact of biochar to sequester soil carbon. A global meta-analysis that included 64 studies shows that biochar potentiality for carbon sequestration depends on various factors such as: experiment setup effect, single and continuous biochar application, duration effect, amount effect, soil depth effect, climate effect, tillage intensity effect, crop, fertilizer, soil texture, soil pH, biochar feedstock (Gross et al., 2021). Considering the biochar feedstock effect, it is noticed that biochar characteristics differ in their ability to modify soil properties due to the different structural components of the raw material, called feedstock. Biochar from plant material contribute to higher carbon sequestration potential than biochar from fecal matter. Regarding the amount of biochar applied, it is revealed that there is an increase in soil organic carbon with increasing of biochar amounts. Soil organic carbon varies in terms of soil depth, previous studies revealed higher SOC stock in shallow than deep soils. For instance, Gross et al. (2021) noted SOC stocks of 15.1 Mg ha^{-1} for a soil depth of 0 – 15 cm and 8.4 Mg ha^{-1} for 0 – 30 cm in shallow and deep soil regions. A study conducted in Australia revealed an increase of soil organic carbon after wood biochar application in avocado orchard (Joseph et al., 2020). These findings show the great role of biochar in carbon sequestration.

2.4 Effect of biochar and compost on crops yields

2.4.1 Effects of biochar on crops yields

Due to its large surface area and porousness (Farhangi-Abriz et al., 2021), biochar is known to provide an improved growing media for crops (Backer et al., 2016). Numerous studies have shown that adding biochar to soil can increase soil parameters such bulk density, hydraulic conductivity, soil structure, water retention, ion exchange capacity, microbial activity and porosity as well as crop performance (Sharma et al., 2021). Applied biochar in farmlands has the potential to increase agricultural performance and productivity, according to reports that are currently accessible. In the subtropical Taihu Lake region of China, the addition of biochar to the soil greatly enhanced wheat grain yield (GY) and the efficiency with which nitrogen was used (He et al., 2018; Farhangi-Abriz et al., 2021). A three years experiment was conducted in Sainte-Anne-de-Bellevue, QC, Canada where the objective was to investigate if pine wood biochar at rates of 0, 10, and 20 Mg ha^{-1} have effects on nutrient availability in soil, SOC stocks and yield of corn (*Zea mays* L.), soybean (*Glycine max* L.), and switchgrass (*Panicum virgatum* L.) on two coarse-textured soils (loamy sand, sandy clay loam). The results of the study revealed that, three years after application, 20 Mg ha^{-1} of biochar on loamy sand enhanced corn yields by 14.2% in comparison to the control (Backer et al., 2016). In Iran, a study was conducted using biochar from a mixture of poplar and plane tree wood and bio-fertilizers on soybean yield and its qualitative properties. The biochar was applied in rates of 0, 2.5, 8, and 16 t ha^{-1}. According the results of the study, authors conclude that biochar and bio-fertilizers can increase soybean grain yield by up to 51% compared to the control which they related to the application of biochar, which reduces soil acidity and raises the number of pods per plant and grain yield (Arabi et al., 2018). Liu et al. (2016), found in their study that Rice Straw biochar increase rice grain yield by 8.5 – 10.7% than the control. They related this result to the increase of nutrient availability. Further studies tend to understand the combined effect of biochar and nitrogen fertilizers. For this purpose, a plot experiments were conducted on a farmland in China in subtropical climate. Three levels of biochar (0, 15 and 30 t ha^{-1}) and three levels of N fertilizer (204, 240 and 276 kg N ha^{-1}) were considered. Authors conclude that the application of N fertilizer and biochar together is a successful technique to increase the use of N fertilizer and crop production for maize by improving soil fertility, enhancing plant crop uptake, and fostering plant growth (Li et al., 2023). A 40-day pot experiment conducted in Ghana to investigate the effect of corn cob biochar alone or in combination with compost on maize yield. The result of the study revealed that applying biochar alone or in combination with compost has the potential to improve soil quality and increase maize productivity (Mensah & Frimpong, 2018).

2.4.2 Effect of compost on crops yields

Composting is a biological process in which organic waste is recycled while being aerobically digested to create a product with nutritional value that may be used safely as crop fertilizer or animal feed (Ho et al., 2022). During this process, aerobic microorganisms break down organic matter, releasing CO_2, ammonia, water, heat, and a relatively stable organic end product. Given its diverse composition, green waste decomposes heterogeneously, with different compounds breaking down at varying rates.

In order to preserve soil fertility and reduce nutrient losses, organic matter must be present in the soil. As a result, compost is an excellent organic fertilizer since it also contains macronutrient essentials for plants (Nitrogen, Phosphorus, Potassium) and micronutrients including Iron, Manganese, Zinc, Copper, Boron etc. (Vázquez et al., 2015). In addition to contributing to the physical composition of soils, organic matter also serves as a platform for biological activity and contributes most to soil production. It gives the soil nutrients, increases its ability to store water, and aids in maintaining excellent tilth, which enhances aeration for seed germination and the growth of plant roots (Adugna, 2016). In Italy, a 7-year study was conducted to investigate the effects of two compost-based fertilization technics on soil fertility and yields of seven vegetables. The biowaste compost was derived from the organic fractions of municipal solid waste. The application of compost alone and combination with nitrogen fertilizer increased the yields of the various vegetables such as: eggplant, tomato, onion, escarole, muskmelon (Morra et al., 2021). An experiment in Kenya on maize revealed results of 4.4 Mg ha^{-1} with fertilizer treatment, 2.8 Mg ha^{-1} with composts treatment and 1.4 Mg ha^{-1}. The findings of this study show that composts have the potential to increase soil biodiversity and crop yield (Mbau et al., 2015). Hernandez et al. (2019) conducted a 2-year field experiment on a loam-clay soil in Spain to evaluate two different types of compost (compost manure and sewage sludge compost) alone or in combination of chemical fertilizers) in barley and soft wheat crops. Results showed that quality organic composts can be used as a good substitute for inorganic fertilization for cereal cultivation, improving soil characteristics while providing a similar yield and crop quality as traditional inorganic fertilization, when used at appropriate rates, alone or in combination with inorganic fertilizers.

2.4.3 Effect of biochar and compost mixture on crop yields

Biochar is most often applied to improve the fertility of soils lacking in nutrients and crops yield (Frimpong et al., 2021). According to several authors, biochar carbon is mainly resistant to microbial degradation and does not readily surrender to it, therefore it remains in soil for hundreds or millennia. Biochar has huge advantages as per its benefits described in the literature, but using it alone to improve soil fertility and agricultural productivity has drawbacks, especially when it is made from plants. Plant-based biochar frequently lacks phosphate and nitrogen (Frimpong et al., 2021). Then, authors revealed that adding pure biochar to soil does not always increase soil quality or crop production (Hagemann et al., 2017; Iacomino et al., 2022). According to Iacomino et al. (2022), composted materials offer a sustainable source of readily available nutrients that might promote plant growth by enhancing the physicochemical and microbiological characteristics of the soil. The drawback of utilizing compost is that it typically decomposes and mineralizes quickly, necessitating application every season. Furthermore, compost is generally applied in considerable quantities, which increases labor inputs and farm operation costs (Phares & Akaba, 2022).

A study conducted in Ghana, showed that the effects of biochar on soil lasted and affected crop yields throughout three crop cycles. The study also showed that the use of biochar in conjunction with compost, NPK, or both had a more significant influence on soil fertility, leading to higher yields of maize (*Zea mays*), okra (*Abelmoschus esculentus*), and cassava (*Manihot esculenta*) than when biochar was not present (Frimpong et al., 2021).

During the past ten years, the usage of co-composted biochar (COMBI), which is produced by adding biochar at the start of the composting process, has significantly risen in agriculture. A comprehensive literature review based on 125 studies concluded that when applied to agricultural fields, the resulting COMBI with enhanced physicochemical qualities is more advantageous than applying biochar and compost separately or a combination of the two products to improve soil attributes. Therefore, an appealing trend towards a low-carbon agricultural economy in the future will be the production and usage of COMBI to increase agricultural productivity and safeguard the environment (Antonangelo et al., 2021). Figure 2 below summarizes the various characteristics of biochar.

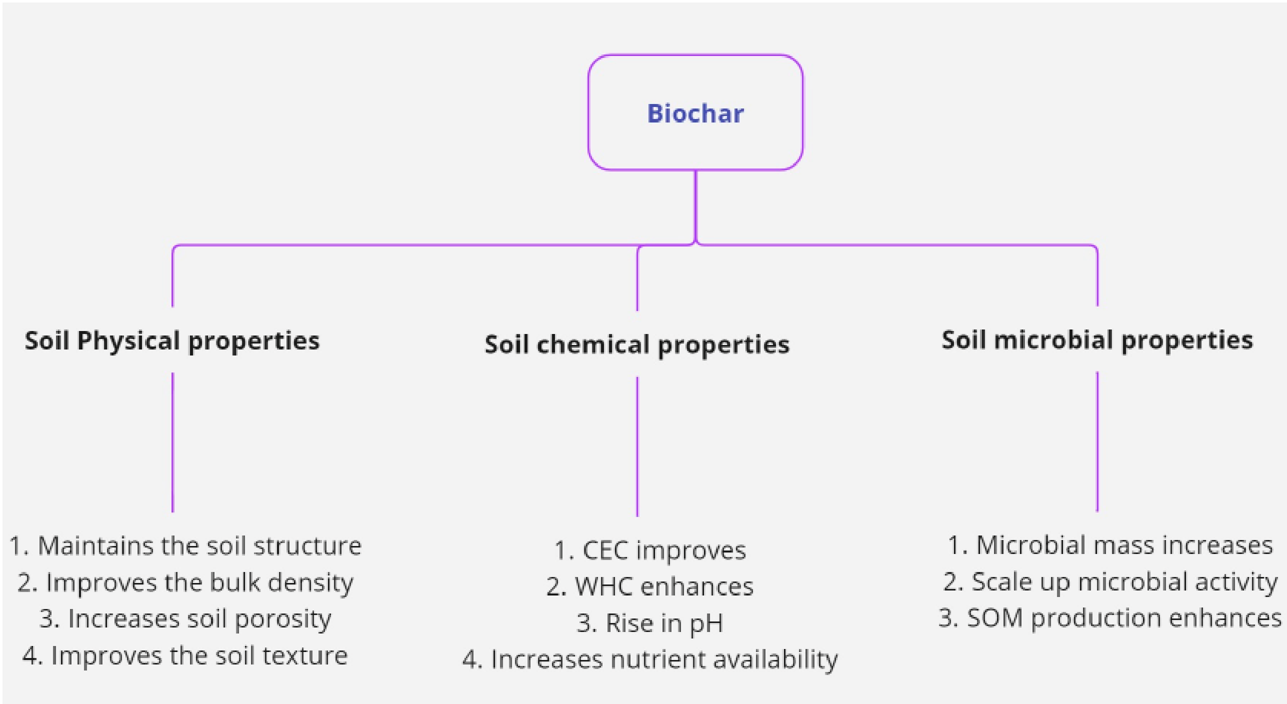

Figure 2: Impact of biochar addition on different soil properties. Adapted from (Murtaza et al., 2021)

2.5 Climate variability and crops yields

Climate variability is defined as natural changes in the climate parameters (Ahmad et al., 2021). The impacts of climate change have affected natural and human systems across all continents. Crop yields have been more frequently negatively impacted by climate change, according to assessments of numerous studies covering various regions and crops. Global temperatures have likely caused a reduction in cold days and nights, while increasing warm days and nights (IPCC, 2014).

Agricultural production and yield are heavily influenced by climate as rainfall and temperature have a direct impact on cultivation, and even small changes can affect crop yield and production. The effects of climate variability on agriculture are a growing concern worldwide, with multiple studies showing the significant impact of climate parameter variations on average crop yield (Panda et al., 2019). A study conducted in south Asia shows that climate variables, such as temperature and precipitation, have a significant impact on crop development and growth. The strength of the relationship between crop yield and climate variables varies greatly depending on the season and location. While climate variables play a crucial role in crop development and growth, the degree of their impact on crop yield differs significantly across seasons and locations

(Ahmad et al., 2021). A study conducted in Sudan examined the effects of long-term climate variables (temperature and rainfall) on the yield of five major crops. Results indicated that between 1984 and 2018, the annual maximum temperature (Tmax) increased by 0.03 °C per year, and the minimum temperature (Tmin) increased by 0.05 °C per year. Yield for all five crops of interest of the study exhibited a negative correlation with both Tmin and Tmax. However, the study found a strong positive correlation between annual rainfall and sorghum yield (Osman et al., 2021). Koudahe et al. (2018) found that in southern Togo, the increase in temperature had a significant effect on maize and bean in Kouma-Konda, while a non-significant effect on crop yields was observed in Atakpamé and Tabligbo.

2.6 Dynamic modelling of soil organic carbon

The inability to directly measure SOC stocks can be due to a number of factors, including the inability to reach representative sampling places, a lack of equipment, or the need for more samples that are practical to cover an area of interest. Additionally, the data gathered by direct measurements is frequently insufficient to provide comprehensive answers to all pertinent queries on SOC stock and dynamics. Process-based models have been developed (Table 1) to characterize soil properties and processes (FAO, 2019). One popular process-based model is the compartmental models CENTURY (Parton et al., 1988), the RothC (Coleman & Jenkinson, 1996; Corbeels et al., 2005) and their derivatives. These models are dedicated to simulating nutrient cycling and carbon turnover in the soil in response to environmental changes, deposition and biomass, thus, can also be named as biochemical models. Process-based crop models also simulate vegetation dynamics in response to soil and climate characteristics (Jones et al., 2017) and could be coupled with biogeochemical models. Some modelling platforms contain a collection of submodules with various agroecosystem algorithms (e.g., biogeochemical, crop, livestock, erosion, etc) that could be readily combined for a more integrated analysis of the soil-plant (livestock)-atmosphere system. Examples of such platforms include the Decision Support Systems for Agrotechnology Transfer (DSSAT), the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2014), the "Simulateur mulTIdisciplinaire pour les Cultures Standard" (STICS) (Brisson et al., 2003), and the Scientific Impact Assessment and Modeling Platform for Advanced Crop and Ecosystem Management (SIMPLACE) (Enders et al., 2023), which are listed in Table 1. The DSSAT platform is one of the widely used platforms and tested for range of environmental conditions. It also contains rich features for model setup, data analysis, model calibration and sensitivity integrated in a graphical user interface. In the following sections with a more detailed description of the DSSAT platform with focus on soil organic carbon dynamics and other biogeochemical approaches.

2.6.1 DSSAT model for soil organic carbon dynamics simulation

DSSAT (Jones et al., 2003a) is part of agroecosystem models (FAO, 2019). This model is based on biophysical concepts within the soil-plant (livestock)-atmosphere system to simulate crop development and growth as a function of weather, soil parameters, and management practices. The DSSAT model, which is complex and non-linear, simulates crop development and yield as a function of a wide range of input parameters, including plant and soil parameters (Corbeels et al., 2020). Weather, soil, plant, soil/plant/atmosphere interface, and management components are the primary modules (Figure 3). These components reflect the time changes in soil and plants that occur on a single land unit as a result of weather and management. Unlike previous versions of DSSAT and its crop models, the DSSAT/CSM merges crop models from all crops into a single set of code, allowing all crops to use the same soil model components (Jones et al., 2003). Over 28 Cropping Systems Models (CSMs) comprise the DSSAT model. Daily meteorological data, soil surface and profile information, and precise crop management information are all required by the DSSAT model. The CENTURY soil organic model was integrated with the DSSAT model to improve DSSAT simulation performance of SOM simulation under low input agriculture (Gijsman et al., 2007; Liu et al., 2017; Porter et al., 2010). The CENTURY-based module was included to allow for the modeling of soil organic sequestration capacity for various crop rotations over lengthy time periods after only initializing soil C and other variables once at the start of the simulation. The primary distinctions are that the CENTURY-based module:

- separates the SOM into multiple fractions, each with a variable C:N ratio and the ability to mineralize or immobilize nutrients,
- contains a residual layer on top of the soil,

the decomposition rate is texture dependent (Jones et al., 2003).

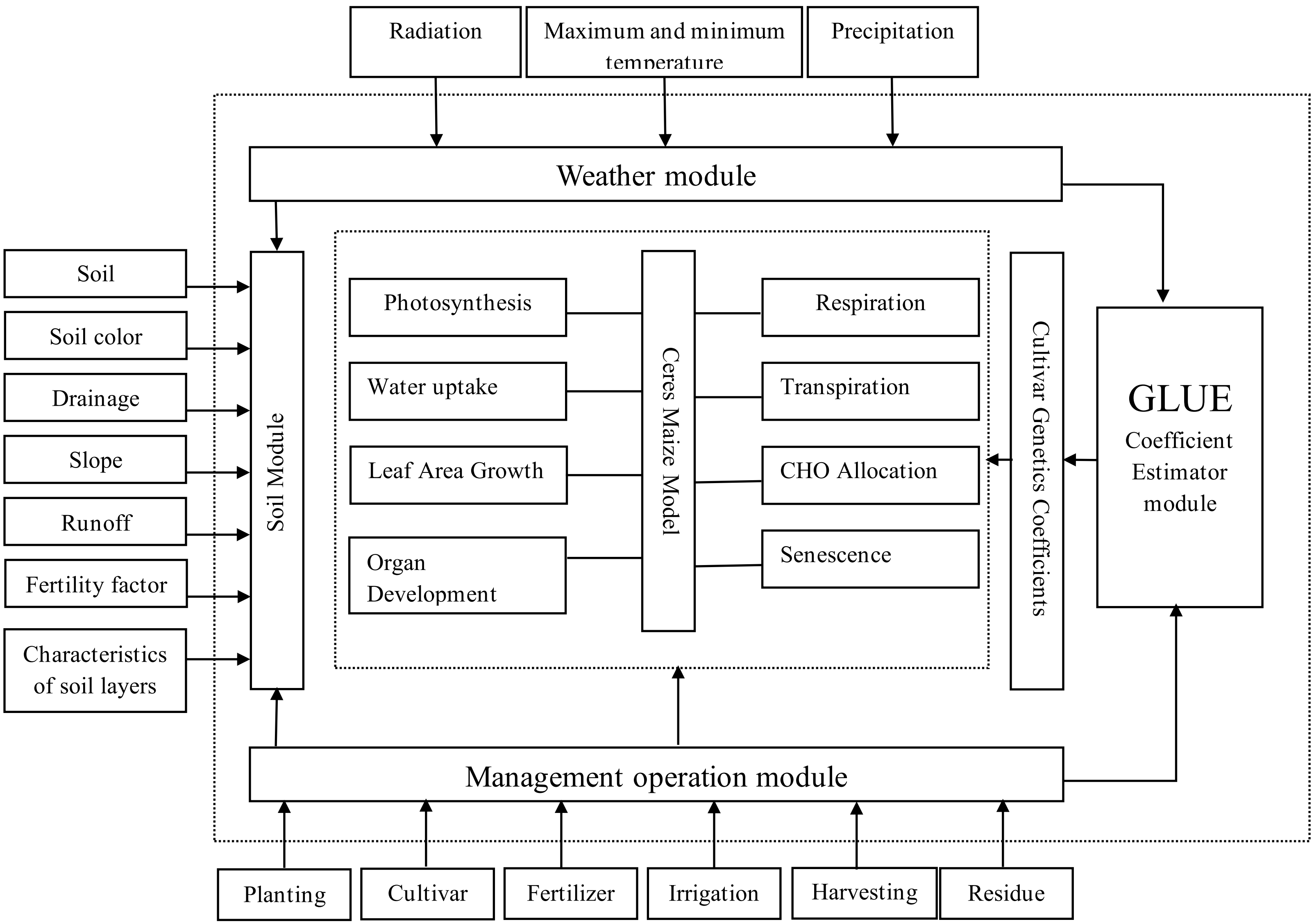

Figure 3: DSSAT Ceres Maize structure overview. Source: (Lin et al., 2015)

2.6.2 RothC model

The Rothamsted Carbon Model (RothC) version 26.3 is a model that takes into account the impacts of the soil type, temperature, moisture content, and plant cover on the turnover process in top soils that are not waterlogged (Coleman & Jenkinson, 2014). This model is typically employed in order to assess how SOC has changed and how it has responded to agricultural practices and climate change (Qingsong et al., 2023). The two operating modes of RothC-26.3 are "forward," which uses known inputs to compute changes in soil organic matter, and "inverse," which calculates inputs based on known changes in soil organic matter. Originally designed and parameterized to simulate the decay of organic C in arable top soils from the Rothamsted Long Term Field Experiments, RothC-26.3 was named after its purpose. Subsequently, it was expanded to simulate organic matter decomposition in grassland and woodland, as well as to function in diverse soil types and climates (Coleman & Jenkinson, 2014). RothC simply requires minimal input data, whereas CENTURY is more sophisticated and has a significant input data demand (Mishra et al., 2019). RothC can also be coupled to other crop modules such as the SUCROS model as described and tested by Herbst et al. (2008).

2.6.3 SIMPLACE model

SIMPLACE (Scientific Impact assessment and Modeling Platform for Advanced Crop and Ecosystem management) is a modeling framework that relies on the concept of encapsulating the solution to a modeling problem within discrete, interchangeable, and replaceable software units known as SimComponents or sub-models (Enders et al., 2023). These sub-models address key processes influencing the development of crops, encompassing root growth as well. Lintul5 is a crop growth model of a generic nature, capable of simulating crop growth based on potential, as well as limitations stemming from water and nutrients, such as nitrogen (N), phosphorus (P), and potassium (K). The model operates by way of a function which takes into account intercepted radiation and radiation use efficiency in order to simulate plant growth (Faye et al., 2023). The 'SoilCN' sub-model within the SIMPLACE model computes the turnover of soil organic carbon and nitrogen in soil profiles with multiple storage pools across multiple layers. This sub-model employs a mechanistic approach that includes the role of soil organisms in the decomposition process of N mineralization-immobilization turnover (Srivastava et al., 2019).

Table 1: Overview of modelling platforms and their respective algorithms for SOC and crop growth dynamics

Model	**Abbreviation**	**Soil sub-model**	**Crop sub-model**	**Model reference**
Agricultural Production Systems sIMulator	APSIM	SoilN	APSIM	Holzworth et al. (2014)
CELSIUS	CELSIUS	CELSIUS	CELSIUS	Ricome et al. (2017)
DayCent	DayCent	CENTURY	CENTURY	Del Grosso et al. (2001)
DeNitrification-DeComposition	DNDC v.CAN	DNDC	DNDC	Smith et al. (2020b)
Decision-Support System for Agro-technology Transfer	DSSAT	CENTURY	CERES maize	Ritchie et al. (1998); Gijsman et al. (2002); Hoogenboom et al. (2021)
Environmental Policy Integrated Climate	EPIC	EPIC	EPIC	Izaurralde et al. (2006)
Expert-N v5.1-Gecros	Expert-N v5.1-Gecros	SoilN	similar to SUCROS	Biernath et al. (2011)
Expert-N v5.1-Spass	Expert-N v5.1-Spass	SoilN	SPASS	Biernath et al. (2011)
Expert-N v5.1-Ceres	Expert-N v5.1-Ceres	SoilN	CERES maize	Biernath et al. (2011)
InfoCrop v2.1	InfoCrop v2.1	InfoCrop	similar to SUCROS	Aggarwal et al. (2006a,2006b)
The Model for Nitrogen and Carbon in Agro-ecosystems	MONICA v3.3.1	DAISY	HERMES/AGROSIM	Aiteew et al. (2023); Nendel et al. (2011)
Rothamsted Carbon Model	RothC			
System Approach for Land Use Sustainability	SALUS	CENTURY	SALUS	Basso et al. (2010)
Scientific Impact assessment and Modeling Platform for Advanced Crop and Ecosystem management	SIMPLACE	SoilCN	Lintul	Enders et al. (2023);Gaiser et al. (2013)
Simulateur mulTIdisciplinaire pour les Cultures Standard	STICS v10	STICS	STICS	Brisson et al. (2003); Beaudoin et al. (2023)

Source: Couëdel et al., 2024

2.7 Soil organic carbon fractions

Soil organic carbon (SOC) is increasingly recognized as a key indicator of soil quality due to its profound influence on the chemical, physical, and biological properties of soil (Sainepo et al., 2018). Although SOC is a valuable indicator of soil quality, examining soil fractions provides greater sensitivity to detect even minor management-induced changes and regulate degradation effectively (Blair et al., 1995; Diekow et al., 2005). Soil organic matter can be classified into several fractions depending on their density. The labile fraction (LF), the most prominent among these, is characterized by its rapid decomposition and high susceptibility to changes in management practices and erosion (Six et al., 2002a; Berhe et al., 2012). Soil scientists have defined the labile fraction in various ways, including as particulate organic carbon (POC) (53–2000 µm), easily oxidizable organic carbon (EOC), light fraction organic carbon (LFOC) (density < 2.0 g cm^{-3}), readily oxidized carbon (ROC), soil microbial biomass carbon (SMBC), and dissolved organic carbon (DOC), light fraction organic C (LFOC), and heavy fraction organic C (HFOC) (Cao et al., 2013; Sainepo et al., 2018; Ding et al., 2024). The labile fraction (LF) comprises mineral-free soil organic matter (SOM) derived from partially decomposed plant and animal residues. This fraction exhibits rapid turnover and has a significantly lower density compared to soil minerals (Alvarez & Alvarez, 2000). Agricultural soils are characterized by lower labile fractions (LF) compared to native land covers such as forests, grasslands, and shrublands. This disparity can be attributed to the frequent disturbances associated with agricultural practices, including tillage and the removal of crop residues (Vieira et al., 2007). In contrast, native ecosystems, with their high litter input and moderated soil temperature regimes, support significantly higher labile fractions (Sainepo et al., 2018). A review study showed that, compared to bare ground, cover crops demonstrated a significant positive impact on soil organic carbon fractions compared to conventional clean tillage, leading to increases in microbial biomass carbon (MBC) by 35.4%, dissolved organic carbon (DOC) by 23.7%, particulate organic carbon (POC) by 36.2%, easily oxidizable carbon (EOC) by 18.4%, light fraction organic carbon (LFOC) by 99.9%, and heavy fraction organic carbon (HFOC) by 5.4% (Ding et al., 2024). Some studies revealed that changes in soil labile organic carbon were time-dependent but not necessarily affected by the biochar application rate (Qiu et al., 2023). Similarly, other studies have shown that biochar application can affect the SOC content and labile organic carbon fractions (Jiang et al., 2022).

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Effect of biochar applied alone or in combination with compost and/or synthetic fertilizers (NPK and Urea) on soil physicochemical properties and maize yields

3.1.1 Study area

The study was conducted at the Agronomic Research Centre of the Littoral of Togolese Institute for Agronomic Research based in Davié (ITRA/CRAL) located in southern Togo (Longitude: 1°12'15.094"E; Latitude: 6°23'21.797"N) as it is shown in figure 4 below. The area is situated within the Littoral agroecological zone of Togo and it is characterized by a bimodal rainfall pattern, with the major wet season occurring between late March and July, and the minor season between September and November. The field experiment was conducted across three cropping seasons starting from the minor rainy season (Sep-2022) throughout the major and minor rainy seasons of 2023. The area experiences two dry seasons, the shorter one occurs in August and the longer one between December and March. The annual rainfall of the area ranges between 1000 and 1300 mm, while the annual average temperature is 28 °C. The soil of the study area is classified as Haplic Acrisol (World Reference Base (WRB), 2022).

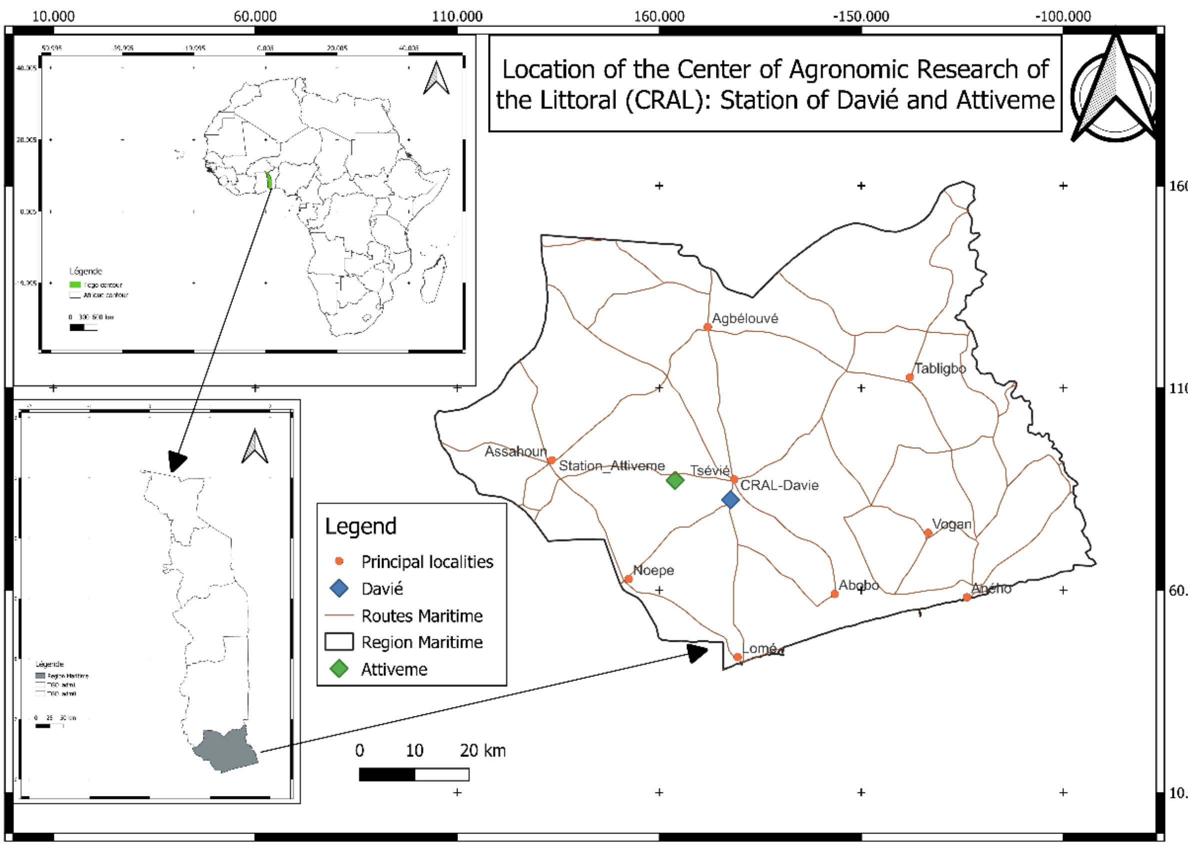

Figure 4: Map of the study area for the Agronomic Research Centre of the Littoral of Togolese Institute for Agronomic Research in Davié (ITRA/CRAL), southern Togo.

3.1.2 Experimental Design, Crop Management and Treatments

The experiment was conducted using a split-split plot design with four replications. The factor rate of compost (C0 and C1) was in the main plot, the factor rate of mineral fertilizer (F0 and F1) in the subplot, and the factor rate of biochar in the sub-subplot. Maize was selected because it is known as a staple food in Togo, representing 60% of the cereals consumed by the population (Agbobli et al., 2007). The maize variety used is a medium cycle (95 days) variety named 'Sammaz 52'. Three maize seeds per hill were sown at a spacing of 80 cm × 20 cm. Ten days after emergence, the germinated maize was manually thinned to one seedling per hill. The crop was grown from 9th September 2022 and harvested on 10th January 2023 for the minor season of 2022 and grown from 14th April and harvested in August 2023 for the major season of 2023, and finally from 13th September and harvested on 31st December 2023 for the minor season of 2023. After each harvest, the aboveground standing biomass was removed, and the soil surface straw was left in the field until the next growing season. It was then incorporated into the soil in the following season, manual tillage with a hoe.

The field was manually prepared and divided into 48 plots (Figure 5) corresponding to 12 treatments with 4 replications. The size of each plot was 2.4 m x 3.2 m (7.68 m^2), where each plot had 5 rows with 15 plants per row. The treatments consisted of a combination of compost, rice husk biochar and mineral fertilization combinations: compost applied at a rate of 10 t ha^{-1} of fresh matter (C1); mineral fertilizers (NPK 15-15-15 and Urea 46% nitrogen) applied at half of the recommended rates (F1), which are 100 kg/ha for NPK and 50 kg/ha for Urea; biochar rates at of 10 and 20 t ha^{-1} (B10 and B20); the combination of biochar with compost has been carried out as follows: 5 t ha^{-1} of biochar has been combined to 5 t ha^{-1} of compost (C1B10), to have 10 t ha^{-1} of organic amendment in total and 10 t ha^{-1} of biochar has been combined with 10 t ha^{-1} of compost to have 20 t ha^{-1} of organic amendment in total (C1B20); biochar combined with mineral fertilizers at rates of 10 t ha^{-1} and 20 t ha^{-1}; biochar and compost combined with mineral fertilizers and mineral fertilizers applied alone. The treatment descriptions are provided in Table 2 below.

The biochar used in the experiment was produced from rice husk using a locally manufactured kiln and pyrolyzed at about 520°C for up to 6h. The compost was acquired from a private company called 'Label d'Or'. Pineapple waste derived from juice production was used as the main feedstock with poultry manure to produce the compost.

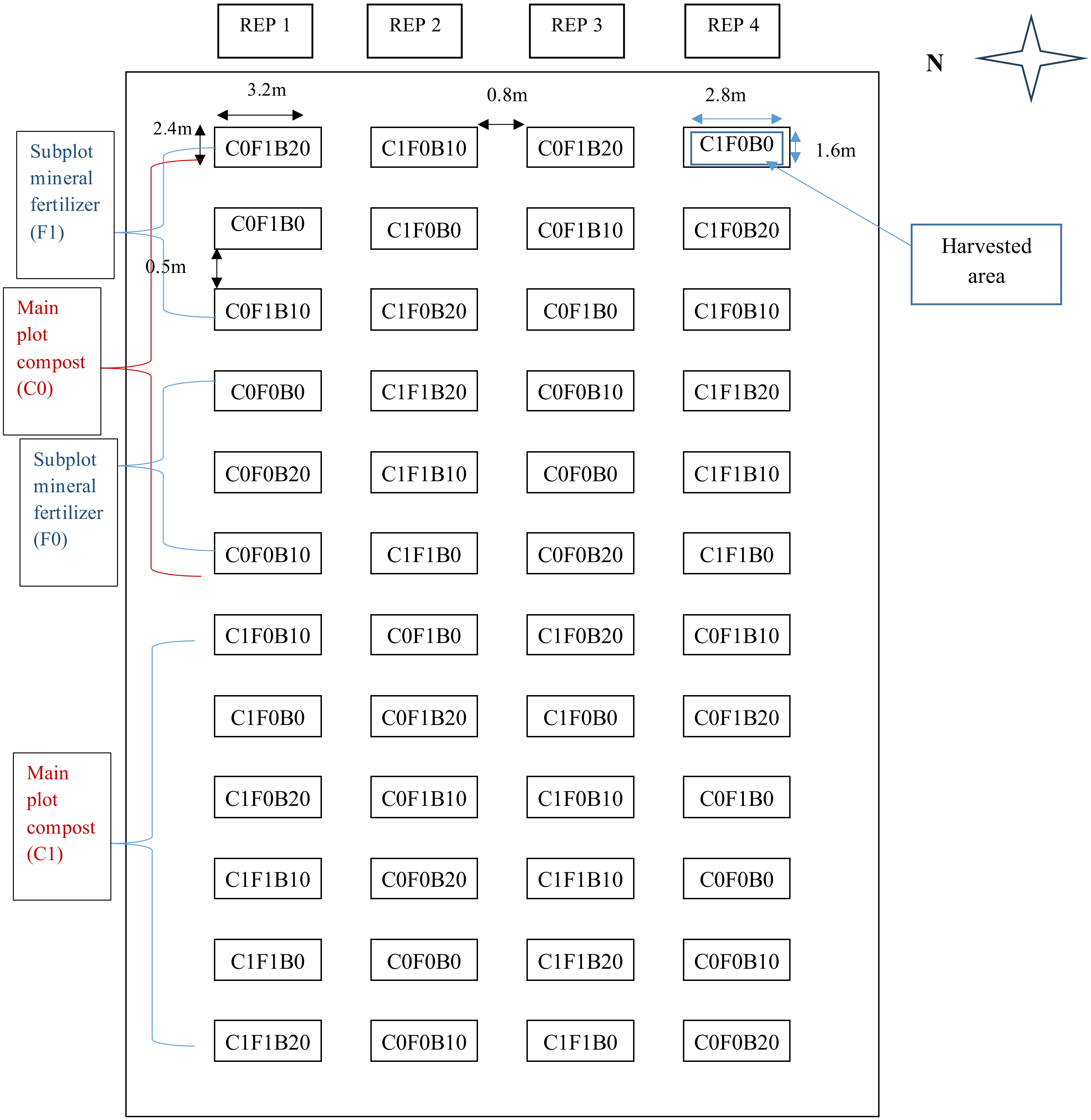

Figure 5: Experimental design. (REP = Repetition)

Table 2: Details of treatments

Factor 1 Rate of compost (C)	Factor 2 (rate of mineral fertilizer)	Factor 3 (Rate of biochar) t FM ha^{-1}	Treatments (with randomization of factors 2 and 3)
COMPOST (0 t FM ha^{-1} : C0)	F0	B0	C0F0B0
		B10	C0F0B10
		B20	C0F0B20
	F1	B0	C0F1B0
		B10	C0F1B10
		B20	C0F1B20
COMPOST (10 t FM ha^{-1} : C1)	F0	B0	C1F0B0
		B10	C1F0B10
		B20	C1F0B20
	F1	B0	C1F1B0
		B10	C1F1B10
		B20	C1F1B20

C0: 0 t FM ha^{-1} of compost; C1: 10 t FM ha^{-1} of compost; F0: 0 kg ha^{-1} of mineral fertilizers (NPK 15-15-15 and Urea 46%N); F1: 100 kg ha^{-1} of NPK + 50 kg ha^{-1} of Urea; B0: 0 t FM ha^{-1} of biochar; B10: 10 t FM ha^{-1} of biochar; B20: 20 t FM ha^{-1} of biochar.

Treatments with biochar and compost were applied one week after sowing in two times: once prior to the beginning of the first cropping season experiment (Sep-2022), and again at the beginning of the third season (Sep-2023). The mineral fertilizer was applied each season for treatments with F1 combination. Biochar and compost were incorporated into the soil surface and manually mixed to ensure a homogenous distribution of biochar to about 10 cm depth. The NPK fertilizer (15-15-15) was applied at a rate of 100 kg ha^{-1} 20 days after sowing, and 50 kg ha^{-1} of Urea (46% N) was applied 35 days after sowing. The mineral fertilizers were applied in a hole of 3 to 5 cm depth near each plant at a distance of about 5 cm. Three manual weeding were carried out throughout the growing cycle to eliminate the competition with weeds and foster better development of the plants. Water was not supplied throughout the experiments to be closer to the farmer's realities.

3.1.3 Soil Sampling

Two soil sampling campaigns were conducted, one before the experiment's activities commenced and another after sixteen (16) months. The disturbed soil sampling has been adopted for soil chemical properties determination using an auger. The samples were collected on 33 points (33 samples) according to the established treatments at a depth of 0 – 15 cm of the experiment field to capture the initial state of the soil. These samples were subjected to organic carbon and Nitrogen Analysis as well as POM (Particulate Organic Matter) analysis at the Soil Science Department lab of INRES of the University of Bonn. The samples were air-dried, passed through a 2-mm sieve, and grind before the analysis. A second soil sampling was conducted in late November 2023 on plots that do not receive any amount of biochar (0 t ha^{-1} biochar: C0F0B0, C0F1B0, C1F0B0, C1F1B0) and on plots that received a rate of biochar of 20 t ha^{-1} (C0F0B20, C0F1B20, C1F0B20, C1F1B20) which were expected to show a significant impact of biochar applications. In total, we collected 200g of soil samples per plot across three repetitions. The samples were collected at the same depths as the first year before the commencement of the trials. The samples were air-dried, sieved with a 2-mm mesh, and ground before proceeding for carbon and nitrogen analysis. An auger was used to collect the soil samples for nutrient measurements. Figures 6 and 7 show soil organic carbon content and stock map

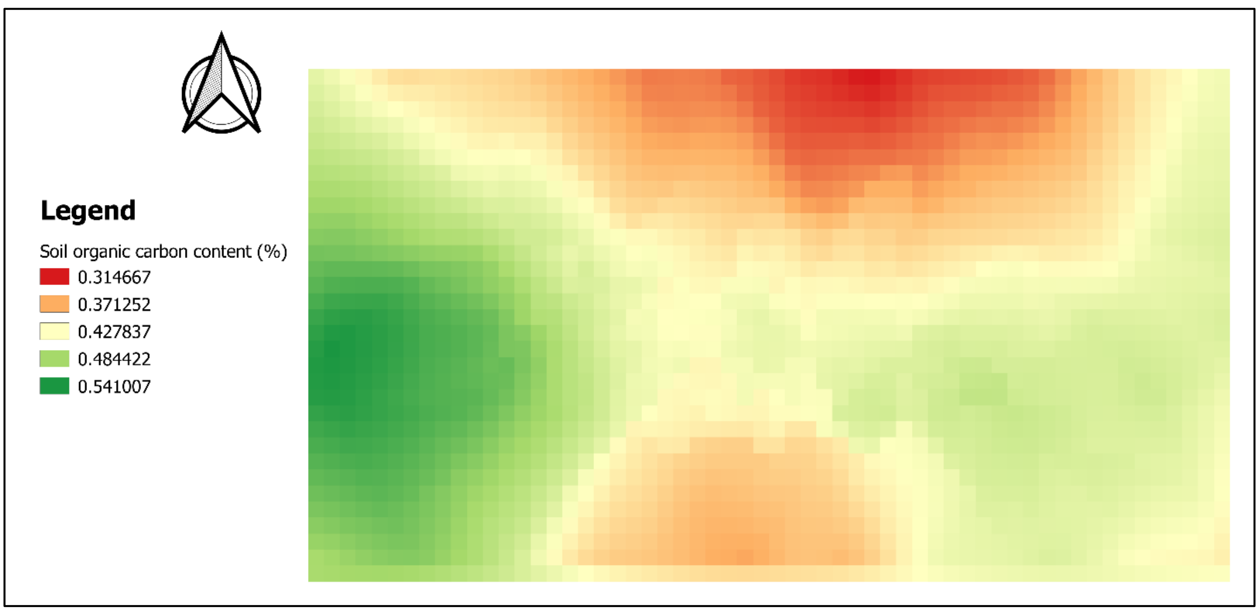

Figure 6: Soil organic carbon content of the experimental field map created using QGIS software version and the Kriging interpolation method.

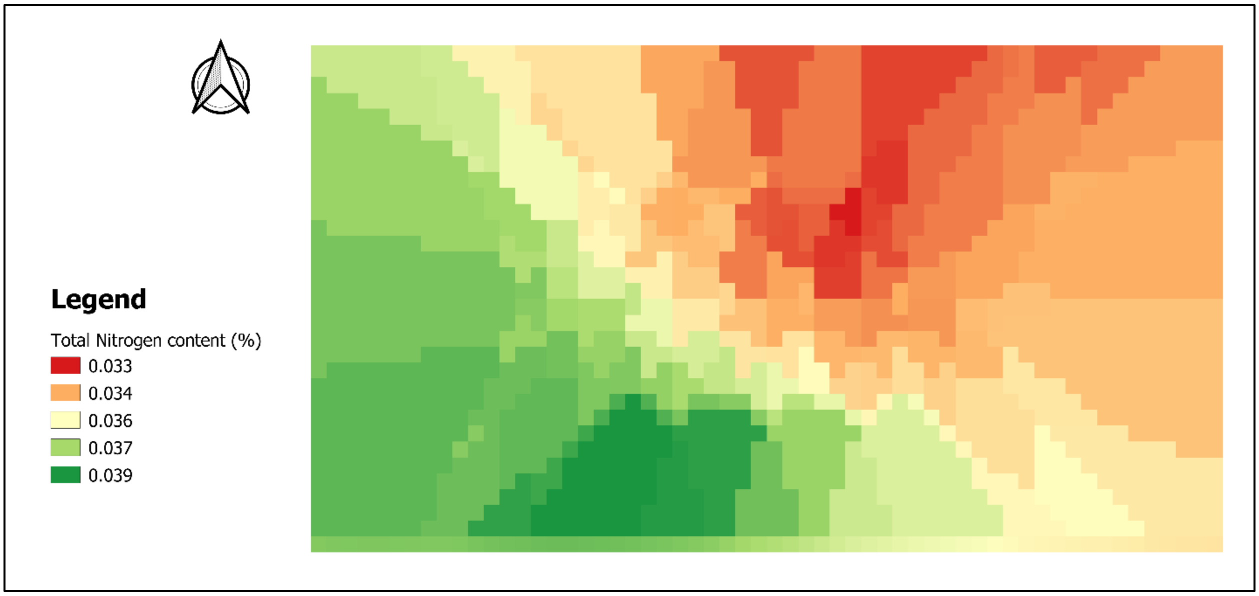

Figure 7: Total nitrogen content map created using QGIS software version and the Kriging interpolation method.

3.1.4 Laboratory analyses

3.1.4.1 Soil physicochemical properties

The soil analyses comprised pH, Electric Conductivity, available P, bulk density, and soil granulometry (silt, sand, clay contents). The analyses were carried out at the soil lab of the Togolese Institute of Agronomic Research (ITRA). The soil carbon and total nitrogen were analyzed at the soil science department of the University of Bonn, Germany. All samples were air-dried and sieved with a 2-mm mesh before the measurements to avoid, debris, rock fragments and litter that might be present (Abdalla et al., 2022). The total soil carbon content and nitrogen were determined by dry combustion (ISO 10694, 1995) using an Elemental Analyser (Vario Micro Cube, Elementar, Langenselbold, Germany). The soil organic carbon is the difference between total soil carbon and soil inorganic carbon (SIC).

The soil pH was measured by immersing the glass electrode of a SevenExcellence pH meter S400-Std-Kit in a 1:2.5 soil: water (w/v) mixture. Available phosphorus content in the soil was determined by Olson's method (Olson et al., 1954). Electrical conductivity was measured by using a conductivity meter. Soil bulk density was calculated by dividing the dry weight of the soil by the fresh volume of the soil sampled with a cylinder (Eijkelkamp) with a known volume (100 cm^3).

3.1.4.2 Biochar and compost chemical analyses

Biochar was analyzed for pH, total nitrogen, available phosphorus, exchangeable K and total organic carbon. Biochar pH was determined by a pH meter (SevenExcellence pH meter S400-Std-Kit) in a 1:2.5 biochar: water (w/v) suspension. Total nitrogen content of biochar was determined by employing the micro Kjeldahl method as described by Allen et al. (1974). Extraction and spectro colorimetric determination method was followed to determine available phosphorus content in biochar. Total organic carbon content was determined by the loss on ignition method. As far as compost is concerned, it was analyzed for pH, total nitrogen, available phosphorus, total organic carbon and exchangeable K. Total nitrogen in the compost was determined by the micro Kjeldahl method. Loss on ignition method was followed to analyzed total organic carbon content in the compost (Lord & Sakrabani, 2019). Compost pH was determined by a pH meter. Exchangeable K of the compost was analyzed by extraction. The results are presented in Table 3.

Table 3: Initial soil basic characteristics for the 30 cm top soil, biochar and compost properties

Parameter	Soil Depth		Biochar	Compost
	0 - 15 cm	15 - 30 cm		
pH	5.96	5.93	8.43	8.4
Total Nitrogen (%)	0.04	0.04	1.26	1.82
Total Organic Carbon (%)	0.43	0.43	32.02	8.97
C/N ratio	11.74	11.74	25.45	4.93
Potassium (mg/kg)	66.3	85.8	0.90	0.90
Available Phosphorus (ppm)	2.87	2.13	0.29	0.96
Salinity (Electric Conductivity)	23.4	23.3		
Bulk density (g/cm^3)	1.65	1.65		
Clay (%)	9.09	12.24		
Fine silt (%)	11.03	10.03		
Coarse silt (%)	12.03	22.03		
Fine sand (%)	25.3	19.3		
Coarse sand (%)	41.92	34.92		
Textural class	Sandy loam	Sandy loam		

3.1.5 Data collection

Data related to crop growth parameters was collected, including plant height, stem girth, number of leaves, leaves length and width, leaf area index, silking date, date of 50% flowering, maize grain and biomass yields, 1000 grain weight.

- Plant height

A net plot was first defined in order to avoid the border effect. Inside the net plot, ten (10) were targeted 15 days after emergence. Plant height was measured using a graduated measuring rod from the base of the plant to the tip of the highest leaf or under the panicle from the flowering stage. Plant height data was collected four times, each 15 days to maturity.

- Stem girth

Stem girth data was collected on the targeted 10 plants three times starting from 20 days after emergence at 15-day interval. The stem girth was measured using a caliper.

- Number of leaves

Number of leaves data collected on the targeted 10 plants among which 5 were selected in order to estimate further the leaf area index.

- Leaves length, width and Leaf Area Index

From the 4th weeks after sprouting leaves length and maximum width were measured. Three leaves were chosen on each among the three plants that are targeted for their determination. The leaves were chosen at down, middle and top of each plant. Then, the measurements were averaged in order to obtain one leaf length and width that were used for leaf area computation and consequently, leaf area index determination. The following formula proposed by Dugje (1992) was used to estimate the Leaf Area Index. This led to determine at first sight the single leaf area.

$$Single\ Leaf\ Area\ (cm^2) = \mathrm{L} \times \mathrm{W} \times \mathrm{K} \quad (1)$$

Where, L = leaf length (cm), W = leaf width(cm), K = 0.75

Then the Leaf Area Index was estimated as follows:

$$LAI = (\mathrm{P} \times \mathrm{L} \times \mathrm{A})/GA \quad (2)$$

Where, LAI = Leaf Area Index ($m^2_{[leaf]}\ m^{-2}_{[land]}$), P = Plant population /ground area (ha), L = number of fully expanded green leave/plant, A = Single Leaf Area, GA = Ground Area (1ha = 10000m^2).

- 50% flowering date

The date of flowering is recorded on each plot. 10 plants were targeted on each plot for data collection on plant height, stem girth etc. From the date on which the first panicle has been appeared on one targeted plant, the number of plants has been counted on a daily basis till the date at least 50% of plants bear panicles.

- Grain Yield

The maize dry cob was harvested manually and kept in different bags 110 days after sowing when no green leaves were observed on any plant. The cobs were immediately dehusked and the grains were about 20% of moisture content. The grains were sun-dried for 1 week and weighed when the moisture content was about 12% and the grain yield (GY) was expressed in dry mass (kg ha^{-1}) . The GY was determined within the net plot (1.6m x 2.8m) by dividing the dry grain weight by the net plot area. For the aboveground biomass (AGB), six plants were chosen within the net plot at harvest, the ears were removed to keep only the straw which was air-dried to a constant weight for two weeks. The average dry weight of the six plants was then calculated. We determined the plant density in the net plot by dividing the number of plants by the net plot area. To estimate the AGB, we multiplied the average dry weight per plant by the plant density and 10000 m^2 to extrapolate into hectare.

- Harvest Index

Harvest index (HI) reflects the crop's ability to allocate photosynthates efficiently toward economic biomass production, and it varies due to both genetic and environmental factors (Camargo-Alvarez et al., 2023). In other words, it is the ratio of Economic yield to aboveground biomass yield. The economic yield is the grain yield and we added the grain yield to the straw yield to get the biological yield. The following formula (Eq. 3) is used to calculate the HI:

$$Harvest\ Index\ (HI) = \frac{Grain\ Yield}{(Grain\ Yield + Aboveground\ \ Biomass)} \tag{3}$$

The Pearson correlation method was used to analyze the correlation between plant parameters (LAI, NoL, CH, HI, GY, Aboveground biomass (AGB), Anthesis Date, Thousand Grain Weight, SOC and total soil nitrogen). The analysis was carried out with R language, including the 'Corrplot' package. In this study, we ignored season 1 data for LAI, AGB, and HI due to some inconsistent values that were due to the loss of some plots which complicated data collection.

Table 4: Activities calendar

Crop management	**Dates**
Soil sampling	28th July 2022 / 28th November 2023
Ploughing	05th September 2022 / 13th April 2023
Plots demarcation and labeling	6th September 2022
Biochar and Compost application	07th September 2022 / 11th September 2023
Sowing	09th September 2022 / 14th April 2023 / 12th September 2023
First manual weeding and thinning	
First mineral fertilizer application	30th September 2022
Pest control	04th October 2022 / 11th May 2023
Second manual weeding	11th October 2022
Second mineral fertilizer application	12th October 2022
Second pest control	
Third manual weeding	
Harvest	10th January 2023 / 18th August 2023 / 4th January 2024

Figure 8 below presents the weather information such as minimum and maximum temperature, rainfall and solar radiation of the experimental field across the three growing seasons. The sowing date and the application date of biochar and compost are also presented in the figure.

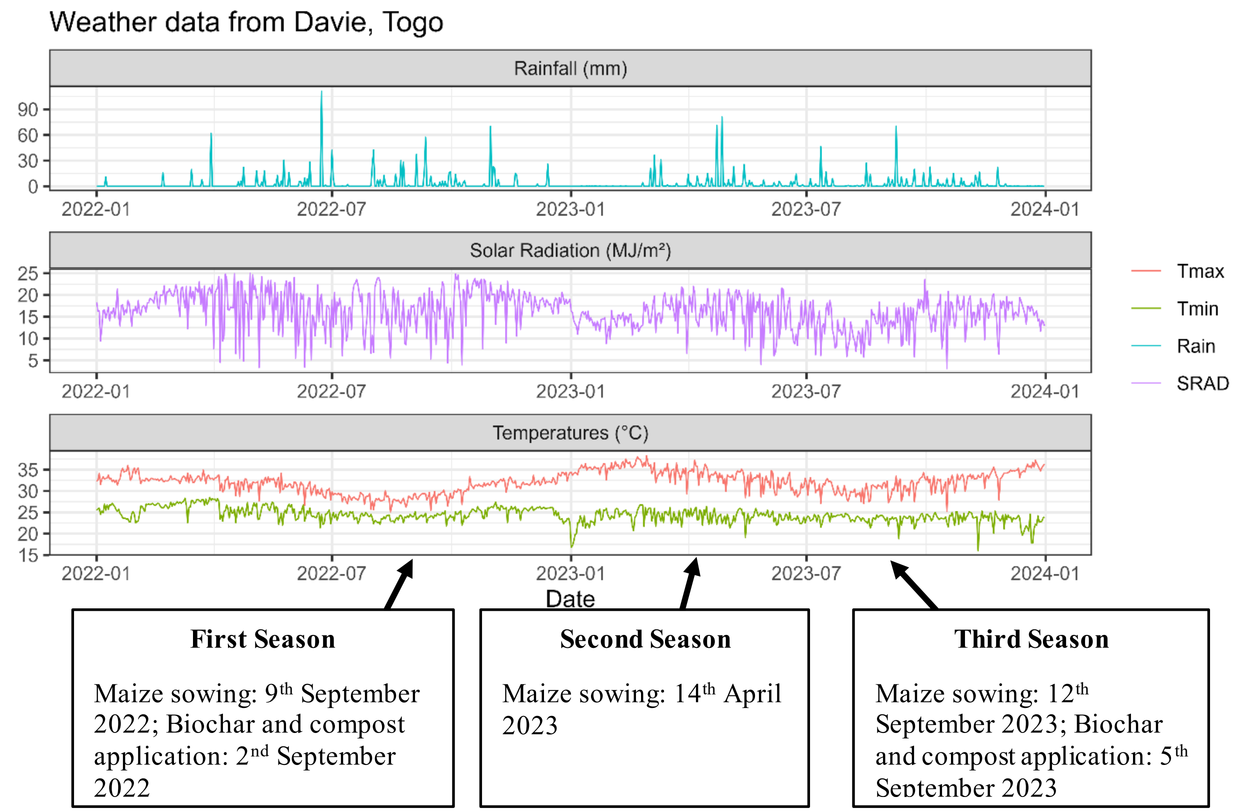

Figure 8: Daily rainfall, solar radiation and maximum and minimum temperature at the experimental field (Davié) covering the three growing seasons from September 2022 to December 2023. Data obtained from the National Meteorological Agency of Togo. The boxes below refer to the timing of management practices during the experiment.

3.1.6 Statistical data analysis

The collected data were recorded into MS Excel and later analyzed using a linear mixed-effects model from a package called "*lme4*" in R scripting language (v. 4.5.0) to account for the hierarchical structure of the experimental design (Bates et al., 2015). The model includes fixed effects for the primary factors and their interactions, as well as random effects for the block and the main plot (nested within the block), in order to account for variability between blocks and main plots. A Pearson correlation matrix was generated to analyze the correlation between plant parameters (LAI, NoL, CH, HI, GY, Aboveground biomass (AGB), Anthesis Date, Thousand Grain Weight, SOC and total soil nitrogen) with the "*Corrplot*" package in R (Wei & Simko, 2024).

3.2 Effect of biochar applied alone or in combination with compost and/or inorganic fertilizer (NPK) on different SOC fractions in the soil and on soil carbon sequestration

3.2.1 Bulk density

The bulk density determination involved sampling the soil in the middle of each plot using a metal cylinder of known volume (100 cm^3). A hole was dug in the middle of the plot, and then the cylinder was placed horizontally in the middle of the targeted soil layer. The bulk density was calculated by dividing the dry weight of the soil core by the volume of the cylinder. The dry weight of the soil was obtained by oven-drying the samples at a temperature of 105°C for 72 hours to reach a constant weight.

$$\boldsymbol{Bulk\ Density}\ ({}^{g}/_{Cm^3}) = \frac{\boldsymbol{Sample\ dry\ weight\ (g)}}{\boldsymbol{Cylinder\ volume\ (Cm^3)}} \quad (4)$$

3.2.2 Soil organic carbon stock and stock change

The estimation of the organic carbon stock of the soil implies the determination of soil bulk density, soil organic carbon content and the targeted soil layer. The results of soil organic carbon content at the beginning of the study are presented in Table 3 above. The SOC stock was computed for the initial state and, in order to investigate the stock change, it was computed after 16 months following the initial application of biochar and compost.

The SOC stocks (t C ha^{-1}) were calculated by multiplying the SOC content by bulk density and the corresponding soil depth (Eq. 5):

$$SOC\ Stocks = SOC\ \times BD\ \times H \quad (5)$$

Where SOC is the soil organic carbon concentration (%) in the layer, BD is the bulk density (g cm^{-3}) and H is the depth of the soil layer (cm).

The SOC stock change is calculated as follows:

$$Stock\ change = \ SOC\ Stock_{2023} - \ SOC\ Stock_{2022} \quad (6)$$

3.2.3 Soil fractionation for the Particulate Organic Matter analysis

For the soil fractionation the size-based physical fractionation of soil organic carbon method was adopted (Six et al., 2002b). A 30 g soil sample is weighed and mixed in 150 ml of deionized water and placed in an ultrasonic. To perform the first sieving a 250-µm sieve was used. The sample is rinsed with water until it is clear. The second sieving required the use of a 53 µm sieve. The sample was passed through the sieve and rinsed with water until it was clear. Following this, the remaining sample liquid is sieved through a 20 µm sieve and rinsed with water until it was clear. The sieved fractions were then dry in an oven at 40°C for 72h. The dried samples were then weighed and recorded. Afterward, the samples were milled and subjected to carbon and nitrogen analysis. Figure 9, below, presents images of the soil fractions after separation.

Figure 9: Soil fractions separated, where the left figure shows the dry samples taken out from the oven, and the right figure shows the samples removed from the beakers, weighed and put in small containers.

3.3 Climate variability on maize yield in southern Togo

3.3.1 Sites Description

Located between the meridians 0° 40' and 1° 50' of East longitude and the parallels 6° and 6° 50 of North latitude, the Maritime Region covers an area of 6,600 km² or about 11.66% of the national territory (Agbewornu, 2018). It borders the Plateaux Region to the north (130 km), the Atlantic Ocean to the south (50 km), the Republic of Benin to the east (100 km) via the Mono River, and the Republic of Ghana to the west (80 km) (Figure 10). The main crops cultivated in this region are maize, cassava, yams, cowpeas, and rice. The climate is subtropical hot and humid. The climate is subtropical hot and humid. The precipitation regime is marked by two dry seasons and two rainy seasons: a long rainy season (April to July), a short dry season (August), a short rainy season (September to October), and a long dry season (November to March) (Atakpama et al., 2021). The annual rainfall of the region is between 800 and 1200 mm (Bawa et al., 2021).

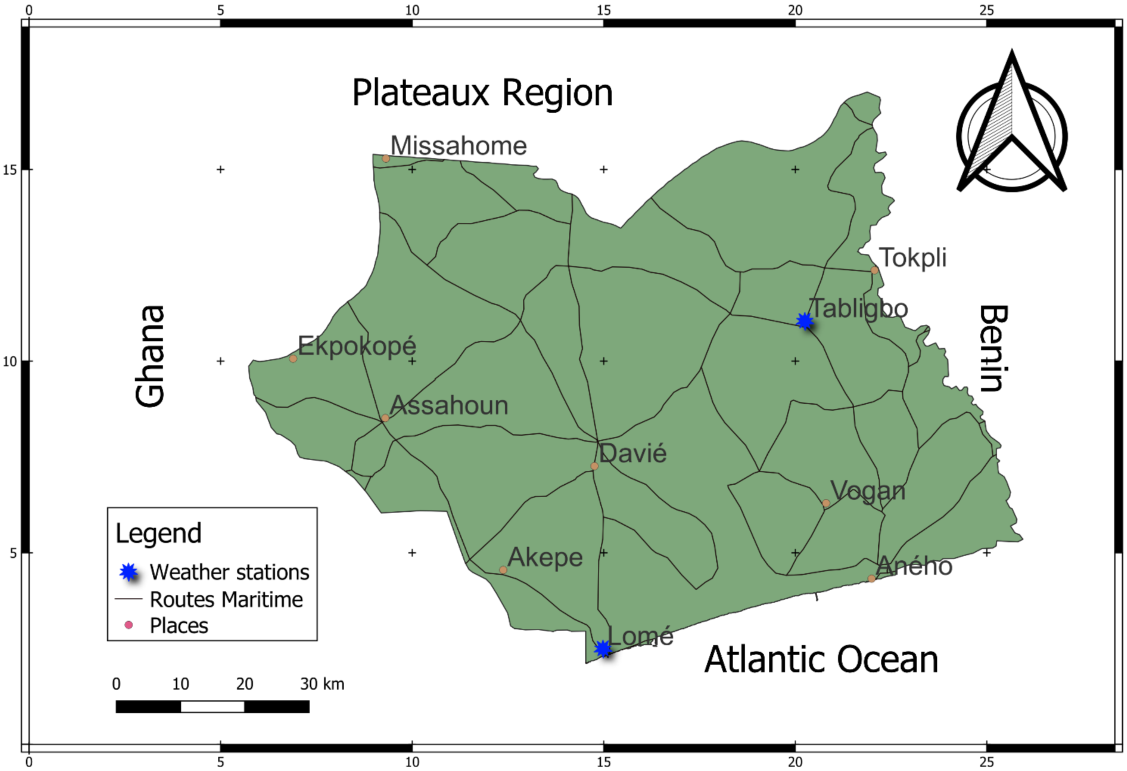

Figure 10: Map of the study area

3.3.2 Data collection

Daily minimum and maximum temperatures, as well as daily rainfall for Lomé and Tabligbo weather stations, were obtained from the National Meteorological Agency of Togo covering the period 1980 – 2022 (43 years of data). Data on the yield of maize was obtained from the Statistics Department of the Ministry of Agriculture for the period 1990 to 2021. The selection of maize was based on the fact that it is the largest staple crop grown in the region.

3.3.3 Data analysis

The average annual minimum and maximum temperature, and rainfall, were computed based on daily data records from the Meteorological Office of Togo. Subsequently, the Modified Mann-Kendall (Mann, 1945; Kendall, 1948) trend analysis was employed by using R software (version R 4.1.2) to these variables to determine any positive or negative trends in temperature and rainfall between 1980 and 2022 (Nkiaka et al., 2017; Liu et al., 2020). The Mann-Kendall test is a nonparametric test that is commonly used for analyzing historical time series data (Osman et al., 2021). This test does not require data to be normally distributed. During the testing process, the null hypothesis (H0) assumes that there is no trend present in the population from which the dataset is sampled. The alternative hypothesis (H1), on the other hand, suggests that there is a trend in the population. The null hypothesis (H0) will be rejected if the p-value is less than 0.1 (Poudel & Shaw, 2016). The Mann-Kendall test was calculated as follows:

$$\sum_{j=1}^{n-1} \sum_{i=j+1}^{n} Sign(xi - xj) \tag{7}$$

Where:

- xi is the data value at the time i
- xj is the data value at time j
- n is the length of the time-series data
- Sign(xi – xj) is the sign function which can be calculated as follow:

$$\text{Sign}(\text{xi} - \text{xj}) = \begin{cases} 1 \text{ if } (\text{xi} - \text{xj}) > 0 \\ 0 \text{ if } (\text{xi} - \text{xj}) = 0 \\ -1 \text{ if } (\text{xi} - \text{xj}) < 0 \end{cases} \tag{8}$$

Sen's slope method was applied to quantify the trend (Sen, 1968). The slope Q was computed as follows:

$$Qi = \frac{xi - xj}{i - j} \;;\; I = 1, 2, 3, \ldots \text{N} \tag{9}$$

Where xi is the data value in the time series at time *i* and xj is the data value at time *j* (*j*=*i*-*1*). Sen's estimator of the slope is calculated as the median of N values of Qi. Qi is calculated differently depending on whether N is even or odd:

- $Qi = Q(\frac{N+1}{2})$ if N is odd (4)
- $Qi = \frac{1}{2}\,(Q\,\frac{N}{2} + Q\,\frac{N+2}{2})$ if N is even (5)

The sign of the slope's value indicates whether there is an increasing trend or not. Positive values indicate an increasing trend and negative values entail a decreasing trend.

3.3.4 Impact of climate parameters on crop yields

Simple linear regression was first applied by using R software version 4.1.2 to analyze the trend of crop yields over time because crop yield is influenced by various factors besides climatic variables (Osman et al., 2021). To assess the strength of the relationship between crop yields and climate parameters, Pearson's correlation coefficient r was used. A multiple regression analysis was performed to assess the impact of climate variation on crop yields by considering climate data (temperature and precipitation) that cover the period 1990 – 2021. The linear equation that explains the change in the yield as a function of minimum, maximum temperature, and precipitation is given as follows:

$$Y = c + b1 * Tmin + b2 * Tmax + b3 * P$$

Where Y is the yield (kg ha^{-1}), c is the intercept of the regression equation, and b1, b2 and b3 are the coefficients of Tmin (minimum temperature), Tmax (maximum temperature) and P (mm) is the precipitation.

3.4 Modelling the impact of integrated management on maize yields and soil organic carbon stock under climate change

3.4.1 Overview of DSSAT model

The DSSAT crop model, known as the Decision Support System for Agricultural Technology Transfer, is widely used by researchers around the world. Its popularity stems from its adeptness in simulating various aspects of crop development, growth, and yield. Additionally, its proficiency in modeling irrigation requirements and accounting for weather fluctuations, which in turn reflect the impacts of climate change, solidifies its reputation as one of the premier crop models available. The CERES-Maize module (Crop Environment Resource Synthesis) that is part of the DSSAT platform is used to simulate the crop growth and development including the phenology, above and belowground biomass formation and yield on a daily basis (Kamara et al., 2023; Wang et al., 2023). It can be used to simulate irrigation scheduling, technical agricultural practices, fertilizers application (inorganic and organic) management considering the effects of weather, soil water and nutrient dynamics. The model is based on a series of mathematical equations to represent the crop behavior to various management practices (Kamara et al., 2023). The minimum input data required by the model include weather data such as minimum and maximum temperature, rainfall, solar radiation, each on a daily basis, soil information (type, texture, pH, CEC, moisture, organic carbon, nitrogen content), crop management (planting date, planting density, row spacing, crop variety and crop genetic coefficient (Ghobadi et al., 2023).

The CENTURY model was included in the DSSAT to simulate soil organic carbon and nitrogen dynamics. After initializing the soil organic carbon at the start of the simulation, the model estimates the potential for soil organic carbon sequestration across various crop rotations over long periods of time (Jones et al., 2003a). Over time, the surface residues undergo decomposition, involving the simulated processes of nitrogen immobilization/mineralization by CENTURY model (Corbeels et al., 2016). Additionally, a portion of the organic matter undergoes transformation into more stable organic matter pools within the soil (Gijsman et al., 2002).

In this study, we use the CSM-CERES model in DSSAT to simulate maize growth, yield, and phenological development under varying climate conditions, soil characteristics, and management practices including using biochar, compost and mineral fertilizer.

3.4.2 Data collection and model input parameters

Daily weather data were obtained from the National Meteorological Agency (ANAMet) for the weather station located at the Coastal Center of Agronomic Research of the Togolese Institute for Agronomic Research (ITRA/CRAL) in Davié where the experimental field is based (Figure 7). Weather data included daily minimum and maximum temperature (°C), rainfall (mm) and solar radiation. Weather information was obtained from the meteorological agency of Togo, containing daily information of minimum and maximum temperatures, rainfall, and solar radiation. Any missing information was gap-filled with Nasa Power Access dataset (https://power.larc.nasa.gov/). The soil profile information used in this study to set up the model came from the SOTER Benin database (Igué et al., 2004) on the coordinates of the study area. The type of soil in the area is known as Haplic Acrisol (The characteristics are presented in table 5 below). We preferred to use this soil information rather than direct measurement soil information from the field due to some missing information that would limit the quality of the simulations.

Table 5: Soil profile characteristics used for model simulations from the SOTER Benin database

Depth (cm)	Clay (%)	Silt (%)	Organic Carbon	pH in water	CEC (cmol/kg)	Total nitrogen (%)	Lower limit	Drained upper limit	Saturation	Bulk density	Root growth factor
0 - 20	9	6	0.6	5.5	4	0.05	0.039	0.08	0.395	1.4	1
20 - 40	12	4	0.26	5	7	0.04	0.046	0.086	0.396	1.5	0.56
40 - 67	24	5	0.17	5.3	9	0.02	0.083	0.149	0.389	1.56	0.27
67 - 130	45	4	0.17	5.3	9	0.02	0.155	0.272	0.389	1.56	0.27

3.4.3 Model parameterization

The field experiment spanned three seasons over two years, with organic amendments applied at the start of the first season and again at the beginning of the third season. Setting up the model aimed to represent the organic and mineral applications for each treatment. Initially, the model was parameterized to simulate all seasons separately, but this approach revealed a limitation as it would run simulations on a year-to-year basis without including the changes to soil status resulting from previous seasons organic amendment application and residue incorporation. To address this, a sequential simulation within the DSSAT interface was configured to treat the experiments as crop rotations using the sequential analysis tool, so soil carry-over effect could be considered.

3.4.4 Model calibration and evaluation

The model was calibrated with the field experimental data from season 1 and 2 and evaluated with season 3. The model was calibrated using observed data from the treatments where the crops were less exposed to stress conditions: C1F1B0, C1F1B10, and C1F1B20. The calibration process involved two steps: (i) updating the cultivar coefficients starting from the phenological development concerning flowering and maturity dates (P1 and P5); (ii) then updating the kernel filling rate and the number of kernels per plant coefficients (G2 and G3). All the other parameter values remained as the same as the default maize cultivar OBATANPA, contained in DSSAT's cultivar database. The measured data used to calibrate the model phenology was the flowering and maturity dates; whereas LAI, aboveground biomass and maize grain yield data were used to calibrate crop growth parameters. The final parameter values were determined through an iterative optimization process implemented in R software. This automated procedure aimed to minimize the error between observed and predicted data returned defined by an objective function.

To evaluate the model, we used the remaining treatments data for the first two seasons, the experimental data for the minor season of 2023 and the major season of 2024. We based the assessment of the model performance on a comparison between observed and simulated data using different statistical indexes (Wallach et al., 2019): Relative Root Mean Square (RRMSE), coefficient of determination (r^2), and the index of agreement (d).

$$RRMSE = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n}(Oi)^2}}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P'_i| + |O'_i|)^2}\right]$$

The maize cultivar coefficients calibrated are presented in Table 6 below.

Table 6: Maize cultivar (SAMMAZ 52) calibrated results for seasons 1 and 2.

Cultivar	P1	P2	P5	G1	G3	PHINT
	(°C days)	(days)	(°C days)	(Nr)	(mg day^{-1})	(°C days)
Sammaz 52	300	0.520	930	550.4	8.30	50

P1: Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days, °C day, above a base temperature of 8 °C) during which the plant is not responsive to changes in photoperiod. P2: Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h). P5: Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 °C). G2: Maximum possible number of kernels per plant. G3: Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1}). PHINT: Phyllochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.

3.4.5 Climate scenarios

We extracted the climate data for the year periods 1981 to 2010, and 2040 to 2070 representing historical and future climate data. The extracted climate data included daily rainfall, minimum and maximum temperatures, and solar radiation to match the requirements of crop models (Srivastava et al., 2018).

For climate change simulations, we obtained the data using the Coupled Model Intercomparison Project Phase 6 (CMIP6) dataset. We used two SSPs among the SSPs developed by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014), namely SSP126 and SSP585.

The SSP126 (low-CO_2) depicts a world prioritizing sustainability: reduced emissions, a shift to renewable energies and equality, and reduced consumption leading to slower population growth. This ambitious scenario aims to limit global warming to 1.6°C by 2100. Conversely, the SSP585 scenario (high-CO_2) represents a "business as usual" trajectory. It assumes continued dependence on fossil fuels and high consumption, leading to a temperature rise of over 4.3°C by 2100 (Adusei et al., 2023). We selected these two scenarios (SSP126 and SSP585) because they represent opposite ends of the policy spectrum. SSP126 depicts a future with low greenhouse gas emissions, while SSP585 represents a scenario with high emissions. These contrasting trajectories translate into varying levels of radiative forcing, i.e. the amount of heat trapped by the atmosphere.

We selected 5 GCMs based on data availability from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP): UKESM1-0-LL: U.K. Earth System Model (https://cera-www.dkrz.de/WDCC/ui/cerasearch/cmip6?input=CMIP6.ScenarioMIP.MOHC.UKESM1-0-LL), MRI-ESM2-0: Meteorological Research Institute Earth System Model Version 2.0 (https://hero.epa.gov/hero/index.cfm/reference/details/reference_id/7713535), MPI-ESM1-2-HR: Max Planck Institute Earth System Model (https://cera-www.dkrz.de/WDCC/ui/cerasearch/cmip6?input=CMIP6.HighResMIP.MPI-M.MPI-ESM1-2-HR), IPSL-CM6A-LR: Institute Pierre-Simon Laplace (https://cmc.ipsl.fr/ipsl-climate-models/ipsl-cm6/) and GFDL-ESM4: Geophysical Fluid Science Laboratory-Earth System Modelling (https://www.gfdl.noaa.gov/earth-system-esm4/). The meteorological variables were bias-corrected to the 1980–2010 baseline using the quantile mapping bias-adjustment methodology of Lange (Lange, 2019).

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Results

4.1.1 Effect of biochar applied alone or in combination with compost and/or synthetic fertilizers (NPK and Urea) on soil physicochemical properties and maize yields

4.1.1.1 Soil organic carbon content and total nitrogen

Due to limited laboratory capacity, soil samples were collected only from the biochar treatments B0 (no biochar) and B20 (20 t ha^{-1}). The linear mixed-effects model analysis indicated that the application of 20 t ha^{-1} of biochar (BiocharB20) significantly increased soil organic carbon (SOC) content at 30 cm depth by 2.20 g kg^{-1} ($p < 0.05$). None of the other main factors, mineral fertilizer and compost, nor the two-way or three-way interactions showed statistically significant effects. Most two-way and three-way interactions even showed non-significant negative trends (Table 7). The figure below (Figure 11) illustrates the SOC levels across all treatment combinations. Regarding total nitrogen, the effects of treatments were small (Table 8). The total nitrogen levels across all treatments are presented in Figure 12.

Table 7: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts *on* soil organic carbon (SOC) content in 30 cm soil depth

Fixed effects	Estimate (g kg^{-1})	Std. Error (g kg^{-1})	p-value
(Intercept)	4.42	0.39	5.54E-08***
CompostC1	0.64	0.51	0.23
FertilizationF1	-0.52	0.48	0.30
BiocharB20	2.20	0.48	0.0006***
CompostC1:FertilizerF1	0.64	0.67	0.36
CompostC1:BiocharB20	-1.36	0.67	0.07
FertilizerF1:BiocharB20	-0.28	0.67	0.69
CompostC1:FertilizerF1:BiocharB20	-0.07	0.95	0.95

Intercept: Estimated soil organic carbon content for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

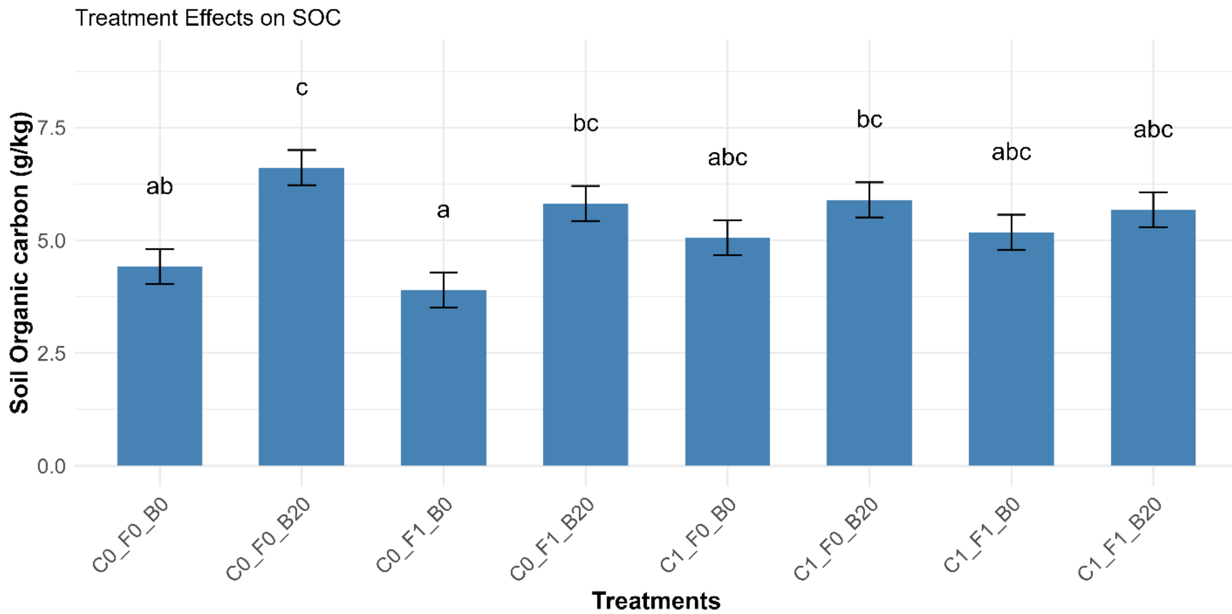

Figure 11: Treatment effects on soil organic carbon in 30 cm soil depth. Tukey adjustment applied for pairwise comparisons. Treatments with the same letters are not statistically different.

Table 8: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts *on* soil total nitrogen content in 30 cm soil depth

	Estimate ($g\ kg^{-1}$)	**Std. Error ($g\ kg^{-1}$)**	**p-value**
(Intercept)	3.77E-01	2.58E-02	9.45E-08***
CompostC1	3.33E-02	3.65E-02	0.38
FertilizerF1	-3.33E-02	2.62E-02	0.23
BiocharB20	4.67E-02	2.62E-02	0.10
CompostC1:FertilizerF1	8.50E-02	3.70E-02	0.04*
CompostC1:BiocharB20	-2.33E-02	3.70E-02	0.54
FertilizerF1:BiocharB20	-1.59E-16	3.70E-02	1
CompostC1:FertilizerF1:BiocharB20	-5.33E-02	5.23E-02	0.33

Intercept: Estimated total nitrogen content for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in Table S2.

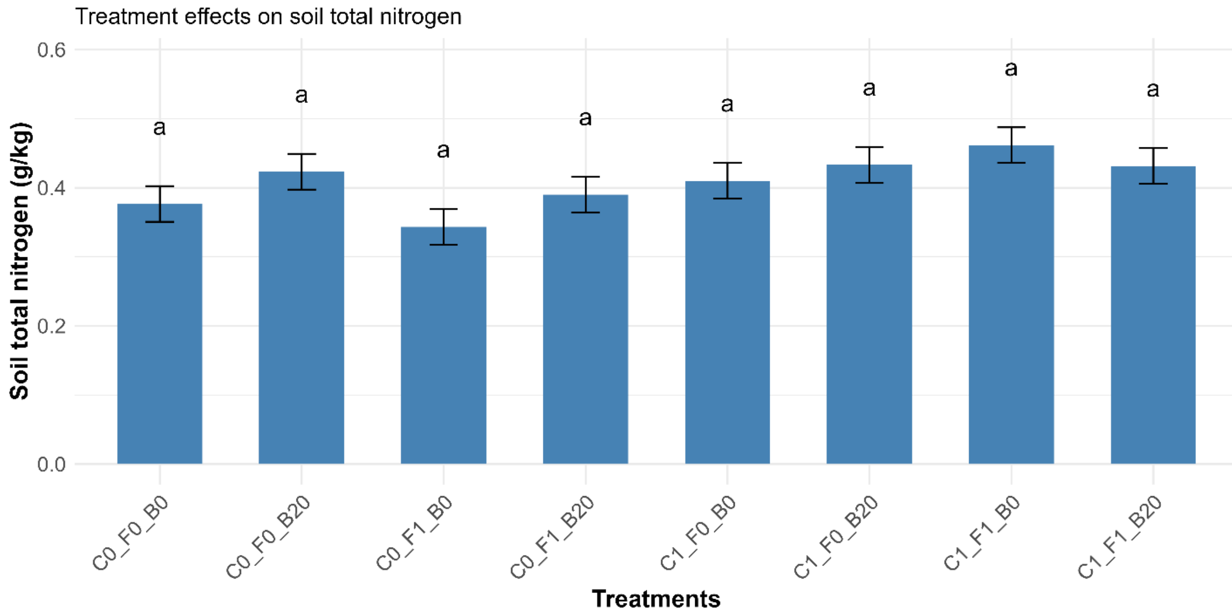

Figure 12: Treatment effects on soil total nitrogen in 30 cm soil depth. Tukey adjustment applied for pairwise comparisons. Treatments with the same letters are not statistically different.

4.1.1.2 Leaf Area Index

Table 9 presents the results of the linear mixed-effects model analyzing the maximum leaf area index (LAI) near the flowering stage. In the first growing season, all three individual factors compost, mineral fertilizer, and biochar significantly increased LAI. Specifically, compost application (CompostC1) increased LAI by 0.63 m^2 m^{-2} (Estimate = 0.63 m^2 m^{-2}, $p = 0.001$), mineral fertilizer (FertilizerF1) by 1.24 units (Estimate = 1.24, $p < 0.0001$), biochar at 10 t ha^{-1} (BiocharB10) by 0.68 units (Estimate = 0.68, $p = 0.0004$), and biochar at 20 t ha^{-1} (BiocharB20) by 0.76 units (Estimate = 0.76, $p = 0.0001$). While several two-way interactions had significant negative effects on LAI, a three-way interaction involving compost, mineral fertilizer, and 10 t ha^{-1} of biochar had a significant positive effect (Estimate = 0.76, $p = 0.036$). The corresponding three-way interaction with 20 t ha^{-1} of biochar showed only a marginal effect (Estimate = 0.60, $p = 0.093$).

In the second growing season, neither the individual factors nor their interactions had statistically significant effects on LAI. During the third season, no significant effects were observed for the individual treatments. However, some two-way interactions had significant positive effects, notably CompostC1 × FertilizerF1 and FertilizerF1× BiocharB20. In contrast, the three-way interaction involving CompostC1, FertilizerF1, and 20 t ha^{-1} of biochar showed a significant negative impact on LAI (Estimate = –0.71, p = 0.03).

Table 9: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on leaf area index across three growing seasons

	Estimate (m^2 m^{-2})	Std. Error (m^2 m^{-2})	p-value
Season 1			
(Intercept)	1.74	0.13	1.85E-15***
CompostC1	0.63	0.17	0.001**
FertilizerF1	1.24	0.17	3.66E-08***
BiocharB10	0.68	0.17	0.0004***
BiocharB20	0.76	0.17	0.0001***
CompostC1:FertilizerF1	-0.55	0.25	0.03*
CompostC1:BiocharB10	-0.55	0.25	0.03*
CompostC1:BiocharB20	-0.56	0.25	0.03*
FertilizerF1:BiocharB10	-0.70	0.25	0.007**
FertilizerF1:BiocharB20	-0.30	0.25	0.23
CompostC1:FertilizerF1:BiocharB10	0.76	0.35	0.04*
CompostC1:FertilizerF1:BiocharB20	0.60	0.35	0.09
Season 2			
(Intercept)	2.13	0.25	3.98E-05***
CompostC1	-0.18	0.23	0.43
FertilizerF1	0.37	0.22	0.10
BiocharB10	-0.18	0.22	0.41
BiocharB20	0.18	0.22	0.42
CompostC1:FertilizerF1	0.42	0.31	0.18
CompostC1:BiocharB10	0.48	0.31	0.13
CompostC1:BiocharB20	0.23	0.31	0.46
FertilizerF1:BiocharB10	0.43	0.31	0.17
FertilizerF1:BiocharB20	-0.03	0.31	0.92
CompostC1:FertilizerF1:BiocharB10	-0.36	0.44	0.42
CompostC1:FertilizerF1:BiocharB20	-0.27	0.44	0.55
Season 3			
(Intercept)	1.74	0.21	5.30E-05***
CompostC1	0.35	0.20	0.11
FertilizerF1	0.19	0.16	0.26
BiocharB10	-0.11	0.16	0.51
BiocharB20	-0.004	0.16	0.98
CompostC1:FertilizerF1	0.56	0.23	0.02*
CompostC1:BiocharB10	-0.14	0.23	0.54
CompostC1:BiocharB20	0.40	0.23	0.08
FertilizerF1:BiocharB10	0.43	0.23	0.07

FertilizerF1:BiocharB20	0.56	0.23	0.02*
CompostC1:FertilizerF1:BiocharB10	-0.11	0.32	0.73
CompostC1:FertilizerF1:BiocharB20	-0.71	0.32	0.03*

Intercept: Estimated LAI for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: p < 0.001; **: p < 0.01; * : p < 0.05. The random effects are provided in the annex.

4.1.1.3 Aboveground biomass

The results of the linear mixed-effects model on aboveground biomass are presented in Table 10. For this analysis, season 1 data on aboveground biomass was ignored due to some inconsistencies in data collection that led to biased results. The analysis indicated that, in the second season, compost, mineral fertilizer, and biochar application rates each had a statistically significant effect on aboveground biomass yield. Compost application (CompostC1) resulted in a biomass increase of 2,382.8 kg ha^{-1} ($p = 0.020$), while mineral fertilizer (FertilizerF1) significantly enhanced biomass by 2,812.5 kg ha^{-1} ($p = 0.0066$). Biochar application at 10 t ha^{-1} (BiocharB10) and 20 t ha^{-1} (BiocharB20) increased biomass by 2,460.9 kg ha^{-1} ($p = 0.020$) and 2,851.6 kg ha^{-1} ($p = 0.006$), respectively. However, none of the two-way or three-way interactions among these factors were statistically significant ($p > 0.05$). In the third season, no significant effects of compost, fertilizer, or biochar application were observed on aboveground biomass yield.

Table 10: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on aboveground biomass yield across two growing seasons

	Estimate (kg ha^{-1})	Std. Error (kg ha^{-1})	p-value
Season 2			
(Intercept)	3906.20	689.30	1.94E-06***
CompostC1	2382.80	974.90	0.02*
FertilizerF1	2812.50	974.90	0.01**
BiocharB10	2460.90	974.90	0.02*
BiocharB20	2851.60	974.90	0.01**
CompostC1:FertilizerF1	-742.20	1378.70	0.59
CompostC1:BiocharB10	-1875.00	1378.70	0.18
CompostC1:BiocharB20	-1796.90	1378.70	0.20
FertilizerF1:BiocharB10	-898.40	1378.70	0.52
FertilizerF1:BiocharB20	-2070.30	1378.70	0.14
CompostC1:FertilizerF1:BiocharB10	898.40	1949.70	0.65

CompostC1:FertilizerF1:BiocharB20	3554.70	1949.70	0.08
Season 3			
(Intercept)	6953.12	1318.73	9.55E-06 ***
CompostC1	1406.25	1822.63	0.45
FertilizerF1	1835.94	1703.35	0.29
BiocharB10	664.06	1703.35	0.70
BiocharB20	1328.13	1703.35	0.44
CompostC1:FertilizerF1	-703.13	2408.9	0.77
CompostC1:BiocharB10	-1757.81	2408.9	0.47
CompostC1:BiocharB20	-1523.44	2408.9	0.53
FertilizerF1:BiocharB10	273.44	2408.9	0.91
FertilizerF1:BiocharB20	742.19	2408.9	0.76
CompostC1:FertilizerF1:BiocharB10	2382.81	3406.69	0.49
CompostC1:FertilizerF1:BiocharB20	2968.75	3406.69	0.39

Intercept: Estimated aboveground biomass yield for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

4.1.1.4 Effect on grain yield

The linear mixed-effects model analysis revealed that in the first season, mineral fertilization had a statistically significant effect on maize yield (Estimate = 599.33 kg ha^{-1}, p = 0.02), indicating that its application increased grain yield by approximately 599 kg ha^{-1}. Although the yield estimates were positive for compost (Estimate = 154.02 kg ha^{-1}, p = 0.53), biochar at 10 t ha^{-1} (Estimate = 204.80 kg ha^{-1}, p = 0.40), and biochar at 20 t ha^{-1} (Estimate = 330.92 kg ha^{-1}, p = 0.18), none of these treatments individually had a statistically significant effect. Similarly, no significant two-way interactions were observed among compost, fertilizer, and biochar ($p > 0.05$). However, a significant three-way interaction among these factors was detected (Estimate = 1478.79 kg ha^{-1}, p = 0.0041), suggesting that their combined application substantially increased maize yield.

In the second season, maize yield significantly increased under fertilizer application (Estimate = 1006.70 kg ha^{-1}, p = 0.007) and biochar at 20 t ha^{-1} (Estimate = 782.37 kg ha^{-1}, p = 0.03). The effect of biochar at 10 t ha^{-1} was marginally significant (Estimate = 603.24 kg ha^{-1}, p = 0.09), while compost had no significant impact (p = 0.56). None of the two-way or three-way interactions were statistically significant during this season.

In the third season, only mineral fertilization significantly increased maize yield (Estimate = 511.72 kg ha^{-1}, p = 0.01), with no other treatment or interaction showing significant effects. Even though 20 t ha^{-1} of biochar had a positive effect on maize yield, it was only marginal (Estimate = 367.19 kg ha^{-1}, p = 0.07). The results are presented in Table 11.

Table 11: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on maize yield across three growing seasons

	Estimate (kg ha^{-1})	Std. Error (kg ha^{-1})	p-value
Season 1			
(Intercept)	886.16	176.48	1.64E-05***
CompostC1	154.02	239.7	0.525
FertilizerF1	599.33	239.7	0.0176*
BiocharB10	204.8	239.7	0.40
BiocharB20	330.92	239.7	0.18
CompostC1:FertilizerF1	-265.07	338.98	0.44
CompostC1:BiocharB10	-169.64	338.98	0.62
CompostC1:BiocharB20	-313.06	338.98	0.362
FertilizerF1:BiocharB10	-257.25	338.98	0.45
FertilizerF1:BiocharB20	-652.9	338.98	0.06
CompostC1:FertilizerF1:BiocharB10	563.62	479.39	0.25
CompostC1:FertilizerF1:BiocharB20	1478.79	479.39	0.004**
Season 2			
(Intercept)	1324.78	268.45	2.65E-05***
CompostC1	217.08	366.27	0.56
FertilizerF1	1006.7	345.89	0.0067**
BiocharB10	603.24	345.89	0.09
BiocharB20	782.37	345.89	0.03*
CompostC1:FertilizerF1	282.92	489.16	0.57
CompostC1:BiocharB10	82.59	489.16	0.87
CompostC1:BiocharB20	589.29	489.16	0.24
FertilizerF1:BiocharB10	-89.84	489.16	0.86
FertilizerF1:BiocharB20	394.53	489.16	0.43
CompostC1:FertilizerF1:BiocharB10	-363.28	691.78	0.60
CompostC1:FertilizerF1:BiocharB20	-569.2	691.78	0.42
Season 3			
(Intercept)	424.11	243.63	0.11
CompostC1	487.72	328.56	0.19
FertilizerF1	511.72	192.83	0.01*
BiocharB10	102.68	192.83	0.60
BiocharB20	367.19	192.83	0.07
CompostC1:FertilizerF1	69.20	272.70	0.80
CompostC1:BiocharB10	101.56	272.70	0.71
CompostC1:BiocharB20	95.98	272.70	0.73
FertilizerF1:BiocharB10	94.87	272.70	0.73

FertilizerF1:BiocharB20	-24.55	272.70	0.93
CompostC1:FertilizerF1:BiocharB10	91.52	385.66	0.81
CompostC1:FertilizerF1:BiocharB20	-47.43	385.66	0.90

Intercept: Estimated yield for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

4.1.1.5 Relative yield change

The comparative yield analysis revealed that most treatments showed an increase in yield from Season 1 to Season 2, with some exceeding 100%. However, from Season 2 to Season 3 and overall, from Season 1 to Season 3, nearly all treatments exhibited negative relative changes (Table 12).

Table 12: Average relative yields and yield changes across seasons

Treatments	Yields_S1	Yields_S2	Yields_S3	Rel_Change_S2_S1 (%)	Rel_Change_S3_S2 (%)	Rel_Change_S3_S1 (%)
C0F0B0	886.16±301.17	1324.78±684.86	424.11±220.26	48.11±68.25	-60.97±22.18	-52.94±14.02
C0F0B10	1090.96±84.73	1928.01±558.88	526.79±280.84	78.63±55.18	-72.92±10.12	-52.16±24.29
C0F0B20	1217.08±30.02	2107.14±768.35	791.29±216.19	74.02±67.19	-60.44±12.75	-34.88±18.40
C0F1B0	1485.49±345.06	2331.47±265.71	935.83±413.87	63.85±43.23	-60.41±16.61	-30.24±45.62
C0F1B10	1433.04±530.18	2844.87±470.03	1133.37±270.34	112.79±58.05	-59.20±13.11	-13.94±32.88
C0F1B20	1163.50±513.41	3508.37±521.07	1278.46±274.35	255.72±181.34	-62.32±11.70	31.67±80.90
C1F0B0	1040.18±410.26	1541.85±493.79	911.83±83.31	62.51±64.32	-36.50±20.67	-1.20±38.18
C1F0B10	1075.33±535.41	2227.68±125.57	1116.07±542.27	150.04±121.70	-50.21±23.53	7.12±30.30
C1F0B20	1058.04±250.92	2913.50±900.52	1375.00±395.26	182.41±98.63	-48.58±20.78	30.87±26.57
C1F1B0	1374.44±139.53	2831.47±468.08	1492.75±581.30	106.82±34.94	-46.74±20.57	10.41±44.66
C1F1B10	1715.96±223.04	3064.17±100.08	1883.37±825.60	80.64±22.54	-38.42±26.53	6.83±34.59
C1F1B20	2218.19±381.21	4028.46±473.97	1883.93±937.33	83.05±13.63	-51.91±25.16	-11.46±49.37

Rel: Relative, S1: Season 1; S2: Season 2; S3: Season 3. Treatment details are presented in Table 1.

4.1.1.6 Correlation between maize studied parameters, soil C and N

The heatmap below (Figure 13) explains the relationship between plant parameters, SOC and Total Nitrogen. The positive correlations are represented in blue while negative correlations are in red. The color intensity and the size of the circle are related to the correlation coefficients to explain the strength of the relationship. The legend on the right side uses color to represent correlation coefficients and explains the meaning of each color. As is shown in the figure, a positive correlation is observed between maize growth parameters, SOC, and total nitrogen. As a result, during the second cropping season, maize grain yield was positively correlated to Thousand Grain Yield (r = 0.97), LAI (r = 0.91), Number of Leaves (r = 0.9), Aboveground biomass (r = 0.88), Harvest Index (r = 0.76), Crop Height (r = 0.75), SOC (r = 0.46), and Total Nitrogen (r = 0.4). In contrast to other parameters, the GY was negatively correlated to the Anthesis date (r = -0.79) explaining that earlier flowering might result in high yields. As in the second season, the correlations were overall positive in the third season. However, the relationships were somehow stronger than in the second season. The Grain Yield, for instance, was positively correlated to the LAI (r = 0.94), Plant Height (r = 0.92), Thousand Grain Weight (r = 0.92), Harvest Index (r = 0.9), Straw Yield (r = 0.83), Number of Leaves (r = 0.67), Total Nitrogen (r = 0.64), and SOC (r = 0.37). Only with the Anthesis Date, a negative correlation was observed.

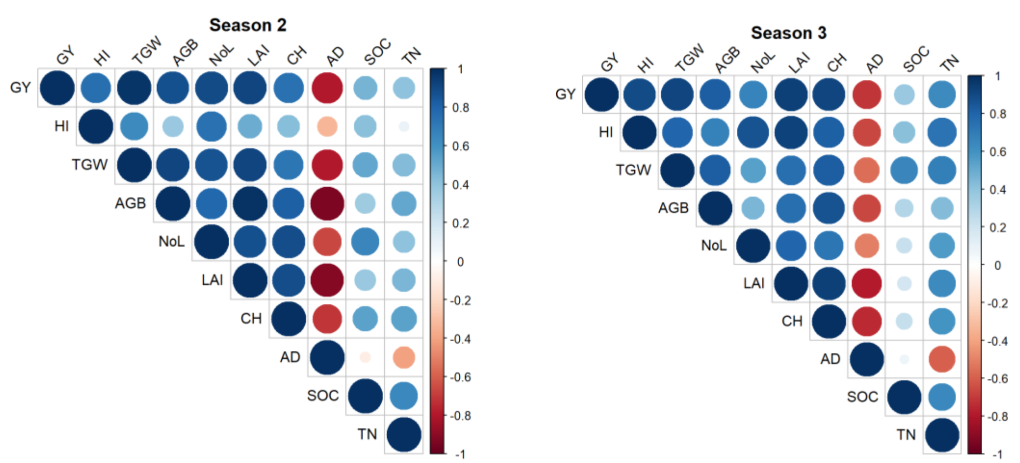

Figure 13: Correlation matrix between yield, yield components, and soil parameters for seasons 2 and 3. GY: Grain Yield (kg ha^{-1}); HI: Harvest Index; TGW: Thousand Grain Weight (g); AGB: Aboveground biomass (kg ha^{-1}); NoL: Number of Leaves; LAI: Leaf Area Index; CH: Crop Height (cm); AD: Anthesis Date (Days After Sowing); SOC: Soil Organic Carbon (g kg^{-1}) of 30 cm soil depth; TN: Soil Total Nitrogen (g kg^{-1}) of 30 cm soil depth. The color intensity and the size of the circle are related to the correlation coefficients to explain the strength of the relationship.

4.1.2 Effect of biochar applied alone or in combination with compost and/or inorganic fertilizer (NPK) on different soil SOC fractions, bulk density and on soil carbon sequestration

4.1.2.1 Soil bulk density

The bulk density results are presented in Table 13. The linear mixed-effect model analysis revealed a significant decrease in bulk density value when compost was applied. The bulk density decreased by 0.19 g cm^{-3} (Estimate = -0.19 g cm^{-3}; $p = 0.03$) when compost is applied. Also, the two-way interaction between mineral fertilizer and biochar showed a significant decrease (Estimate = -0.23 g cm^{-3}; $p = 0.04$). The rates of biochar, mineral fertilizer, and the remaining two-way and three-way interactions did not show a significant influence.

Table 13: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on soil bulk density in 30 cm soil depth

	Estimate (g cm^{-3})	**Std. Error (g cm^{-3})**	**p-value**
(Intercept)	1.70	0.06	1.08E-14***
CompostC1	-0.19	0.08	0.03*
FertilizerF1	-0.01	0.07	0.91
BiocharB20	-0.01	0.07	0.87
CompostC1:FertilizerF1	0.06	0.10	0.58
CompostC1:BiocharB20	0.13	0.10	0.24
FertilizerF1:BiocharB20	-0.23	0.10	0.04*
CompostC1:FertilizerF1:BiocharB20	0.15	0.15	0.31

Intercept: Estimated bulk density for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

4.1.2.2 Soil organic stock and stock change

As biochar application significantly affects SOC content (Table 7), we observed a similar pattern for SOC stock (Table 14). When biochar was applied, the SOC stock significantly increased by 10.98 Mg C ha^{-1} (Estimate = 10.98 Mg C ha^{-1}; $p = 0.002$). Factors rate of compost and rate of mineral fertilizer, and the two and three-way interactions did not influence SOC stock. A similar trend was noticed in terms of SOC stock change (Table 15).

Table 14: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on SOC stock in 30 cm soil depth

	Estimate Mg C ha^{-1}	**Std. Error Mg C ha^{-1}**	**p-value**
(Intercept)	22.47	2.17	4.16E-08***
CompostC1	0.24	2.89	0.93
FertilizerF1	-2.74	2.89	0.36
BiocharB20	10.98	2.89	0.002**
CompostC1:FertilizerF1	4.00	4.08	0.34
CompostC1:BiocharB20	-4.88	4.08	0.25
FertilizerF1:BiocharB20	-5.29	4.08	0.22
CompostC1:FertilizerF1:BiocharB20	2.28	5.77	0.70

Intercept: Estimated SOC stock for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

Table 15: Estimated fixed effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on SOC stock change

	Estimate Mg C ha^{-1}	**Std. Error Mg C ha^{-1}**	**Pr(>|t|)**
(Intercept)	1.70	0.06	1.08E-14
CompostC1	-0.19	0.08	0.03
FertilizerF1	-0.01	0.07	0.91
BiocharB20	-0.01	0.07	0.87
CompostC1:FertilizerF1	0.06	0.10	0.58
CompostC1:BiocharB20	0.13	0.10	0.24
FertilizerF1:BiocharB20	-0.23	0.10	0.04
CompostC1:FertilizerF1:BiocharB20	0.15	0.15	0.31

Intercept: Estimated SOC stock change for the reference group (C0F0B0), CompostC1: (compost application), F1: (mineral fertilizer application), BiocharB10: (10 t ha^{-1} of biochar), BiocharB20: (20 t ha^{-1} of biochar). ***: $p < 0.001$; **: $p < 0.01$; * : $p < 0.05$. The random effects are provided in the annex.

4.1.2.3 Soil organic carbon concentration in fractions

Table 16 shows the SOC content in the three different soil fractions. Regardless of the treatments, the fine particulate organic matter (fPOM) showed the highest SOC concentration 5.04 – 13.53 g kg^{-1}. In the meantime, the coarse particulate organic matter (cPOM) and medium particulate organic matter (mPOM) exhibited the lowest SOC concentrations 0.52 – 4.27 g kg^{-1}. Significant differences were observed in the three fractions (cPOM, $p = 0.0241$; mPOM, $p = 0.00693$; fPOM, $p = 0.00115$) where the treatment with biochar associated to compost (C1F0B20) showed the highest SOC concentration in the cPOM and mPOM and the treatment with only biochar application (C0F0B20) showed the highest SOC concentration in the fPOM. The SOC in the cPOM of the treatment C1F0B20 was 1.26 g kg^{-1} which represents an increase of 121.05% compared to the control treatment (C0F0B0), also it was 4.27 g kg^{-1} in the mPOM corresponding to an increase of 427.16% compared to the control treatment. In the fPOM, the SOC increased by 168.45% and 149.4% for the treatments C0F0B20 and C0F1B20 respectively. Interestingly, the control treatment (C0F0B0) showed the lowest values in the fPOM fractions, while in the cPOM and mPOM fractions, the lowest SOC concentration was noted with the C0F1B0 (treatment with only mineral fertilizer).

Table 16: Treatments effects on soil organic carbon concentration in different soil fractions

Treatments	Soil organic carbon concentration (%)		
	cPOM	mPOM	fPOM
C1F1B20	1.17±0.11 a	3.19±1.13 ab	10.18±2.78 ab
C1F1B0	0.88±0.22 ab	1.18±0.16 bc	8.24±0.82 bc
C1F0B20	1.26±0.58 a	4.27±2.77 a	10.86±1.75 ab
C1F0B0	0.9±0.1 ab	1.33±0.51 bc	7.57±1.63 bc
C0F1B20	1.07±0.33 a	3.52±1.19 a	12.57±3.65 a
C0F1B0	0.52±0.07 b	0.79±0.09 c	6.48±0.76 c
C0F0B20	1.17±0.23 a	3.71±0.96 a	13.53±1.27 a
C0F0B0	0.57±0.05 b	0.81±0.17 c	5.04±2.03 c

cPOM: coarse Particulate Organic Matter; mPOM: middle Particulate Organic Matter; fPOM: fine Particulate Organic Matter; (Refer to Table 2 for treatment descriptions)

4.1.2.4 Share of organic carbon in fractions

The share of organic carbon in the different fractions are presented in table 17 below. In the cPOM fraction, none of the treatments produced significantly ($p<0.05$) high share of organic carbon even if the treatment C1F0B20 seems to produce the highest share of organic carbon and the control treatment, the lowest one. Regarding the mPOM fraction, the ANOVA test revealed significant differences among treatments ($p = 0.03$). The treatment C1F0B20 produced the highest share of organic carbon. Compared to the control treatment, the produced share of organic carbon increased by 285.34%. In the fPOM fraction, the treatment C0F1B20 is the one who produced the highest share of organic carbon ($p<0.04$), leading to 68.39% increase compared to the control treatment. Interestingly, regarding the NonPOM fraction which is the more stable fraction, the behavior was different. The control treatment showed the highest share of organic carbon, while the treatment

C1F0B20 presented the lowest share of organic carbon. Considering the POM fraction as the sum of cPOM, mPOM, and fPOM fractions, the treatment C1F0B20 produced the highest share of organic carbon (p = 0.05), which is equivalent to 120.48% increase compared to the control. Overall, the treatments with biochar application presented better results compared to the case of no biochar application.

Table 17: Treatment effects on the share of organic carbon of the different soil fractions

Treatments	Share of organic carbon (%)				
	cPOM	mPOM	fPOM	NOM	POM
C1F0B20	12.32±6.83 a	20.77±15.57 a	9.44±0.21 ab	57.47±22.44 c	42.53±22.44 a
C0F0B20	9.26±2.61 a	16.48±4.08 ab	11.65±2.03 ab	62.61±7.84 bc	37.39±7.84 ab
C0F1B20	10.04±2.3 a	15.72±2.26 abc	11.72±2.21 a	62.52±6.67 bc	37.48±6.67 ab
C1F1B20	12.2±2.85 a	10.99±1.93 abcd	9.39±1.94 ab	67.41±3.73 abc	32.59±3.73 abc
C1F0B0	9.99±1.68 a	6.57±1.39	8.33±1.34 b	75.1±2.78 ab	24.9±2.78 bc
C1F1B0	9.06±2.43 a	6.41±1.75 bcd	9.59±1.51 ab	74.94±5.6 ab	25.06±5.6 bc
C0F1B0	7.33±1.7 a	5.65±0.51 cd	8.27±1.18 b	78.75±1.03 a	21.25±1.03 c
C0F0B0	6.95±1.37 a	5.39±0.77 d	6.96±2.13 b	80.71±1.66 a	19.29±1.66 c

cPOM: coarse Particulate Organic Matter; mPOM: middle Particulate Organic Matter; fPOM: fine Particulate Organic Matter; NOM: Non Organic Matter; POM: Particulate Organic Matter

4.1.3 Climate variability on maize yield in southern Togo

4.1.3.1 Maximum and minimum temperatures trends analysis

Figures 14, 15, 16, and 17 present minimum and maximum temperatures from 1980 to 2022 in Lomé and Tabligbo. The Mann-Kendall and Sen's slope tests showed significant ($p<0.0001$) increasing trends in maximum and minimum temperatures at all locations. The magnitude differs from one location to another. Minimum temperatures increased by 0.05°C per year in Lomé, and 0.03°C in Tabligbo. Likewise, maximum temperatures increased by 0.03°C per year in Lomé and Tabligbo (Table 1). The annual average minimum temperature in Lomé ranged from 22.43°C to 25.61°C, from 22.08°C to 25°C in Tabligbo. The average maximum temperature varied from 30.53

to 32.63°C in Lomé and 32.17 to 34.47°C in Tabligbo. Lomé experienced the highest minimum and maximum temperature variability (3.01% and 1.67% respectively) followed by Tabligbo (2.51% and 1.51% respectively). By considering the maize growing period (April – July) in Tabligbo by 0.03°C per year (Table 18).

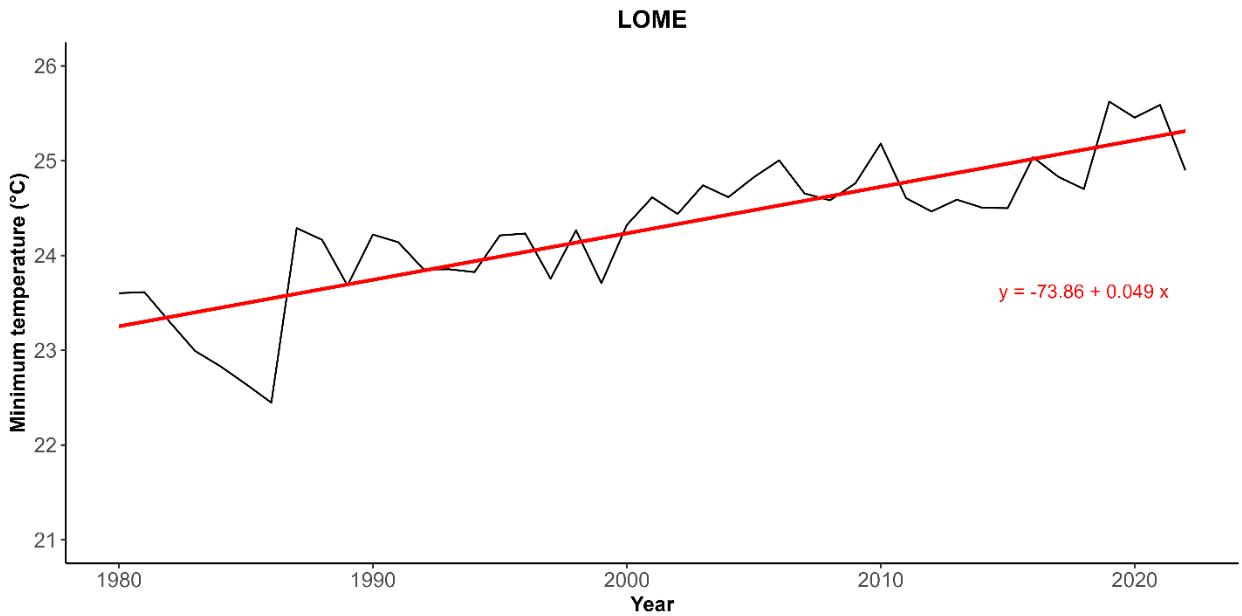

Figure 14: Minimum temperature in Lomé, from 1980 to 2022

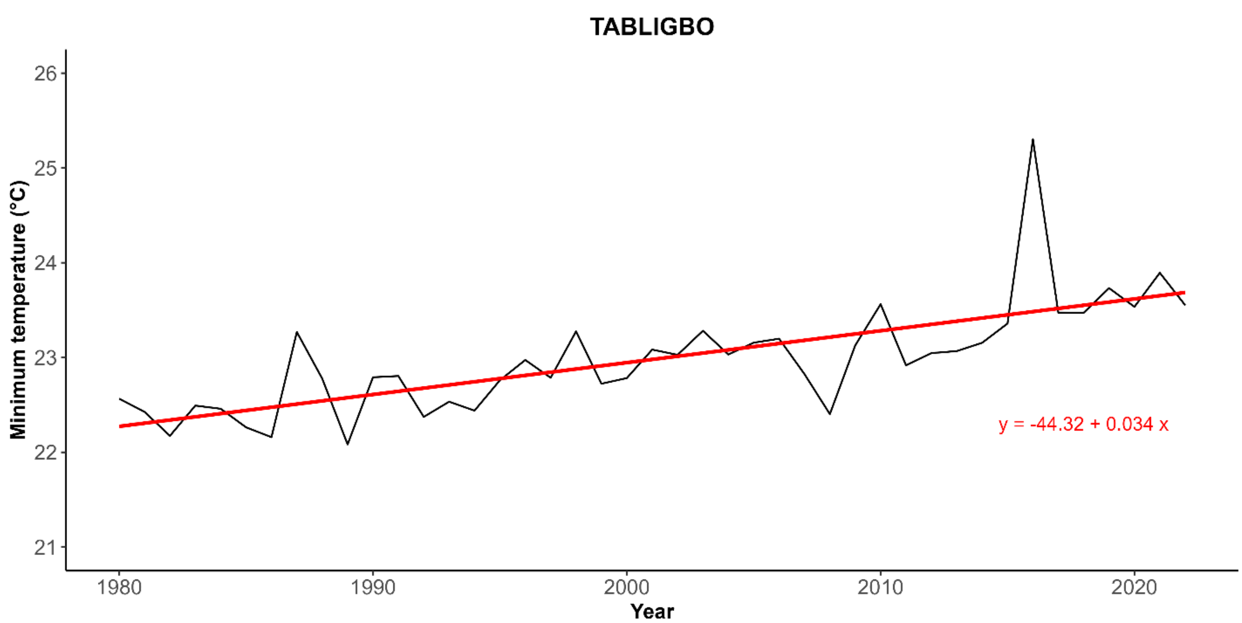

Figure 15: Maximum temperature in Tabligbo from 1980 to 2022.

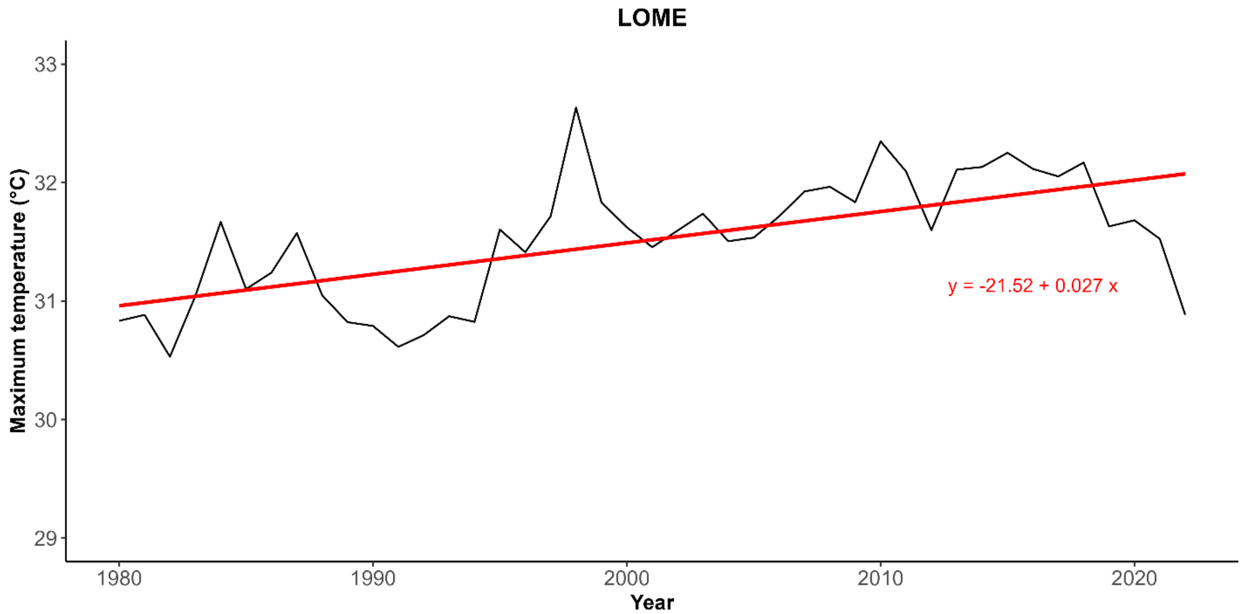

Figure 16: Maximum temperature in Lomé from 1980 to 2022

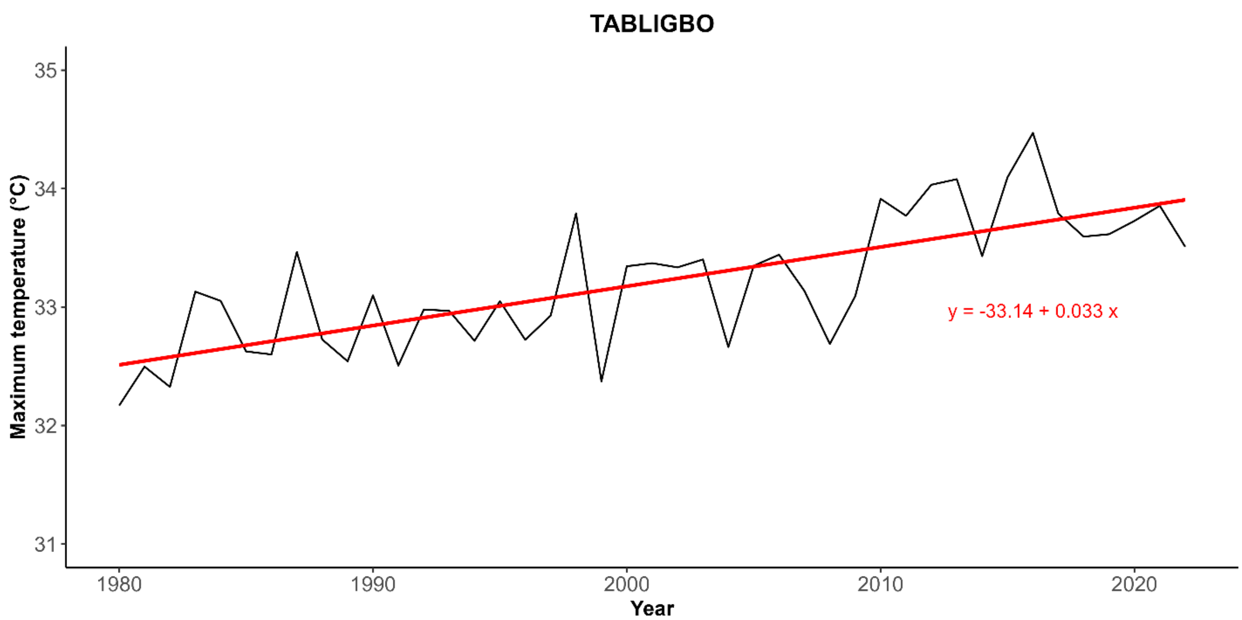

Figure 17: Maximum temperature in Tabligbo from 1980 to 2022

4.1.3.2 Rainfall trends analysis

The average rainfall of the two locations is presented in figures 18 and 19. In Lomé, the annual rainfall values were between 423.9 and 1416.7 mm with a coefficient of variation of 24.45% and an average of 825.36 mm from 1980 to 2022, in Tabligbo between 706.1 and 1428.2 mm with an average of 1041.58 mm and a coefficient of variation of 16.19%. The number of rainy days varies at different stations. In Lomé, the number of rainy days varies from 52 to 120 rainy days with an average of 79 days and in Tabligbo it varies from 68 to 110 rainy days with an average of 91 days. The Mann-Kendall and Sen's Slope tests revealed slight increases at all locations. The rainfall significantly increases ($p<0.05$) in Lomé and Tabligbo by 2.29 and 1.6 mm per year respectively (Table 18). By considering considering the growing season of maize (April – July), the rainfall significantly increased ($p<0.01$) in Tabligbo by 2.4 mm per year (Table 19).

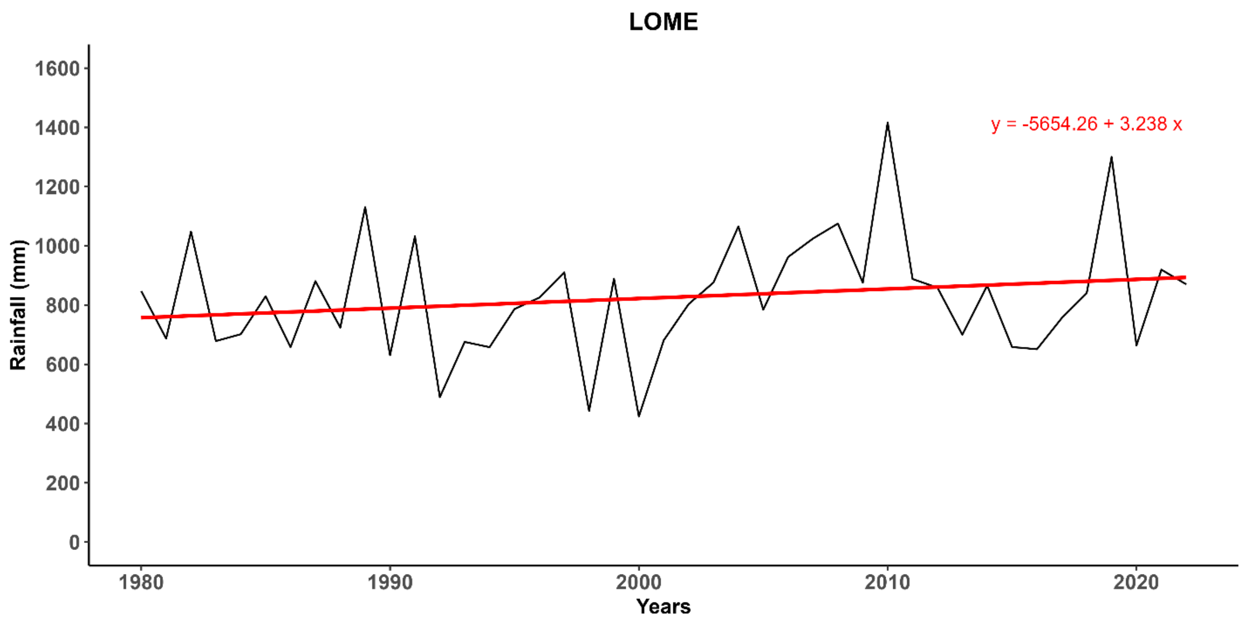

Figure 18: Rainfall in Lomé from 1980 to 2022

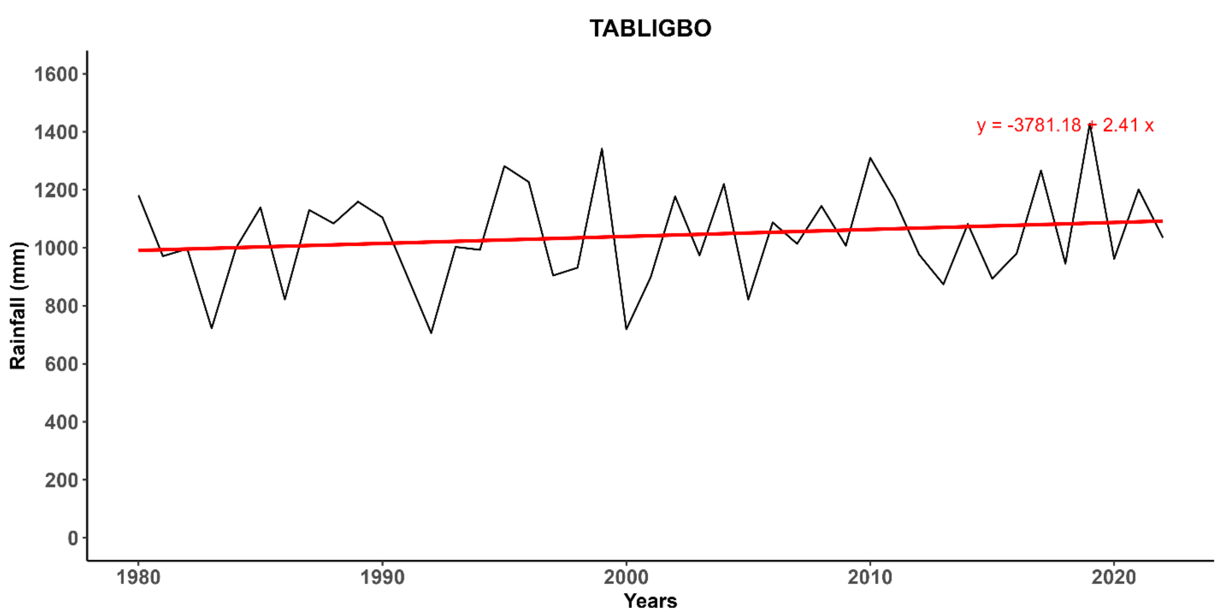

Figure 19: Rainfall in Tabligbo from 1980 to 2022

Table 18: Sen's slope values for annual rainfall, minimum and maximum temperature

Location	Sen's slope	p-value	Alpha Value	Significance
Rainfall (mm)				
Lomé	2.29	0.03	0.05	Yes
Tabligbo	1.6	0.005	0.01	Yes
Minimum temperature (°C)				
Lomé	0.05	6E-27	0.01	Yes
Tabligbo	0.03	5E-41	0.01	Yes
Maximum temperature (°C)				
Lomé	0.03	6E-11	0.01	Yes
Tabligbo	0.03	1E-47	0.01	Yes

Table 19: Sen's slope values for rainfall, the minimum and maximum temperature during the growing period of maize in Tabligbo

Variables	Sen's slope	p-value	Alpha Value	Significance
Rainfall (mm)	2.40	3.02E-07	0.01	Yes
Minimum temperature (°C)	0.03	2.66E-37	0.01	Yes
Maximum temperature (°C)	0.03	9.23E-33	0.01	Yes

4.1.3.3 Rainy days trend analysis

Figure 20 shows the trends in the number of rainy days from 1980 to 2022 in Lomé and Tabligbo. In Tabligbo, the number of rainy days decreased minimally ($p>0.05$) by 0.1 days per year. In Lomé, a slightly non-significative increasing trend was observed by 0.03 days per year.

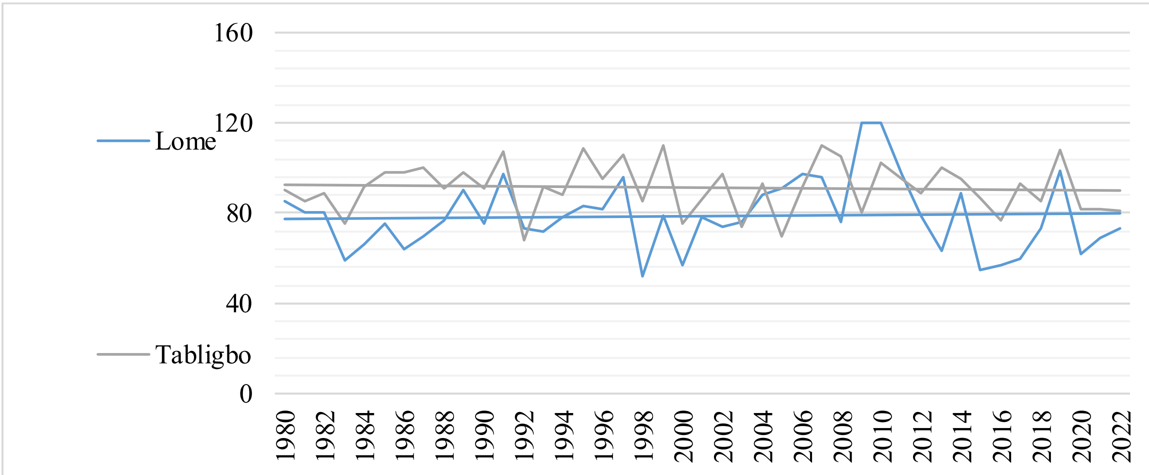

Figure 20: Rain days trends in Lomé and Tabligbo from 1980 to 2022

4.1.3.4 Crop yields trends

The crop yield analysis revealed a positive trend from 1990 to 2021 in Tabligbo (Figure 21). Maize yield significantly increased by 4 kg ha^{-1}, per year ($p<0.05$). The average yield was 754.69 kg/ha with a coefficient of variation of 18.2%.

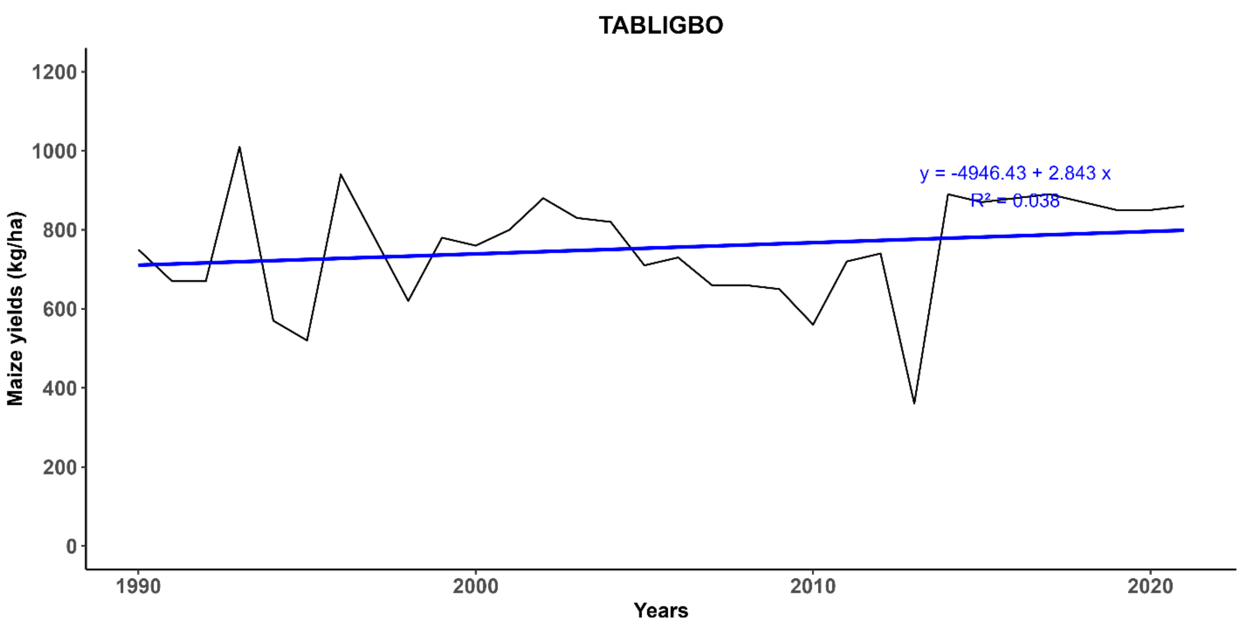

Figure 21: Maize yield trends in Tabligbo from 1990 to 2021. (R^2 = coefficient of determination)

4.1.3.5 Impact of climatic variables on maize yields

The results of the multiple linear regression analysis estimating maize yields change related to climate variables such as minimum and maximum temperatures, and rainfall during the growing season of maize are shown in Table 20. From these results, no significant impact on climate variables (precipitation, minimum and maximum temperature) was revealed in Tabligbo. A non-significant ($p>0.05$) positive impact of rainfall and minimum temperature on maize yields was observed.

Table 20: Multiple regression analysis during growing seasons

Location	Intercept	Tmin (°C)	Tmax (°C)	Rainfall (mm)	R square
Tabligbo					
Coefficient	-3.29901	0.13629	-0.10608	0.000065	0.1748
P-Value	0.607663	0.074773	0.154795	0.738419	

Tmin = Minimum temperature, Tmax = maximum temperature

4.1.4 Modelling the impact of integrated management on maize yields and soil organic carbon stock under climate change

4.1.4.1 Model calibration and validation

Table 21 shows the calibrated values for genotype-specific parameters in the DSSAT-CERES-Maize model. First, we use the ecotype file present in the model to set the radiation use efficiency (RUE) to capture the cultivar's local specificity in terms of sensitivity to the photoperiod. The thermal time requirement in the CERES-Maize model of DSSAT which defines the number of days required to accomplish the various phenological stages like the thermal time required from emergence to the end of juvenile stage and anthesis to maturity stage, are very key. A comparison between simulated and observed maize phenology and grain yield, as derived from model calibration, is presented in figure 22.

Table 21 : Model calibrated value for genotype-specific parameters

Variables	Calibration			Evaluation		
	RRMSE	R^2	d	RRMSE	R^2	d
Grain Yield	0.16	0.89	0.93	0.44	0.38	0.30
LAI	0.44	0.03	0.34	0.77	0.0009	0.79
Aboveground biomass	0.09	0.69	0.74	0.89	0.65	0.85
Phenology	0.07	-	0.15	0.08	0.35	0.26

RRMSE: Relative Root Mean Square Error; R^2: Coefficient of determination; d: d-index

The crop phenological variable related to the anthesis date in our study closely matched the predicted data, as indicated by the low RRMSE (RRMSE < 10%). The simulated grain yield ranged from 1295 kg ha^{-1} to 3091 kg ha^{-1}, with an average of 2244.75 kg ha^{-1}, while the observed grain yield varied from 1374.44 kg ha^{-1} to 3091 kg ha^{-1}, averaging 2438.83 kg ha^{-1}. The simulated grain yield demonstrated a reasonable level of agreement with the observed data, as reflected by the RRMSE (10% < RRMSE ≤ 20%). The model simulation of grain yield during calibration effectively captured the yield response to treatment applications. Among the treatments, the combination of 10 t ha^{-1} of biochar with mineral fertilizer (C0F1B10) resulted in the lowest yield, whereas the treatment incorporating 10 t ha^{-1} of compost, 20 t ha^{-1} of biochar, and mineral fertilizer (C1F1B20) produced the highest yield.

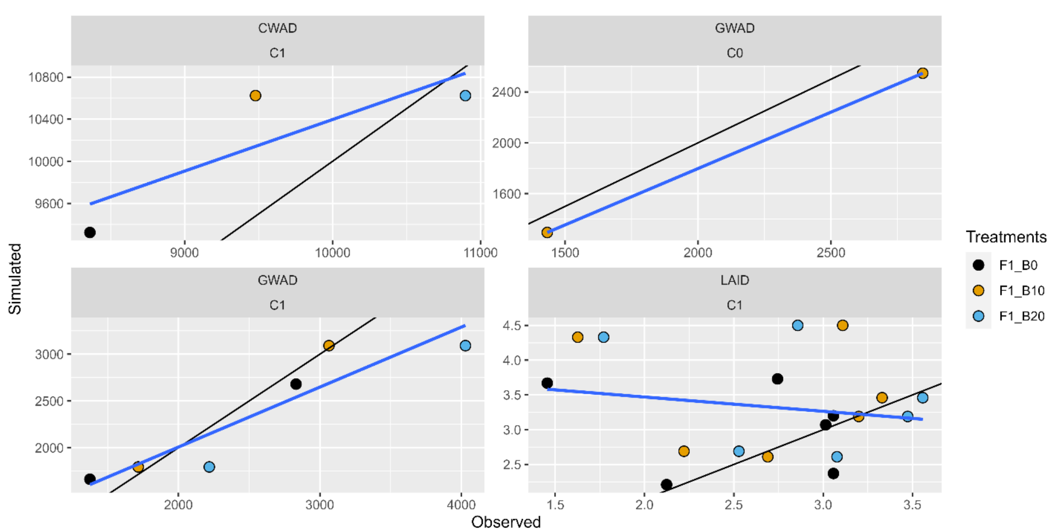

Figure 22: Model calibration: comparison between observed and simulated aboveground biomass (CWAD), grain yield (GWAD), and daily Leaf Area Index (LAID). The black line is the 1:1 line and the blue line is the linear regression line.

The model also showed “Excellent agreement” between simulated and observed aboveground biomass which is indicated by the RRMSE (RRMSE < 10%). However, a “Poor agreement” was observed between the simulated and observed daily Leaf Area Index. The comparison between the simulated and observed crop phenology, grain yield and aboveground biomass in the model evaluation is shown in figure 23. The average observed anthesis date was 55 DAS compared with 59 DAS by the model. The model simulation for the phenology related to anthesis date produced an RRMSE < 10%. However, it overestimated the remaining variables (grain yield, aboveground biomass, and LAI), resulting in poor agreement (RRMSE) between the observed and simulated data (Figure 23). Whether it is phenology, grain yield, or aboveground biomass, in the model evaluation, the model overestimated the results as indicated by the RRMSE. Figure 24 is showing the sequential running of the model during evaluation.

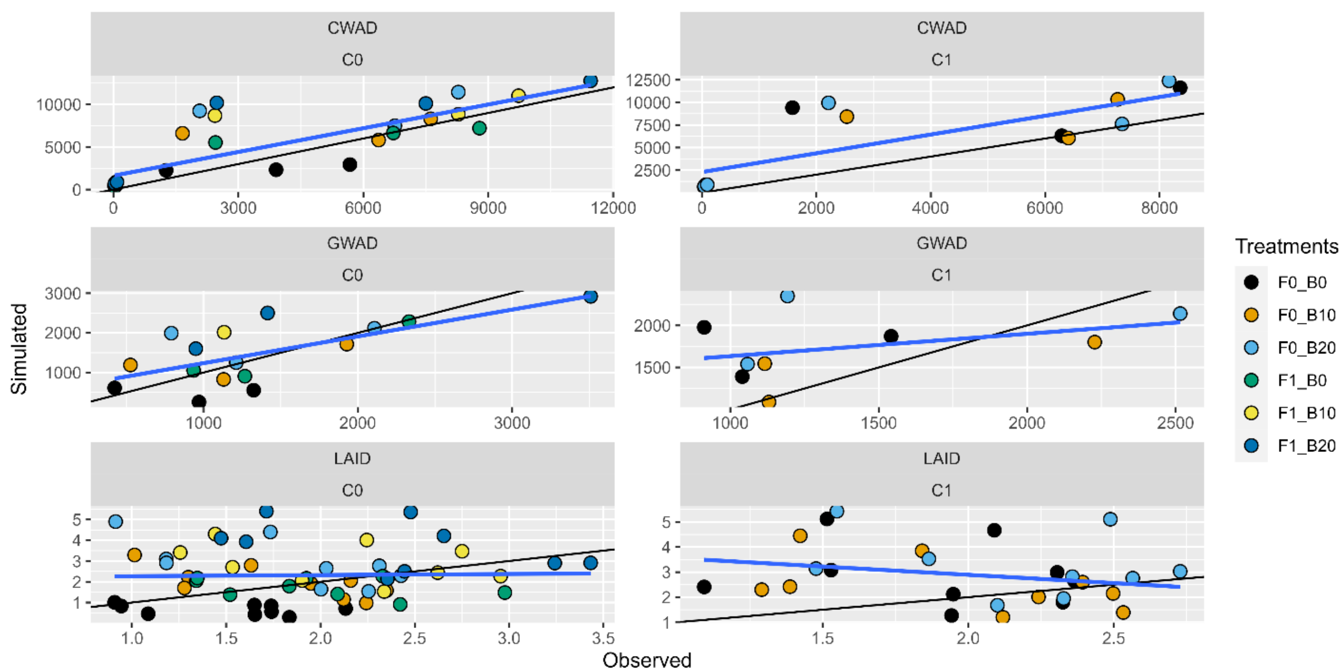

Figure 23: Model evaluation: comparison between observed and simulated aboveground biomass (CWAD), grain yield (GWAD), and daily Leaf Area Index (LAID). Refer to Table 2 for treatment descriptions.

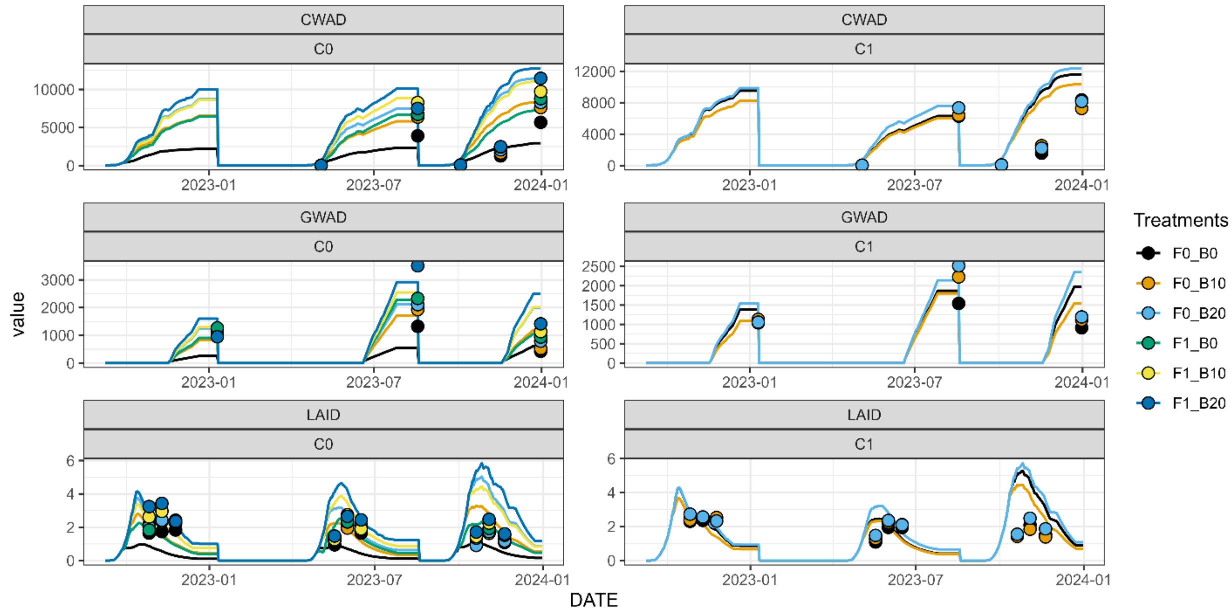

Figure 24: Model evaluation: sequential simulation of aboveground biomass (CWAD), grain yield (GWAD), and daily Leaf Area Index (LAID). Refer to table 2 for treatment descriptions.

4.1.4.2 Characterization of future climate

Figures 25 to 27 describe the average temperature, average annual precipitation, average solar radiation across all five selected GCMs and three scenarios. The pessimistic scenario (SSP 585 with high CO_2 emission) displayed a slightly higher increase in average temperature than the optimistic (SSP 126 with low CO_2 emission) and historical scenarios. Compared to the baseline scenario (Historical), the GCM UKESM1-0-LL_SSP585 showed the highest percentage of increase (11.2 %), followed by GCM IPSL-CM6A-LR_SSP585 (9.1%) and MRI-ESM2-0_SSP585 (7.4%) (Table 14). The modified Mann-Kendall test revealed increasing trends for almost all GCMs except the Historical and optimistic scenarios of the GCM MPI-ESM1-2-HR, where decreasing trends were noticed. The Sen's Slope confirms temperature increase ranging from 0.00096°C to 0.09°C per year (Table 15). Concerning annual average rainfall results, four GCMs yielded higher results for the SSP126 scenario than the SSP585 which showed a slightly higher result only for the GCM MPI-ESM1-2-HR (Figure 18). Only the GCMs MPI-ESM1-2-HR and UKESM1-0-LL showed a decrease in annual average rainfall corresponding to percentages of -13.2 and -11% for MPI-ESM1-2-HR_SSP126 and MPI-ESM1-2-HR_SSP585 respectively; likewise, -1.1 and -6.1% concerning UKESM1-0-LL_SSP126 and UKESM1-0-LL_SSP585 respectively. The modified Mann-Kendall test revealed decreasing trends in annual rainfall for the SSP585 across all GCMs except for GFDL-ESM4 where an increasing trend has been noticed; the SSP126 showed increasing trends for the same GCM. Regarding the Sen's Slope, it confirms the increasing trend ranging from 0.13mm to 8.73mm per year and decreasing from -0.75 to 10.22mm per year for the GCMs mentioned above. The GCMs GFDL-ESM4, MRI-ESM2-0, and UKESM1-0-LL reveal an increase in the accumulated radiation of 1.5; 0.2; 1.5% respectively. All the rest showed a decrease varying from -2.4% to -11% compared to the historical scenario.

Table 22: Percentage of change between the baseline scenario (historical) and future scenarios.

GCMs	Scenario	Mean Temp.	Precipitation	Radiation
GFDL-ESM4	ssp126	4	3.1	1.5
GFDL-ESM4	ssp585	6.2	1.3	-5.6
IPSL-CM6A-LR	ssp126	4.7	6.1	-2.9
IPSL-CM6A-LR	ssp585	9.1	3.8	-5.8
MPI-ESM1-2-HR	ssp126	3	-13.2	-2.4
MPI-ESM1-2-HR	ssp585	3	-11	-11
MRI-ESM2-0	ssp126	4.3	9.9	0.2
MRI-ESM2-0	ssp585	7.4	6.4	-5.5
UKESM1-0-LL	ssp126	6.9	-1.1	1.5
UKESM1-0-LL	ssp585	11.2	-6.1	-4.9
Ensemble	ssp126	4.58	0.7	-0.42
Ensemble	ssp585	7.38	-1.36	-6.55

Mean temp. = Mean temperature

Table 23: Mean temperature trend analysis

GCMs	Scenario	Tau	Sen's slope	p value	significance	Trend
GFDL-ESM4	Historical	0.489655	0.02	2.55E-23	Yes	Increasing
GFDL-ESM4	ssp126	0.075862	0.00096	0.126924	No	Increasing
GFDL-ESM4	ssp585	0.747126	0.05	3.72E-64	Yes	Increasing
IPSL-CM6A-LR	Historical	0.466667	0.03	1.02E-24	Yes	Increasing
IPSL-CM6A-LR	ssp126	0.245977	0.01	3.61E-06	Yes	Increasing
IPSL-CM6A-LR	ssp585	0.747126	0.07	5.74E-19	Yes	Increasing
MPI-ESM1-2-HR	Historical	-0.05287	-0.002	0.274267	No	Decreasing
MPI-ESM1-2-HR	ssp126	-0.07586	-0.004	0.160742	No	Decreasing
MPI-ESM1-2-HR	ssp585	0.65977	0.03	5.51E-62	Yes	Increasing
MRI-ESM2-0	Historical	0.296552	0.01	0.000184	Yes	Increasing
MRI-ESM2-0	ssp126	0.383908	0.02	7.69E-12	Yes	Increasing
MRI-ESM2-0	ssp585	0.572414	0.05	4.93E-18	Yes	Increasing
UKESM1-0-LL	Historical	0.494253	0.02	2.88E-07	Yes	Increasing
UKESM1-0-LL	ssp126	0.296552	0.01	2.83E-15	Yes	Increasing
UKESM1-0-LL	ssp585	0.852874	0.09	1.27E-53	Yes	Increasing

Table 24: Precipitation trend analysis

GCMs	Scenario	Tau	Sen's slope	p value	significance	Trend
GFDL-ESM4	Historical	0.01	0.13	0.931284	No	Increasing
GFDL-ESM4	ssp126	-0.07	-1.58	0.32593	No	Decreasing
GFDL-ESM4	ssp585	0.02	0.67	0.659195	No	Increasing
IPSL-CM6A-LR	Historical	0.11	4.93	0.065273	No	Increasing
IPSL-CM6A-LR	ssp126	0.09	1.85	0.146427	No	Increasing
IPSL-CM6A-LR	ssp585	-0.14	-4.61	0.012881	Yes	Decreasing
MPI-ESM1-2-HR	Historical	0.2	6.67	2.24E-06	Yes	Increasing
MPI-ESM1-2-HR	ssp126	0.3	8.73	3.77E-09	Yes	Increasing
MPI-ESM1-2-HR	ssp585	-0.2	-7.79	0.01667	Yes	Decreasing
MRI-ESM2-0	Historical	-0.12	-2.86	0.003827	Yes	Decreasing
MRI-ESM2-0	ssp126	0.12	4.44	0.060762	No	Increasing
MRI-ESM2-0	ssp585	-0.27	-10.22	5.9E-10	Yes	Decreasing
UKESM1-0-LL	Historical	-0.03	-0.75	0.543393	No	Decreasing
UKESM1-0-LL	ssp126	0.21	6.03	0.011659	Yes	Increasing
UKESM1-0-LL	ssp585	-0.09	-2.32	0.174271	No	Decreasing

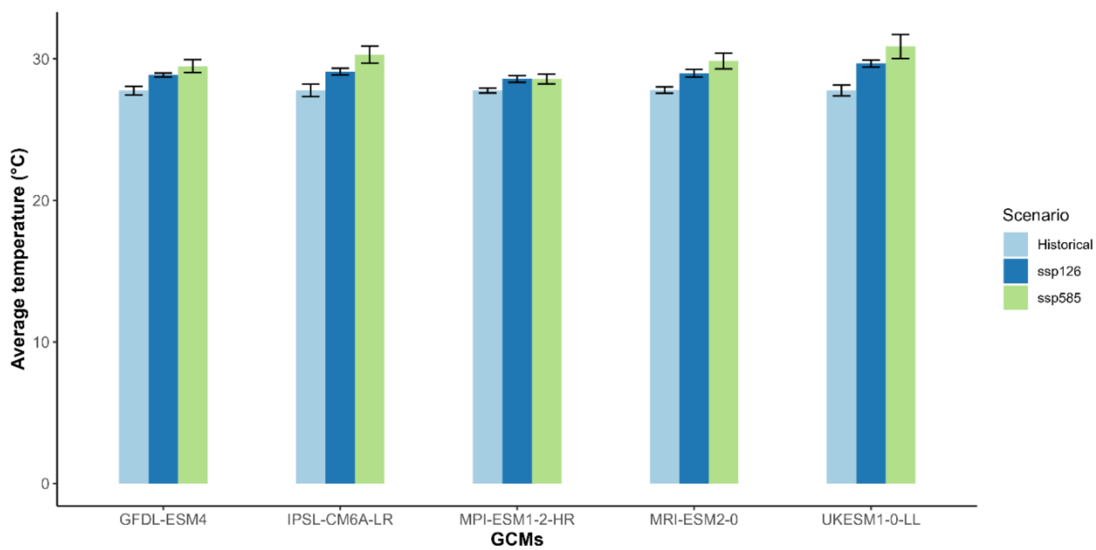

Figure 25: Average temperature across the five GCMs and three scenarios

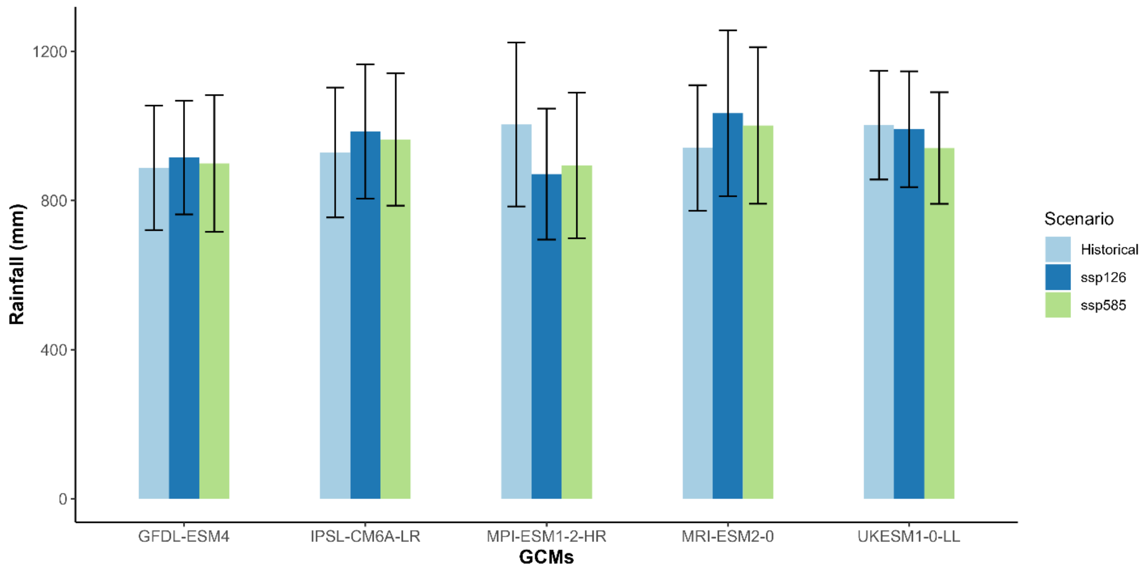

Figure 26: Annual average rainfall across the five GCMs and three scenarios

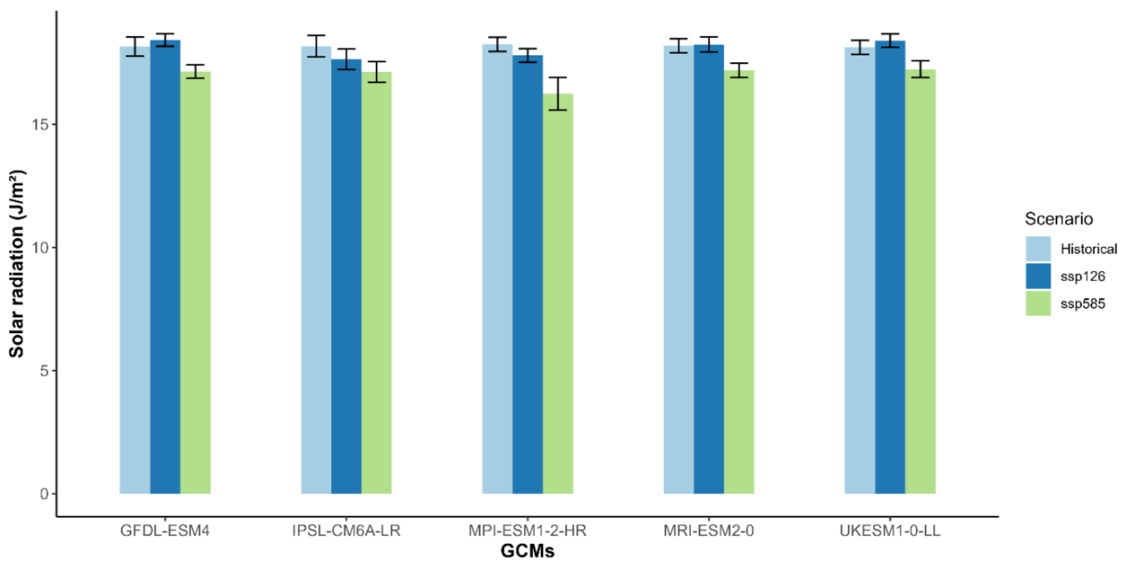

Figure 27: Average solar radiation across the five GCMs and three scenarios

4.1.4.3 Impact of climate change on future maize yields

Figure 28 illustrates the projected impact of future climate (2041-2070) on maize yield, compared to a baseline period (1981-2010), while figure 29 presents the future climate impact on maize yield per GCMs and scenarios. Under both the optimistic (SSP126) and pessimistic (SSP585) climate scenarios, maize yields are projected to decrease across all treatments.

While no statistically significant difference was found between the two scenarios, the magnitude of yield decline varied. The optimistic scenario (SSP126) was projected to lead to a decrease of

0.84% to 13.03%, while the pessimistic scenario (SSP585) is expected to result in a more significant decline of 9.05% to 24.11%. On average, maize yields are projected to decrease by 10.9% under SSP126 and 20.01% under SSP585 across all treatments.

Interestingly, the treatment C1F1B20, which exhibited the highest yield in the baseline period, is also projected to experience the largest decline in yield under both scenarios.

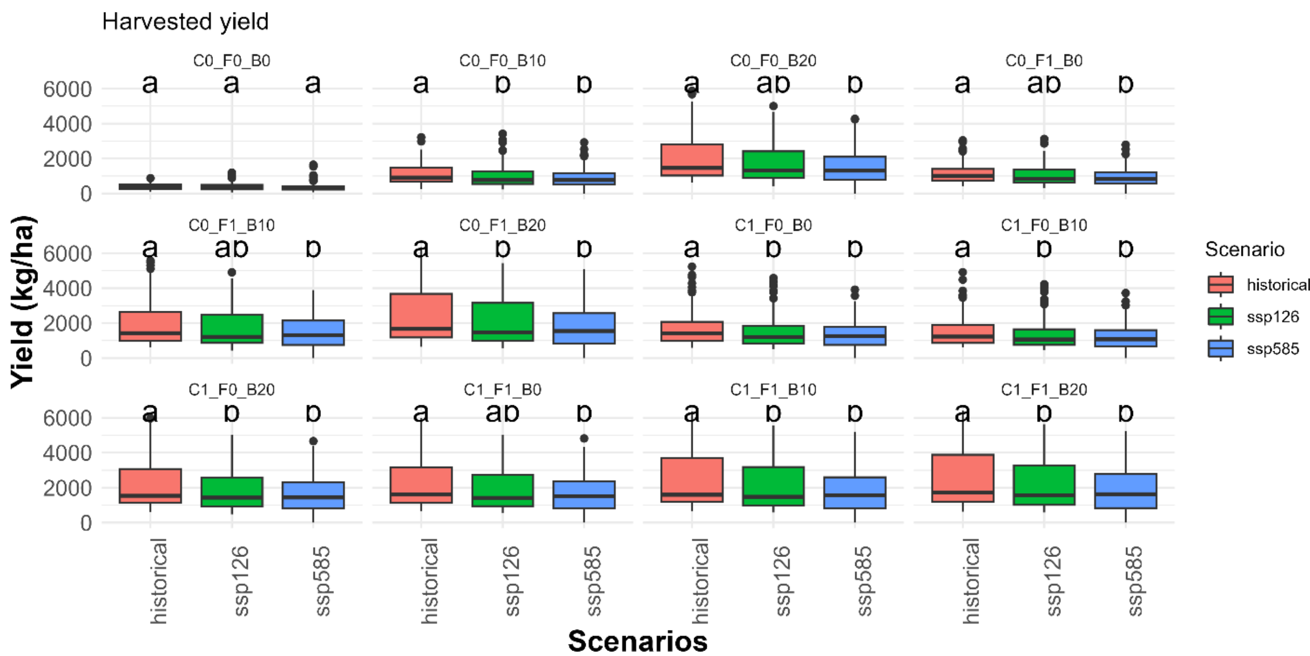

Figure 28: Average yield across the different climate scenarios. The letters on the boxplots show statistical differences among scenarios. Scenarios with the same letters are not statistically different.

In table 25 below is presented mean yield and SOC values per treatment and future climate scenarios.

Table 25: Maize yield and SOC per treatment and climate change scenarios

Treatment	Historical		SSP126		SSP585		Mean	
	Mean Yield (kg ha^{-1})	Mean SOC (kg ha^{-1})	Mean Yield (kg ha^{-1})	Mean SOC (kg ha^{-1})	Mean Yield (kg ha^{-1})	Mean SOC (kg ha^{-1})	Mean Yield (kg ha^{-1})	Mean SOC (kg ha^{-1})
C0F0B0	387.13±168.88	7100.39±130.35	383.86±201.99	7092.621±155.41	352.09±210.4	7036.88±176.79	374.3615±195.26	7076.37±157.83
C0F0B10	1104.32±565.3	8708.8±482.8	963.43±566.59	8591.556±492.06	886.05±485.03	8481.31±452.64	984.6±547.8	8592.64±483.98
C0F0B20	2006.03±1275.49	12608.47±19	1763.21±1121.88	12209.56±2017.99	1564.82±944.55	11999.83±1916.44	1778.02±1135.75	12268.97±1976.4
C0F1B0	1135.23±501.28	7663.94±165.42	1038.65±555.74	7602.906±145.95	941.24±472.05	7529.32±142.31	1038.374±516.91	7598.01±160.77
C0F1B10	1889.66±1153.37	10326.56±1146	1696.15±1072.25	10070.59±1153.36	1504.43±886.29	9907.84±1078.5	1696.747±1054.38	10099.22±1136.85
C0F1B20	2399.27±1552.59	12723.14±2000.71	2084.81±1347.56	12295.71±2051.58	1817.38±1158.09	12075.25±1938.5	2100.487±1381.86	12360.81±2011.02
C1F0B0	1652.77±855.97	10715.47±1324.95	1454.7±819.54	10457.02±1344.91	1351.75±719.33	10292.79±1265.98	1486.408±810.35	10485.96±1320.82
C1F0B10	1460.37±743.09	10401.04±1172.97	1284.98±727.89	10169.1±1199.73	1202.76±626.62	10020.16±1132.23	1316.035±709.87	10194.55±1176.47
C1F0B20	2159.59±1350.07	12880.13±2076.04	1880.02±1178.23	12460.03±2132.99	1669.86±1002.71	12243.4±2026.17	1903.159±1201.44	12524.03±2091.02

C1F1B0	2189.01±1353.48	10875.15±1398.83	1932.27±1198.17	10580.69±1404.01	1698.24±1019.7	10397.34±1309.86	1939.84±1213.96	10614.93±1382.29
C1F1B10	2432.06±1597.53	11986.48±1739.33	2110.79±1373.34	11603.29±1768.86	1847.12±1193.4	11392.3±1660.12	2129.99±1417.09	11657.15±1736.84
C1F1B20	2501.36±1628.83	13183.23±2206.59	2170.03±1398.51	12725.79±2256.67	1893.44±1213.9	12490.32±2131.24	2188.277±1444.36	12795.61±2212.55

SSP126: Optimistic scenario; SSP585: Pessimistic scenario

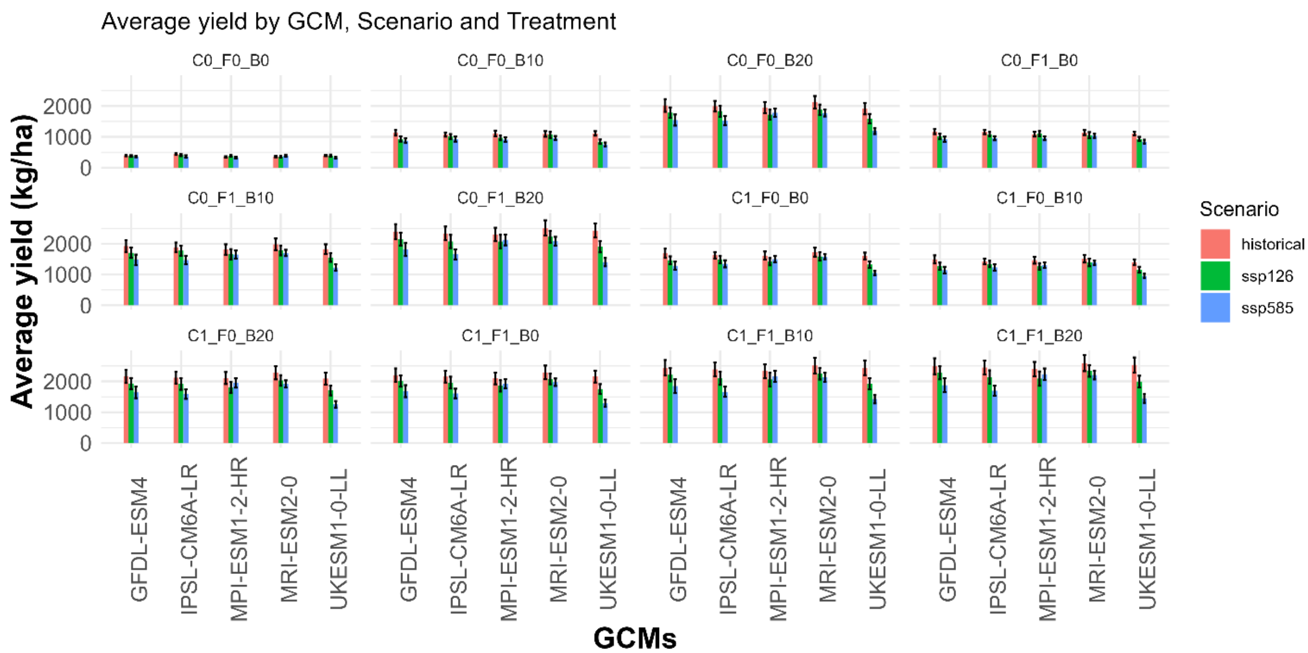

Figure 29: Average yield by GCM, scenario, and treatment

4.1.4.4 Impact of climate change on future SOC

Figure 30 illustrates the projected impact of future climate (2041-2070) on average soil organic carbon stock, compared to a baseline period (1981-2010), while figure 31 is showing the impact of future climate on SOC stocks by GCMs and scenarios. Under both the optimistic (SSP126) and pessimistic (SSP585) climate scenarios, soil organic carbon stocks are projected to decrease across all treatments.

Overall, a statistically significant difference was found between the two scenarios, but the magnitude of SOC stock decline varied. The optimistic scenario (SSP126) is projected to lead to a decrease of 0.11% to 3.47%, while the pessimistic scenario (SSP585) resulted in the most drastic decline ranging from 0.89% to 5.26%. On average, SOC stocks are projected to decrease by 2.38% under SSP126 and 3.87% under SSP585 across all treatments.

Similarly to maize yield, the treatment C1F1B20, which exhibited the highest SOC stocks in the baseline period, is also projected to experience the most decline in SOC stock under both scenarios.

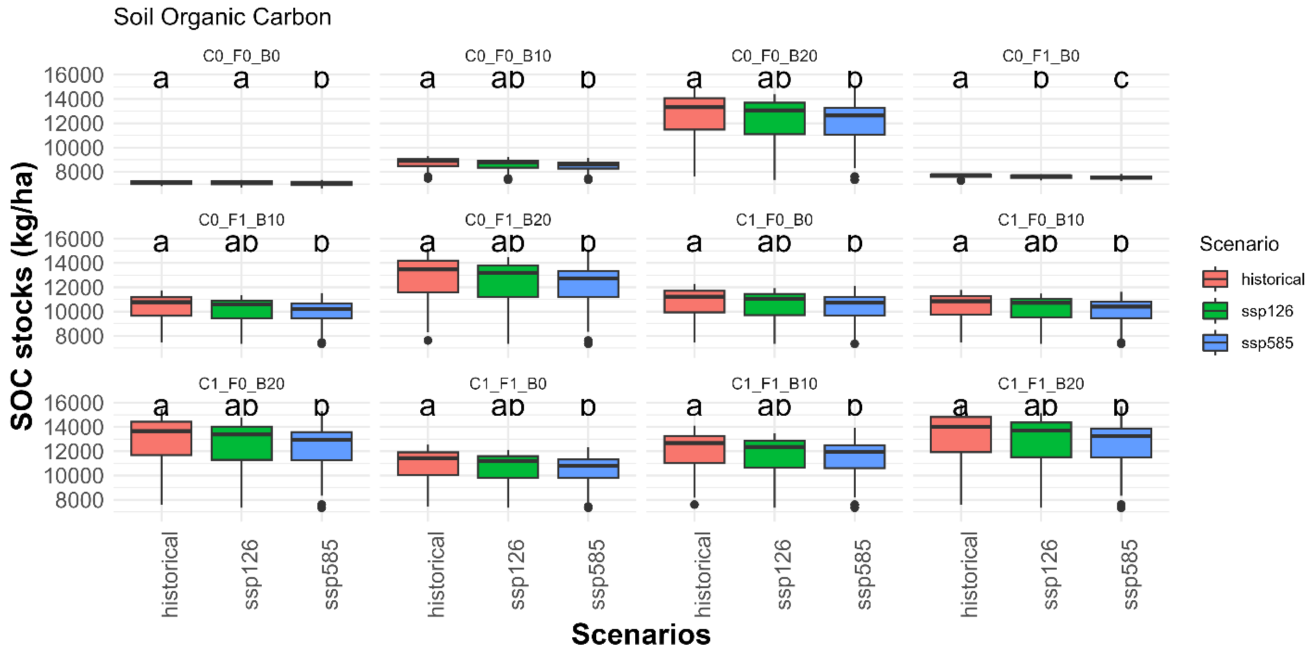

Figure 30: Simulated average soil organic carbon in 20 cm soil depth. The letters on the boxplots show statistical differences among scenarios. Scenarios with the same letters are not statistically different.

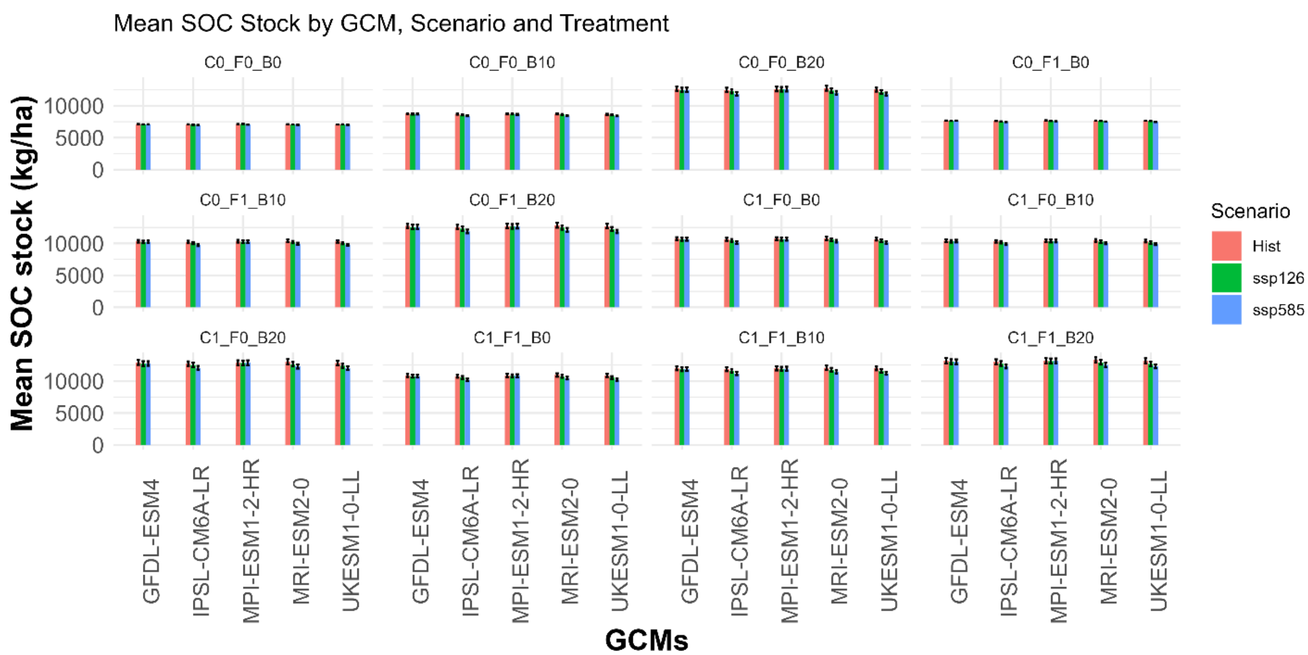

Figure 31: Average SOC stock by GCM, scenario and treatment. Hist = Historical

4.2 Discussions

4.2.1 Effect of biochar applied alone or in combination with compost and/or synthetic fertilizers (NPK and Urea) on soil physicochemical properties and maize yields

4.2.1.1 Effect of biochar on soil organic carbon and nitrogen concentration

Enhancing crop yields through improved soil productivity by increasing soil organic carbon levels is crucial to ensure food security in the face of climate change. As our study revealed that SOC content was increased following the application of biochar at a rate of 20 t ha^{-1}, this result was consistent with previous studies (Dong et al., 2022; Liu et al., 2021; Hematimatin et al., 2024). The increase in SOC content was mainly because biochar is a carbon-rich material that adds, at this specific application rate, more exogenous carbon to the soil (Shyam et al., 2025). This is consistent with the hypothesis that biochar would play a crucial role in climate change mitigation by contributing to SOC sequestration. Moreover, biochar may improve soil microbial activities, enhance crop growth, which leads to the absorption of atmospheric CO_2, aiding in the replenishment of soil organic carbon (SOC) (Hossain et al., 2020). Biochar application increases soil organic carbon content, which raises the C/N ratio by adding carbon without a proportional increase in nitrogen. It also reduces nitrogen loss through leaching and volatilization, helping to retain nitrogen in the soil. Additionally, biochar can influence microbial activity, leading to short-term nitrogen immobilization, which temporarily further increases the C/N ratio (Clough et al., 2013; Han et al., 2020). Biochar can raise soil pH in acidic tropical soils, which might increase the efficiency of N mineralization by creating more favorable conditions for nitrifying bacteria. In addition, some studies explained that the application of biochar could increase the amount of aromatic carbon compounds of small aggregates with sizes between 0.25 – 2 mm. This makes it more stable in regards to decomposition (Li et al., 2024).

While the application of 20 t ha^{-1} biochar demonstrated an increase in SOC content, we observed that compost at a rate of 10 t ha^{-1} did not significantly increase the SOC content, which contradicts several studies that showed positive impacts (Nobile et al., 2022; Phares & Akaba, 2022; Fornes et al., 2024; Gioacchini et al., 2024). This could be explained on one hand by the rate of compost applied (10 t FM ha^{-1} at the beginning of the experiment and 10 t FM ha^{-1} before the third growing season), which might not be sufficient to increase the SOC content. In addition, compost is not as carbon rich as biochar and most of the carbon compounds in the compost are less stable in the soil.

The compost used in our study has a relatively low carbon content. Furthermore, because of its rapid mineralization, compost does not retain stable carbon. Its carbon content is easily decomposed and lost over time. This is consistent with previous studies (Kimetu & Lehmann, 2010; Agegnehu et al., 2015; Nobile et al., 2022; Chen et al., 2024). The type and maturity of compost are also key elements that need to be considered. The relatively low compost rate we applied may also lead to such results, as some studies suggest that compost needs to be applied in high doses to achieve significant positive effects (Hannet et al., 2021; Phares & Akaba, 2022). Additionally, compost is easily degraded by microorganisms over time, requiring frequent reapplication (Nobile et al., 2022).

Sole application of biochar at 20 t ha^{-1}, even repeated after one year did not significantly affect soil nitrogen content. This may be due to the ability of biochar to adsorb ammonium and nitrate which reduce their availability to plants in the short term (Clough et al., 2013; Haider et al., 2015). Additionally, biochar's high C/N ratio can lead to nitrogen immobilization by soil microbes, delaying nitrogen availability (Lehmann et al., 2011). Furthermore, the interaction between biochar and chemical fertilizer did not result in a significant increase in SOC. This suggests, on the one hand, that the rate of biochar applied may not be sufficient to enhance soil nitrogen content. On the other hand, the limited amount of nitrogen fertilizer applied did not aid in the retention of nitrogen by the biochar (Sun et al., 2014; Seki et al., 2022). The non-significant results might be because the rates of compost and fertilizer applied were not sufficient to cause a detectable change (Hannet et al., 2021).

In southern Togo, the soil type is commonly known as ferruginous tropical which is characterized by low organic matter, leading to weak nutrient retention capacity (Koudjega et al., 2019). This characteristic leads to limited microbial activity and poor structure. In such environment, good management coupled with biochar properties (high porosity, stable organic carbon, alkaline structure), biochar could significantly enhance SOC levels, improve water holding capacity and nutrient retention (Tomczyk et al., 2020).

4.2.1.2 Effect on maize yields

Biochar has been proven by multiple studies conducted under tropical climates and on a Haplic Acrisol like the soil of this study (Frimpong et al., 2021; Oppong Danso et al., 2019), to improve soil fertility and crop productivity. Its application with nitrogen fertilizers has a positive impact on crop yields. Our findings revealed that a single application of biochar to soil did not lead to a significant increase in the yield of maize during the first growing season. However, in the second season, the application of 20 t ha^{-1} of biochar resulted in a significant improvement in yield while in the third season a marginal positive impact was noted. This could be explained on one hand by the property of biochar to immobilize nitrogen for the short term (Sarker et al., 2018) and slowly release it to plants, leading to long-term benefits (Taghizadeh-Toosi et al., 2012). Such results were consistent with previous studies. For example, a seven-year study conducted on wheat and maize under semiarid and semi-humid warm temperate monsoon climate and a sandy loamy soil at the Fengqiu National Agro-Ecosystem Observation and Research Station (China), reported that no significant effect of biochar was observed on crop yield during the first three years (Xie et al., 2021). Some other studies found an immediate effect of biochar during the first year of application. A three-cropping season study (Frimpong et al., 2021) conducted at the University of Cape Coast (Ghana) using 10 t ha^{-1} of biochar derived from corn cob and compost at 10 t ha^{-1} each. They reported that combined biochar (10 t ha^{-1}) and compost (10 t ha^{-1}) and combined biochar (10 t ha^{-1}) and NPK (100 kg N ha^{-1}, 60 kg P ha^{-1}, 60 kg K ha^{-1}) treatments enhanced maize yields after the first season by 75.3% and 87.0%, respectively. This faster effect of biochar is explained by some studies by the negligible amount of labile nutrients in biochar which could be released in the first and second cropping season (Glaser et al., 2002; Lehmann et al., 2003). Additionally, they observed that when biochar was combined with compost and NPK fertilizer, the yield of maize was improved by 219% (Frimpong et al., 2021). In China, a two-season greenhouse experiment (Abdelghany et al., 2023) found a significant effect of agricultural waste (cotton, corn straw, and tree pruning waste) biochar on tomato yields after the first season but the effects were slower during the second (73.8% and 93.7% of yield improvement). Such results justify the fact that the effects of biochar depend on the types of crop grown, field conditions, application rates, and methods of biochar application (Singh et al., 2022). Our study revealed a positive correlation between maize grain yield and SOC. Such results suggest that practices that aim to promote higher SOC content may also contribute to maize yield improvement and overall crop performance.

4.2.2 Effect of biochar applied alone or in combination with compost and/or inorganic fertilizer (NPK) on different SOC fractions in the soil and on soil carbon sequestration

4.2.2.1 Soil organic carbon stock

Our study revealed an increase of 10.98 Mg C ha^{-1} in soil organic carbon (SOC) stocks following the application of biochar at a rate of 20 t MF ha^{-1} applied twice (B20). This result corroborates previous research highlighting the potential of biochar to improve SOC levels in agricultural soils (Lehmann et al., 2006; Jeffery et al., 2011). Numerous studies have demonstrated that biochar amendments can enhance soil carbon sequestration, but the extent of this enhancement often varies depending on several factors. These include soil type, climatic conditions, initial SOC levels, and particularly biochar characteristics such as feedstock, pyrolysis temperature and application rate (Spokas et al., 2011; Liu et al., 2024). In our case, the significant increase in SOC after 16 months suggests that the biochar applied was relatively stable and contributed to the accumulation of recalcitrant carbon in the soil. This supports the growing body of evidence indicating that biochar acts not only as a soil amendment, but also as a long-term carbon sink, capable of mitigating climate change by reducing atmospheric CO_2 through soil carbon storage (Mehmood et al., 2020; Woolf et al., 2010).

In contrast, compost application did not significantly alter SOC stocks, although a modest increase was observed (Table 3). This result is consistent with previous studies reporting limited effects of compost on long-term SOC sequestration, particularly when applied in small quantities or over short periods (Bünemann et al., 2006; Diacono & Montemurro, 2010). The compost used in our experiment could contain a high proportion of labile organic matter, more easily decomposed by soil microbes and thus contributing less to long-term carbon stabilization. Furthermore, the total amount of compost applied may not have been sufficient to induce statistically detectable changes in SOC over the duration of the study. These results suggest that while compost contributes to nutrient cycling and microbial activity in the short term (Lal, 2004), its influence on stable SOC pools may be limited without repeated or large-scale applications.

In summary, these results highlight the importance of considering the nature and dose of organic amendments when designing soil fertility management strategies aimed at increasing SOC. Biochar, by virtue of its recalcitrant nature, appears to offer greater potential for long-term carbon sequestration in the specific agroecological context of southern Togo, while compost may fulfil more immediate agronomic functions.

4.2.2.2 Share of organic carbon in fractions

The particle size distribution of soil organic carbon (SOC) revealed that non-particulate organic matter (NOM), mainly associated with silt and clay particles (<53 µm), contributed most to total SOC. Notably, the control showed the highest proportion of carbon in this fraction. In contrast, the contributions of coarse (cPOM), medium (mPOM) and fine (fPOM) particulate organic matter were considerably lower. This trend underlines the role of mineral-associated organic matter (MAOM) in long-term carbon stabilization, with silt and clay particles effectively binding organic matter and protecting it from microbial decomposition (Six et al., 2002a; Cotrufo et al., 2013).

In tropical agroecosystems, high temperatures and constant moisture availability favor intense microbial activity, which accelerates the decomposition of labile organic matter (Paul, 2014). Consequently, particulate organic matter fractions, especially those not complexed with minerals, tend to be rapidly mineralized, thus contributing minimally to the stable pool of SOCs. Previous studies have shown that POM fractions are the most dynamic and sensitive to changes in land use and management practices (Yu et al., 2013; Sainepo et al., 2018; Ahogle et al., 2022). Our results corroborate this finding, with cPOM, mPOM and fPOM fractions being relatively lower in all treatments, particularly under disturbed conditions.

Although fPOM and mPOM fractions initially accumulate higher amounts of organic carbon, their lack of mineral association makes them more vulnerable to microbial decomposition. These fractions represent transient pools that can contribute either stable SOC or mineralized CO_2 depending on the environmental and management context (Cotrufo et al., 2015). Conversely, MAOM constitutes a more persistent carbon pool thanks to its chemical protection mechanisms, including sorption to mineral surfaces and physical occlusion in microaggregates (Lehmann & Kleber, 2015). This implies that promoting MAOM formation represents a key pathway for increasing long-term SOC stocks, particularly in highly weathered tropical soils.

Soil management practices such as tillage and erosion significantly influence the distribution and stability of SOC fractions. Tillage disrupts soil aggregates and exposes organic matter to oxygen, accelerating microbial mineralization and reducing carbon retention in POM fractions (Lal, 2004; Blanco-Canqui & Lal, 2008). Erosive processes also remove the organic-rich topsoil, further reducing the potential for carbon accumulation. Thus, conservation practices such as reduced tillage, organic amendments and erosion control structures are essential to preserve POM and promote the transformation of labile carbon into stable forms of MAOM.

In summary, our results underline the importance of considering both the physical and biochemical mechanisms of SOC stabilization when assessing the long-term effects of organic amendments. While biochar and compost can increase labile carbon pools in the short term, sustained increases in SOC require strategies that promote MAOM accumulation, particularly under tropical climatic conditions. This study highlights the key processes governing carbon sequestration in tropical soils and provides valuable insights for the development of sustainable agricultural practices aimed at improving soil fertility while mitigating climate change.

4.2.3 Climate variability on maize yield in southern Togo

The results of the study revealed an increasing trend in temperatures, 0.05°C per year for minimum temperature in Lomé and 0.03°C in Tabligbo; 0.03°C per year for maximum temperature between 1980-2022 at both locations. These results imply in Lomé that the minimum temperature rose more rapidly than the maximum temperature. Poudel & Shaw (2016) in Nepal obtained similar results of an increase of up to 0.06°C per year for minimum temperature and 0.02°C per year for maximum temperature. Koudahe et al. (2018) reached to a similar conclusion in Togo with an increase of 0.5°C per decade in minimum temperature and 0.4°C per decade for minimum temperature between the period 1971 – 2014, results that are similar to ours.

Our results revealed that rainfall significantly increased in Lomé and Tabligbo. These results agreed with some studies (Koudahe et al., 2018), but are in contradiction with others Djaman & Ganyo (2015) who found a slight decrease in rainfall in Lomé and Tabligbo from 1961 to 2011. Globally, the rainfall increases at all locations, this situation could be explained by the increase in temperatures that led to the increase of evapotranspiration.

We found that the number of rainy days slightly decreased in Tabligbo, while rainfall and annual temperatures increased. These results agreed with the synthesis report of IPCC (2014) which revealed that global warming leads to a decrease in rain days and then contributes to more extreme rainfall regimes.

Maize yield trends increased in Tabligbo but it varied from year to year. This finding implies that because maize is a solely rainfed crop, there could be a link between the amount of rainfall and the yield of maize in the area (Baffour-Ata et al., 2021). Also, for rainfed crops, water could be a limiting factor as well as soil management practices (van Ittersum et al., 2013).

The results of the multiple regression analysis revealed non-significant effects of climatic variables on maize yields. In Tabligbo, minimum temperature and rainfall were positively correlated with maize yields. But these effects were not significant ($p<0.05$). These results suggest that maize yields depend also on some other environmental factors like soil health or management (Osman et al., 2021). Similar results were obtained by Baffour-Ata et al. (2021) in Ghana and Tunde et al. (2011) in Nigeria who suggest that the minimum impact of climatic variables on some selected crop yields could be due to some other parameters known as non-climatic factors like soil fertility, type of soil etc. These non-climatic factors are susceptible to increase the yield gap which is the difference between the potential yield of a crop cultivar and the actual yield by farmers (Lobell et al., 2009). Crop yields are known to be influenced by agricultural practices such as conservation agriculture, and field management practices (Boansi, 2017). In the same way, studies confirmed that yields of crops depend not only on climatic factors but also on non-climatic factors (Amikuzino & Donkoh, 2012). This is a justification for the use of a crop simulation model to minimize the effects of non-climatic factors (Srivastava et al., 2020; Tooley et al., 2021). This could be somehow because maize needs much water to grow perfectly in the hotter environment (Baffour-Ata et al., 2021) since the temperature in Kara is known to be high. The variation in climate variables constitutes the main threat to agricultural productivity (Llano et al., 2011), and is expected to substantially affect rainfed-based such as in Togo. Maize growing as many other bowls of cereal is climate-sensitive, its yields could continue to decrease when the environment is not optimal. Maize is most often grown in the southern part of Togo between April and July by using long cycle variety and between September and October by using short cycle variety.

4.2.4 Modelling the impact of integrated management on maize yields and soil organic carbon stock under climate change

The DSSAT CSM-CERES-Maize model is a powerful tool for simulating maize growth. It can accurately predict key crop parameters, such as phenological stages, biomass, and grain yield, by considering the impacts of different management practices and environmental factors (Abbas et al., 2023). Our study demonstrates the successful parameterization and calibration of the CSM-CERES-Maize model in predicting phenology, growth, and grain yield.

Our study demonstrates successful calibration of the CSM-CERES-Maize model, resulting in improved model performance statistics for aboveground biomass, grain yield. However, the subsequent evaluation phase revealed lower predictive accuracy compared to the calibration results. Other studies found an RMSE of <30% and 3.2% (Attia et al., 2021; Srivastava et al.,

2016) modelling maize in West Africa. The calibrated genetic cultivar coefficient estimated in this study fell within the range reported by Jones et al., 2003a. The P1 value of our maize variety is 300°C which refers to an early naturing variety. Values of P2 and P5 were set to 0.520 day and 930 °C day respectively referring to an intermediate to late maturing maize variety. In the model calibration, the model depicted good agreement between observed and simulated phenology, grain yield and aboveground biomass indicating its ability to capture the anthesis date, and its ability to simulate grain yield and aboveground biomass yield. This in line with previous studies which demonstrate the robustness of DSSAT in simulating crop phenology, grain yield and biomass yield (Corbeels et al., 2016; Kamara et al., 2023). Regarding model evaluation, the model was not able to simulate crop growth parameters leading to an overestimation mainly for C1 treatment in the third season of grain and biomass yields, and leaf area index with RRMSE well above 30%. This overestimation could be due to parametrization of model parameters like Radiation Use Efficiency (RUE) and the requirements in thermal or in some extent to the inability to capture the interactions between crop, soil and climate variables. The response induced by the treatment C0F1B10 leading to a lower yield compared to the treatment C1F1B20 clearly shows that the model was able to capture the impact of management practices on crop growth. This is consistent with previous studies that found the ability of dynamic crop models to capture management practices (Jiang et al., 2019).

The future climate characterization revealed significant variability in climate variables (temperature, precipitation, solar radiation) throughout different climate scenarios and GCMs. In the pessimistic scenario (SSP585), the mean temperature showed an increase compared to the optimistic (SSP126) and historical scenarios. The scenario SSP585 of the GCM "UKESM1-0-LL" showed the highest increase in the average temperature (11.2%). This result is consistent with general trends indicating that warming accelerates under high-emission scenarios (IPCC, 2021). This increasing temperature trend was confirmed by the modified Mann-Kendall test and the Sen's slope analysis with annual increases ranging from 0.00096°C to 0.09°C. Our findings are consistent with previous research that projected significant warming in tropical and subtropical regions. These projected increases in temperature are expected to have adverse consequences for crop growth and yield in these regions (Challinor et al., 2014; Ahmed et al., 2015).

Surprisingly, the trend in the precipitation showed more variability with some GCMs which even projected decreases under the higher CO_2 emission scenario (SSP585). As for an example, the GCMs MPI-ESM1-2-HR and UKESM1-0-LL predicted declines in annual rainfall under the

SSP585 scenario. This is likely to exacerbate water stress in agricultural systems (Rosenzweig et al., 2014). The variability in future climate projections call for region-specific actions to mitigate the impacts of a changing climate and reinforced the resilience of food production systems.

Although climate change generally had a negative impact across all treatments, comparisons revealed that biochar application has the potential to enhance crop yields and significantly increase carbon sequestration compared to treatments without biochar.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

At first instance, we investigate the effect of biochar applied alone or in combination with compost and/or synthetic fertilizers (NPK and Urea) on soil physicochemical properties and maize yields. The results showed that, the application of 20 t ha^{-1} of biochar (B20) significantly increased SOC concentration. Meanwhile, B10 and C1 did not significantly influence SOC. The effect on total nitrogen from different treatments was not significant. Grain yield increased significantly under biochar at rates of 10 t ha^{-1} and 20 t ha^{-1} for the second and third growing seasons while mineral fertilizers showed a significant effect for all three seasons thanks to their immediate response. This clearly demonstrates the potential of biochar to significantly enhance maize yield.

The second specific objective of our work was to investigate the effect of biochar applied alone or in combination with compost and/or inorganic fertilizer (NPK) on different SOC fractions in the soil and on soil carbon sequestration. The results revealed that the treatment of the combination of compost and biochar (C1F0B20) gave the highest SOC concentration in the cPOM and mPOM fractions, and the treatment of only biochar application (C0F0B20) leaded to the highest SOC concentration in the fPOM fraction. In terms of the share of organic carbon produced in the different fractions, while the treatment C1F0B20 produced the highest share of organic carbon in the cPOM, mPOM and fPOM fractions, the control treatment gave the highest share of organic carbon in the NPOM fraction which is related to the mineral POM indicating the more stable organic carbon that is not easily decomposed.

At third, we conducted a climate variability on maize yields study of the period 1980 - 2022 in the southern Togo where study site is located by considering the neared weather station of Tabligbo which is close to our area (Davié). The results of the study revealed that minimum temperatures increased up to 0.05°C per year in Lomé and 0.03°C in Tabligbo, and maximum temperatures increased up to 0.03°C at both locations. A positive trend in annual rainfall was expressed differently as per the locations and did not show a significant correlation on maize yields. We reached the conclusion which stipulates that crop yields depend not only on climatic variables but also on other environmental conditions like the biochemical state of the soil, biotic stressors, and crop management.

Finally, the DSSAT model was able to capture the phenology of the maize variety and well respond to grain yield and aboveground biomass simulation in the model calibration with low RRMSE values (0.07, 0.16, 0.09 respectively), while the model evaluation had a lower performance for the same variables (0.08, 0.44, 0.89 respectively). The climate change study conducted revealed variability in climate variables and some GCMs predict warmer climate and rainfall variability in the near future (2070).

5.2 Recommendations

To strengthen integrated soil fertility management in the context of climate change, we recommend expanding this research through broader field validation and long-term trials. Such development would enhance its practical relevance and novelty, ultimately supporting farmers in sustaining their livelihoods and food production systems under changing climatic conditions.

The findings of this study highlight the significant role of combining biochar and compost applications in improving maize yields and enhancing soil organic carbon (SOC) sequestration. The use of the DSSAT crop model has proven effective in simulating the effects of organic amendments and projecting the long-term impacts of climate change on crop productivity and SOC dynamics.

These insights can inform decision-making processes for both farmers and policymakers. Encouraging investment in organic amendments derived from agricultural residues could be a sustainable strategy to restore soil fertility, boost crop productivity, and contribute to climate change mitigation efforts.

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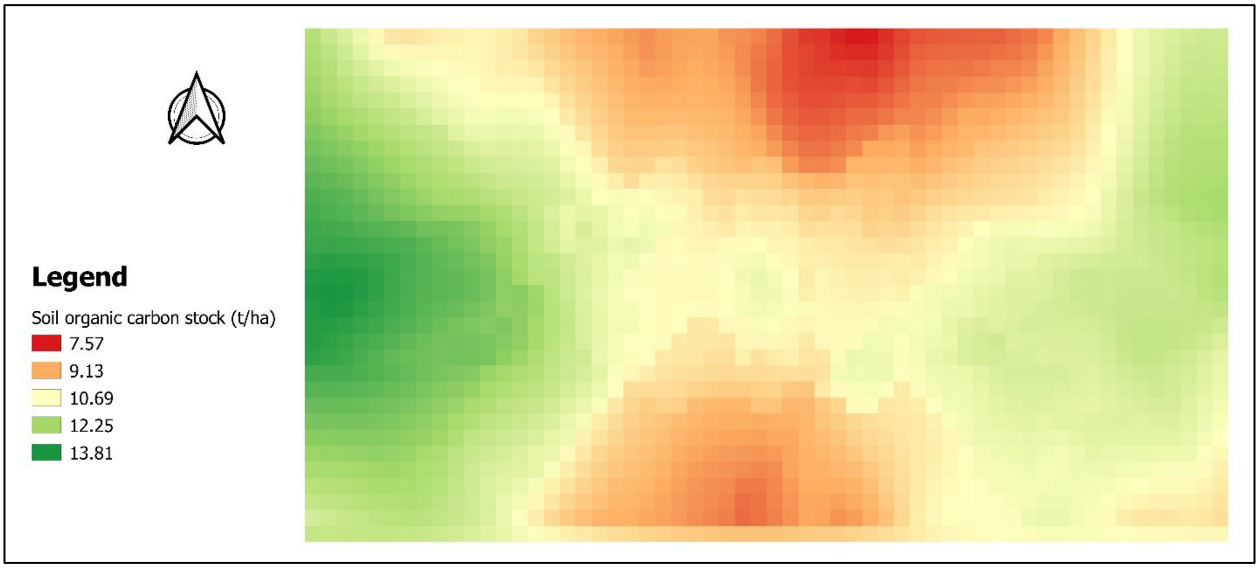
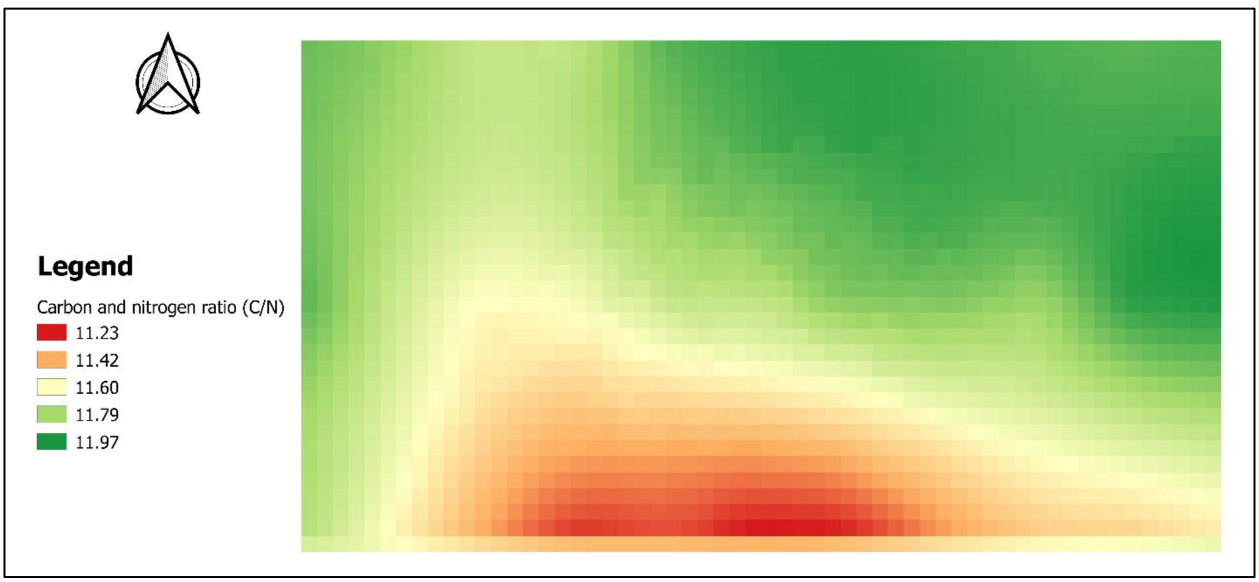
Annexes

Annex 1: **Maps of the soil initial soil organic carbon stock**



Annex 2: **Map of soil carbon and nitrogen ratio**



Annex 3: **Soil characteristics use in the DSSAT parameterization**

Soil properties	Soil depth (cm)			
	20	40	67	130
SDUL (cm^3 cm^3)	0.08	0.086	0.15	0.272
SSAT (cm^3 cm^3)	0.395	0.396	0.389	0.389
Root growth factor	1	0.56	0.27	0
SSKS (cm/h)	14.58	0.41	0.59	0.59
Bulk density (g cm^{-3})	1.4	1.5	1.56	1.56
Organic carbon (%)	0.6	0.26	0.17	0.17
pH (1:2.5 H_2O)	5.5	5	5.3	5.3
Total nitrogen (%)	0.05	0.04	0.02	0.02
Clay (%)	9	12	24	45
Silt (%)	6	4	5	4

DUL: Soil water; drained upper limit, SAT: Volumetric water content at saturation, SKS: Saturated hydraulic conductivity

Annex 4: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts soil organic carbon (SOC) content in 30 cm soil depth

Random effects	Variance	Std.Dev.
MainPlot:Block	0.04703	0.2169
Block	0.06623	0.2574
Residual	0.33902	0.5823

Std.Dev. = Standard Deviation

Annex 5: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on soil total nitrogen content in 30 cm soil depth

Random effects	Variance	Std.Dev.
MainPlot:Block	0.000973	0.03119
Block	0	0
Residual	0.001027	0.03205

Std.Dev. = Standard Deviation

Annex 6: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on leaf area index across three growing seasons

Random effects	Variance	Std.Dev.
Season 1		
MainPlot:Block	0	0
Block	0.004339	0.06587
Residual	0.060307	0.24557
Season 2		
MainPlot:Block	0.01275	0.1129
Block	0.1402	0.3744
Residual	0.09543	0.3089
Season 3		
MainPlot:Block	0.03088	0.1757
Block	0.08672	0.2945
Residual	0.05212	0.2283

Annex 7: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on aboveground biomass yield across two growing seasons

Random effects	Variance	Std.Dev.
Season 2		
MainPlot:Block	0	0
Block	0	0
Residual	1900736	1379
Season 3		
MainPlot:Block	841182	917.2
Block	312179	558.7
Residual	5802781	2408.9

Annex 8: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on maize yield across three growing seasons

Random effects	Variance	Std.Dev.
Season 1		
MainPlot:Block	0	0
Block	9675	98.36
Residual	114909	338.98
Season 2		
MainPlot:Block	29023	170.4
Block	19957	141.3
Residual	239277	489.2
Season 3		
MainPlot:Block	141534	376.2
Block	21526	146.7
Residual	74366	272.7

Annex 9: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on SOC stock

Random effects	**Variance**	**Std.Dev.**
MainPlot:Block	0	0
Block	1.666	1.291
Residual	12.488	3.534

Annex 10: Estimated random effects from Linear Mixed-Effects Models fitted by Restricted Maximum Likelihood (REML) assessing treatment impacts on soil bulk density

Random effects	**Variance**	**Std.Dev.**
MainPlot:Block	0.001558	0.03948
Block	0	0
Residual	0.007993	0.0894

Annex 11: **Publications and conferences**

- **Publications**

- **Dodji Komlan Aziandeke**, Murilo dos Santos Vianna, Ekpetsi Chantal Bouka, Ixchel M. Hernández-Ochoa, Gbénonchi Mawussi, Alou Coulibaly, Thomas Gaiser. The influence of rice husk biochar, compost, and their mixture on maize yields and soil organic carbon content in Southern Togo. Submitted to *Geoderma Regional*. (**Under review**)
- **Dodji Komlan Aziandeke**, Chantal Ekpetsi Bouka, Murilo dos Santos Vianna, Gbénonchi Mawussi, Thomas Gaiser, Alou Coulibaly (2023). Impact of Climate Variability on Maize Yields in Southern Togo (Tabligbo). International journal of science and research. DOI: 10.21275/SR23929160411

- **Conferences**

- Colloque des Sciences, Cultures et Technologies Campus universitaire d'Abomey-Calavi ; 25 – 29 September 2023, online.
- World PhD students and postdoctoral researchers' summit, "meeting the challenges of climate change 2024". 27th November 2024, online. Title: Climate Change Impact on Soil Organic Carbon and maize yields in southern Togo.