Estimation of Variation in Productivity of South Asian Terrestrial Ecosystem and Carbon Balance Using LPJ-GUESS DGVM Model

By

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DEDICATION

This research is a grateful homage to my beloved parents, whose unwavering love and support helped me turn my dream of earning this degree into a beautiful reality. My gratitude for them is so deep that words cannot fully express it.

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Abstract

Human induced change in climate has already started affecting the ways ecosystems function and interact with each other. The major impact, and which in turn also becomes the driving factor in climate change is disruption of carbon cycle. Apart from other consequences, one of the major impacts disruption of carbon cycle is going to have is on the growth of vegetation. As with the changes in atmospheric CO_2 concentrations, Net Primary Production (NPP) of plants and Net Environmental Exchange (NEE) also vary. South Asia like many other parts of the world is also undergoing climate change and is facing changes in land cover and land use. As, population in South Asia is growing at an extremely high rate, the resources required to cater the needs of growing population are also increasing. Consequently, the terrestrial ecosystems and their interaction with atmosphere is also undergoing a change. To measure and estimate these changes, several Dynamic Global Vegetation Model (DGVM) are used. Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) is also one of them. LPJ-GUESS is a process-based framework which models the dynamics and structure of the ecosystem. It is comprised of several sub-models, where each sub-model includes processing of associated ecological processes. Input data required for LPJ-GUESS is consisted of climate parameters (Temperature, Precipitation, Solar radiation) and concentration of carbon dioxide in atmosphere. This study intends to estimate and analyze the changes that vegetation growth in South Asia is experiencing and will continue to experience as a consequence of changing climate, by using LPJ-GUESS model. This study can be of great assistance to formulate climate mitigation and adaptation policies for South Asia.

Chapter 1

Introduction

1.1 Background

Climate change has emerged as a pressing global concern, and its impact on terrestrial ecosystems, especially in the South Asian region, is profound and far-reaching. This phenomenon is primarily driven by human activities, including deforestation, land-use changes, and the combustion of fossil fuels. The consequences of climate change are primarily manifested through variations in global and regional climates over time, leading to significant environmental, social, and economic implications (*AR5 Synthesis Report*, n.d.).

The greenhouse effect plays a crucial role in understanding the mechanisms behind climate change. Human activities, such as the burning of fossil fuels for energy production and transportation, release substantial amounts of carbon dioxide (CO_2) and other greenhouse gases into the atmosphere. These gases act as a blanket, trapping heat from the sun and preventing it from escaping back into space. Consequently, the earth's surface and lower atmosphere experience a rise in temperature, resulting in global warming.

South Asia is particularly vulnerable to the impacts of climate change due to its geographical location and socio-economic factors. The region is characterized by diverse ecosystems, including forests, grasslands, wetlands, and coastal areas, all of which face numerous challenges from climate change.

One of the most significant consequences of climate change in South Asia is the alteration of rainfall patterns. Changes in precipitation levels and distribution have severe implications for agriculture, water availability, and food security in the region. Shifts in rainfall patterns can lead to prolonged droughts or intense rainfall events, both of which can disrupt crop cycles, impair soil fertility, and trigger water scarcity issues.

Rising sea levels pose a significant threat to low-lying coastal areas in South Asia. As global temperatures increase, polar ice caps and glaciers melt, contributing to the rise in sea levels. Coastal communities in countries like Bangladesh and the Maldives are already experiencing the impacts, including increased coastal erosion, saltwater intrusion into freshwater sources, and the displacement of vulnerable populations.

Another critical concern is the loss of biodiversity in South Asian ecosystems due to climate change. The alteration of temperature and rainfall patterns can disrupt ecological balance, leading to changes in habitat suitability, species migration, and disruption of critical ecological processes. This loss of biodiversity not only affects the intrinsic value of ecosystems but also has adverse consequences for human well-being, as many communities in the region heavily rely on ecosystem services such as fisheries, timber, and medicinal plants.

Furthermore, climate change exacerbates existing socio-economic inequalities in the South Asian region. Vulnerable communities, including marginalized groups, small-scale farmers, and coastal populations, are often the hardest hit by climate-related impacts. Limited access to resources, infrastructure, and information further compounds their vulnerability and hampers their ability to adapt to changing conditions.

The productivity of ecosystems, as measured by Net Primary Productivity (NPP), and the carbon balance, as measured by Net Ecosystem Exchange (NEE), play crucial roles in understanding the impacts of climate change on these natural systems.

Net Primary Productivity refers to the rate at which ecosystems convert solar energy into organic matter through photosynthesis, minus the amount of organic matter lost through respiration by plants. It is a fundamental measure of an ecosystem's productivity and its ability to capture and store carbon. Climate change can affect NPP in various ways. For instance, rising temperatures can accelerate plant metabolism, potentially increasing photosynthesis rates and NPP. However, in certain cases, extreme heat events or prolonged droughts can negatively impact plant growth and reduce NPP.

Changes in NPP have cascading effects on the entire ecosystem. Reduced NPP can lead to decreased food availability for herbivores, impacting the overall structure of food webs. Additionally, shifts in NPP can alter the carbon balance of ecosystems, affecting their capacity to sequester carbon dioxide from the atmosphere. This is where Net Ecosystem Exchange becomes crucial.

Net Ecosystem Exchange measures the net balance of carbon fluxes between an ecosystem and the atmosphere. It accounts for both carbon uptake through photosynthesis and carbon release through respiration. Positive NEE indicates that an ecosystem is absorbing more carbon than it emits, acting as a carbon sink. Negative NEE, on the other hand, suggests that an ecosystem is releasing more carbon than it sequesters, acting as a carbon source.

Climate change can impact NEE by altering the balance between carbon uptake and release within ecosystems. For example, rising temperatures and increased atmospheric carbon dioxide levels can stimulate plant growth and photosynthesis, potentially leading to higher carbon uptake and a more substantial carbon sink effect. However, other factors like changes in water availability, nutrient limitations, and disturbances such as wildfires or pest outbreaks can offset these positive effects and result in increased carbon emissions.

Variations in NPP and NEE serve as important indicators of ecosystem health and carbon dynamics in the face of climate change. Monitoring and understanding these metrics can help researchers and policymakers assess the vulnerability of ecosystems, identify areas at risk, and develop appropriate mitigation and adaptation strategies.

Furthermore, changes in NPP and NEE have implications beyond the boundaries of individual ecosystems. The carbon sequestration capacity of terrestrial ecosystems is crucial for mitigating climate change at a global scale. Healthy ecosystems with high NPP and negative NEE play a vital role in absorbing and storing carbon dioxide, thereby helping to reduce greenhouse gas concentrations in the atmosphere and mitigate global warming.

However, if climate change leads to a decline in NPP or a shift towards positive NEE, it could result in a reduced capacity of ecosystems to sequester carbon. This would create a positive feedback loop, as increased carbon emissions from ecosystems contribute to further climate change, exacerbating its impacts.(Chapin et al., 2002).

Furthermore, climate change influences agricultural productivity, a critical concern for South Asia, where agriculture is a vital part of the economy. Changes in temperature and precipitation patterns can affect crop yields, posing challenges for food security in the region (Lobell et al., 2008). Therefore, estimating total crop yield and comparing it with observed yield data is essential for assessing the impact of climate change on agriculture.

To study these complex interactions and estimate these variations, Dynamic Global Vegetation Models (DGVMs) like LPJ-GUESS are employed. These models simulate vegetation dynamics and biogeochemical cycles, providing insights into ecosystem productivity and carbon balance under changing climatic conditions (Sitch et al., 2003).

1.2 Problem Statement

Climate change is a pervasive global issue, significantly altering the terrestrial ecosystems, particularly with respect to their productivity, carbon balance, and overall ecological structure. These alterations have profound implications for the carbon cycle, which, in turn, impacts vegetation growth. South Asia, an area marked by rapid population expansion and consequential changes in land use and cover, is particularly vulnerable to these effects. The region's ability to meet the increasing demand for resources hinges on the health and productivity of its terrestrial ecosystems. Yet, there exists a significant gap in our understanding of the precise nature and extent of climate change impacts on these ecosystems.

Specifically, comprehensive and data-driven estimation and analysis of variations in Net Primary Production (NPP) and Net Ecosystem Exchange (NEE) due to changing atmospheric CO_2 concentrations in the South Asian context are lacking. Furthermore, an in-depth understanding of the implications of these variations on the carbon pool, carbon flux, and crop yield is missing, inhibiting the formulation of effective climate mitigation and adaptation strategies for the region. The deployment of Dynamic Global Vegetation Models (DGVM), such as the Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS), provides an opportunity to bridge this knowledge gap. However, the use of such models for these specific applications remains under-explored.

Therefore, this research aims to address the aforementioned gaps by using the LPJ-GUESS model to estimate and analyze changes in vegetation growth in South Asia due to climate change. It intends to offer critical insights into the regional carbon cycle disruption and its impacts on terrestrial ecosystems, thereby contributing to the development of well-informed and region-specific climate mitigation and adaptation policies.

1.3 Objectives of the Study

The primary objectives of this study are as follows:

1. To estimate the variation in Net Primary Productivity (NPP) and Net Ecosystem Exchange (NEE) in South Asia.

- These metrics will provide insights into the productivity and carbon balance of terrestrial ecosystems in the region.
- The LPJ-GUESS DGVM model will be utilized to simulate and analyze NPP and NEE dynamics.

2. To estimate the variation in Carbon Pool and Carbon Flux in South Asia.
   - This objective aims to assess the changes in carbon storage and exchange processes within South Asian terrestrial ecosystems.
   - The LPJ-GUESS DGVM model will be employed to quantify carbon pools and fluxes, considering factors such as vegetation growth, decomposition, and soil processes.
3. To assess total crop yield and compare it with observed yield data for South Asia.
   - This objective focuses on evaluating the potential impacts of climate change on agricultural productivity in the region.
   - Observed yield data will be collected and analyzed, and the LPJ-GUESS DGVM model will be utilized to estimate crop yields under varying climate scenarios.

The outcomes of these objectives will enhance our understanding of the productivity, carbon balance, and agricultural dynamics in South Asian terrestrial ecosystems under the influence of climate change. They will also contribute to the broader field of climate change research and support informed decision-making for ecosystem management and agricultural practices.

1.4 Scope of the Study

The scope of this study focuses primarily on terrestrial ecosystems within the South Asian region, with a special emphasis on Pakistan. South Asia, which includes countries such as India, Pakistan, Bangladesh, Nepal, Bhutan, Sri Lanka, and the Maldives, is home to diverse ecosystems ranging from tropical rainforests to arid deserts, grasslands, and montane ecosystems (DeFries et al., 2013). The ecological diversity of this region presents an excellent opportunity to understand the variations in productivity and carbon balance across different ecosystems.

Pakistan, in particular, is an intriguing case study due to its rich biodiversity and unique climatic and geographical features that include vast arid regions, fertile plains, coastal areas, and high-altitude ranges. However, the region is under considerable environmental stress due to climate change and anthropogenic activities, affecting ecosystem productivity and carbon balance (Ali et al., 2017).

The study will utilize the Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) Dynamic Global Vegetation Model (DGVM) to estimate variations in Net Primary Productivity (NPP), Net Ecosystem Exchange (NEE), carbon pools, carbon flux, and crop yields across the region. The application of the LPJ-GUESS DGVM model will allow a systematic, data-driven analysis of ecosystem productivity and carbon balance in the region, contributing to our understanding of these critical ecological processes and their implications for sustainable ecosystem management.

1.5 Significance of the Study

Understanding the productivity of terrestrial ecosystems and their carbon balance is crucial for several reasons, particularly in the context of climate change and sustainable land management. This study, focusing on South Asia and particularly Pakistan, plays a pivotal role in providing insights into these aspects using the Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) Dynamic Global Vegetation Model (DGVM).

Firstly, terrestrial ecosystems play a significant role in the global carbon cycle, acting as both sources and sinks of carbon dioxide (CO_2) (Le Quéré et al., 2015). They absorb CO_2 from the atmosphere during photosynthesis and release it back during respiration and decomposition. Hence, any changes in the productivity of these ecosystems can have a substantial impact on the global carbon cycle and, consequently, on atmospheric CO_2 concentrations. By estimating variations in Net Primary Productivity (NPP) and Net Ecosystem Exchange (NEE) in South Asia, this study contributes to our understanding of how these ecosystems are responding to environmental changes and their potential impact on the global carbon cycle.

Secondly, terrestrial ecosystems store a considerable amount of carbon in their biomass and soils. These carbon stocks play a crucial role in regulating the global climate by offsetting anthropogenic CO_2 emissions. However, changes in land use and management practices can alter these carbon stocks and influence carbon fluxes, affecting the ecosystems' role as carbon sinks. By estimating variations in carbon pools and carbon fluxes in South Asia, this study helps to understand how land use and management changes might be affecting the region's carbon balance.

Additionally, the study's focus on crop yield estimation is particularly significant. Agriculture plays a vital role in South Asia's economy, and crop yield estimation is crucial for food security planning and agricultural policy-making (Ray et al., 2012). By assessing total crop yield and comparing it with observed yield data, this study provides valuable insights that can inform agricultural practices and policies in the region.

The use of the LPJ-GUESS DGVM model adds another layer of significance to the study. This model has been extensively used in global vegetation and carbon cycle simulations, but its application in the context of South Asia, particularly Pakistan, is less explored (Smith et al., 2014). Therefore, this study not only contributes to the understanding of terrestrial ecosystems in South Asia but also expands the knowledge of the applicability and effectiveness of the LPJ-GUESS DGVM model in this context.

In short, this study holds significant value for various stakeholders, including environmental scientists, climate change researchers, policymakers, and land managers. The findings of this study can inform sustainable land management practices, climate change mitigation strategies, and agricultural policies in South Asia.

Chapter 2

Literature Review

2.1 Dynamics of Carbon Dioxide (CO_2) in the Atmosphere

The greenhouse effect serves as a vital mechanism, maintaining the Earth's temperatures at levels that render it conducive to life. However, over the previous centuries, human-driven actions have contributed to a significant surge in greenhouse gas discharges. This upsurge in atmospheric concentrations of such gases has translated to a rise in the planet's average overall temperature.

Predominantly, the emission of these environmentally harmful gases stems from two chief activities: the utilization of fossil fuels and extensive agricultural practices. Although the individual heat-retaining capacity of a Carbon Dioxide (CO_2) molecule is comparatively lower than other greenhouse gases, the escalation in atmospheric CO_2 concentration has critically disrupted the carbon equilibrium.

According to a report by the US Environmental Protection Agency in 2016, the warming impact of CO_2 is due to its extended atmospheric residence time, averaging around five years. This aspect sets it apart from other greenhouse gases and amplifies its contribution to global warming.

Compared to the pre-industrial era conditions, the concentration of greenhouse gases has witnessed a staggering spike during the past century (Ainsworth et al. 2020). One significant observation in the recent trend of atmospheric CO_2 concentration is a striking peak of almost 420 parts per million (ppm), a considerable rise from less than 320 ppm in 1960, as per the data by the National Oceanic and Atmospheric Administration (NOAA, 2021).

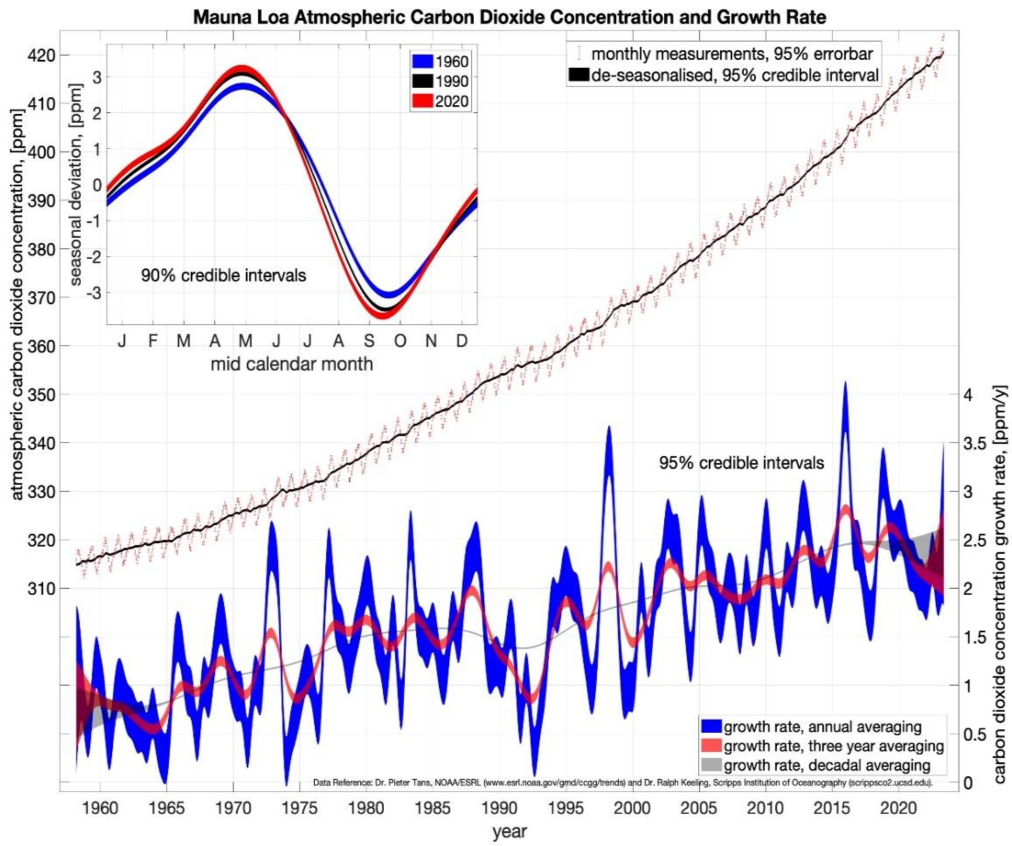


Figure 1: Carbon Dioxide Concentration and Growth

The above Figure illustrates the trend in Atmospheric CO_2 Concentration from 1960 to 2023 (NOAA, 2023). This graphically depicts the severity of the escalating levels of atmospheric CO_2, underlining the urgent need for measures to combat this escalating environmental crisis.

2.2 Agriculture's Role in the Carbon Cycle

Agriculture and the carbon cycle are intertwined in a complex, multifaceted relationship, characterized by mutual influences that can be both advantageous and detrimental. Changes in land use, such as the transformation of forested areas into managed lands like grasslands or crop fields, have profound effects on the carbon cycle.

These shifts can hasten soil erosion and deplete soil carbon reservoirs, a phenomenon examined in various studies (Tang et al., 2019). The severity of this depletion is closely tied to climate variables; extreme weather patterns can throw off the balance of the terrestrial carbon cycle, disturbing the natural give-and-take system that typically exists. The manner in which carbon is distributed within vegetation presents a significant point of uncertainty within this terrestrial carbon cycle.

As atmospheric carbon concentration rises, so does the rate of photosynthesis. This increase contributes to the replenishment of the terrestrial carbon sink, which subsequently decreases atmospheric carbon levels. This decrease is then counteracted by exchanges with terrestrial and marine carbon sinks, creating a continuous cycle of effects and counter-effects. This dynamic feedback system evidence how atmospheric and terrestrial factors influence each other reciprocally.

The economic landscapes of South Asian countries have been undergoing transformations since the 1980s, with a notable emphasis on agriculture. As these nations have honed their agricultural expertise, they have succeeded in boosting agricultural exports (Joshi et al., 2004).

Agriculture forms the backbone of South Asia's economy, ensuring livelihoods and food security for its vast population. However, this sector also stands as a significant contributor to greenhouse gas emissions (Kumara, 2020). With South Asia's susceptibility to the impacts of climate change, these emissions not only pose environmental concerns but also threaten the livelihoods of millions, further emphasizing the intricate links between agriculture, the carbon cycle, and human societies.

2.3 South Asia's Agricultural Landscape

With global population numbers on the rise, we are experiencing a correlating increase in the demand for food. Elevating agricultural output in a sustainable way to meet this escalating demand is a critical challenge faced by the agricultural sector and food security initiatives alike (Liu et al., 2020). Considering the constraints of limited arable land and labour availability, one of the most viable solutions lies in augmenting agricultural productivity. Doing so would not only meet rising food requirements but also address issues like malnutrition, poverty alleviation, and environmental preservation.

However, the effects of climate change on agriculture cannot be ignored, especially when looking towards the future. Projections for South Asia indicate that, by the mid-21st century, crop productivity may plunge drastically. Wheat varieties might suffer as much as a 50% decrease in productivity compared to levels in 2000, while declines of about 17% for rice and 6% for maize are predicted. These changes are due to the direct and indirect impacts of our changing climate. (IFPRI, 2009).

Looking at the potential impact on malnutrition, scenarios excluding climate change anticipate a drop from 76 million to 52 million malnourished children in South Asia from 2000 to 2050. However, when climate change is factored in, this figure is expected to rise to 59 million (IFPRI, 2009). A study conducted on South Asia indicated a nonlinear trend in agricultural output, with productivity declining after reaching a peak. This decline is attributable to shifts in factors like agricultural land use, labour, and fertilizer use (Liu et al., 2020).

In terms of research and focus on agricultural productivity, much of it has been concentrated on sub-Saharan Africa and China, leaving South Asia relatively under-examined. While some South Asian countries witnessed growth in agricultural productivity in the past, a downturn became apparent around 2002. This decline was precipitated by unsustainable land use and development practices.

A critical issue within this region's agricultural sector is the absence of social and environmental sustainability. Innovation and technology incorporation can potentially remedy these challenges. Technological advancements have been evident in the region, yet they have not halted the drop in agricultural productivity. The logical resolution appears to be the adoption of sustainable farming practices.

Observations from individual South Asian countries illustrate the varying impact of these developments. Bangladesh, India, Nepal, Pakistan, and Sri Lanka have all witnessed marginal improvements in productivity due to technological enhancements. Conversely, Bhutan has experienced a productivity decline, likely attributable to weakened technology implementation (Liu et al., 2020).

2.4 Understanding Agricultural Dynamics with the LPJ-GUESS Model

Crop Functional Types (CFTs) encapsulate broad agricultural characteristics of plant species, offering a level of generalization that facilitates their use in climate modeling. Aside from minor adaptations for yield-producing components, CFTs align well with Plant Functional Types (PFTs) used to depict Potential Natural Vegetation (PNV). CFTs effectively represent groupings of crops sharing similar traits. The model's scope is broadened by not replicating the behavior of specific plants. Instead, it considers the plasticity of crops through the identification of variety-dependent features under local conditions. For CFTs, a daily carbon allocation scheme is utilized to gauge the influence of environmental conditions and management practices on crop development and yield (Bondeau et al., 2007).

The terrestrial ecosystem functions dually as a sink and a source for carbon emissions. According to the Intergovernmental Panel on Climate Change (IPCC), it can sequester approximately 2 GtC/year. Both vegetation and soil contribute to the absorption of atmospheric carbon. This leads researchers to a novel challenge in climate change mitigation: the optimization of land use management practices to preserve existing carbon stocks and augment them. Documenting these processes is a requirement stipulated by the IPCC.

Land use practices can instigate shifts in land cover, which, in turn, affect the associated carbon stocks. The transition from one ecosystem to another could stem from natural processes or be the result of human activities. The carbon storage capacity of soil is influenced by factors such as vegetation type, rainfall, and temperature. Any disruption to the carbon stock equilibrium can prompt the soil to function as a source or sink for carbon until a new balance is reached (Guo and Gifford, 2002).

Understanding these interactions between land use, vegetation, and carbon storage is crucial in our ongoing efforts to mitigate climate change impacts. The LPJ-GUESS model, with its incorporation of CFTs, provides a valuable tool for examining these dynamics and informing sustainable land management practices.

2.5 LPJ-GUESS Model Related Studies

In a 2022 study, Ma et al. (2022) delved into the simulation of symbiotic nitrogen fixation in grain legumes using the LPJ-GUESS model. Their research simulated daily plant growth parameters based on the developing plant's heat requirements. The net primary productivity and CO_2 emissions were modeled as components of autotrophic respiration. Once the development stage concluded, nitrogen consumption was halved. The resultant data was compared to the FAO data and a Pearson correlation was used for data analysis. The research concluded that modelled data closely aligns with observed data, particularly in site-specific simulations. An intriguing linear relationship between biological nitrogen fixation and legume yield was established, with a negative correlation discovered between the nitrogen fertilizer rate and nitrogen fixation.

In another publication, Ma et al. (2022) explored the effects of varying agricultural management practices on carbon stocks, nitrogen, and crop productivity, again employing the LPJ-GUESS model. They examined seven different management strategies and their impact on the soil carbon pool, nitrogen loss, and yield. Most simulations indicated a decline in soil organic carbon (SOC) due to tillage and other management practices compared to regions with conservative agricultural strategies. They concluded that conservative agricultural practices could be the key to sustainable food security, particularly in regions with poor soil conditions.

Emmet et al. (2021) assessed the ability of the LPJ-GUESS-LMfireCF model to simulate fire, regional biomass, and plant biogeography. They evaluated model performance by comparing historical simulations from LPJ-GUESS-LMfireCF with GlobFIRM historical simulations. Despite some discrepancies, the LPJ-GUESS-LMfireCF model proved to be quite capable in simulating plant regrowth post-fire events.

Pongracz et al. (2021) probed the biogeochemistry of the Arctic and the sensitivity of the permafrost using LPJ-GUESS. They adopted a multi-layer snow scheme instead of a single-layer scheme, which led to a 5-10% reduction in the overestimation of permafrost decline. They discovered that the multi-level snow scheme more accurately simulated cold weather conditions than a static scheme, and that the carbon pool is generally low across the region.

Meanwhile, Herzfeld et al. (2021) examined the dynamics of soil organic content from agricultural management practices using the LPJml model. They projected a decline in SOC stock in future scenarios due to increased decomposition from managed agricultural cropland. They revealed that tillage practices and residue management could significantly influence future SOC stock.

Similarly, Oberpriller et al. (2021) studied sensitivity in vegetation dynamics considering both modelling parameters and climatic drivers using LPJ-GUESS. They suggested that the uncertainty in predictions increases with a rise in temperature and that climatic variables significantly influence the model predictions.

Moreover, Lindeskog et al. (2021) examined forest management to estimate forest carbon stocks using LPJ-GUESS. The study discovered an increase in the simulated carbon stock by 32% for the years 1991-2015.

Usman et al. (2021) investigated the primary productivity of the Himalayan Hindu Kush (HKH) Forest under climate change using LPJ-GUESS. Their research reported that the HKH region would remain a significant carbon sink under both ideal and extreme climate scenarios.

In a slightly different approach, Forest et al. (2020) integrated LPJ-GUESS with EMAC to induce vegetation dynamics in the general circulation model enabled by atmospheric chemistry. They coupled the eco-physiological framework of LPJ-GUESS with EMAC, yielding intriguing results.

Earlier studies by Pugh et al. (2015) and Lindeskog et al. (2013) respectively simulated carbon emissions due to land-use changes and the impact of land-use change in the ecosystem carbon cycle using LPJ-GUESS. The authors concluded that management practices significantly influence food security but only marginally impact land-use change emissions.

These studies have elucidated a wealth of information on the intricate interplay between agriculture, climate change, and carbon stocks. The LPJ-GUESS model, thanks to its ability to simulate intricate interactions, has proven a valuable tool in these analyses. These findings underscore the importance of prudent land and agricultural management in mitigating climate change impacts and enhancing food security.

Chapter 3

Materials and Methods

3.1 Study Area

South Asia, a diverse and vibrant region located at 25.0376° N and 76.4563° E, is distinguished by its natural boundaries, the Himalayas to the north and the Indian Ocean to the south. This vast region comprises six countries: Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka, each with its unique culture, traditions, and ecosystems. Remarkably, despite occupying only 3% of the world's land area, it is home to approximately 24% of the global population, marking it as one of the most densely populated regions on earth.

The geography and climate of South Asia vary drastically from towering snow-capped mountains to tropical coastlines, fertile plains to arid deserts, fostering a wide array of terrestrial ecosystems. Himalayan alpine forests, the fertile Gangetic plains, the tropical rainforests of the Western Ghats and Sri Lanka, the mangroves of the Sundarbans, the Thar Desert in India and Pakistan, and the unique ecosystem of the northeastern states of India exemplify the ecological diversity of the region. These ecosystems not only house rich biodiversity but also provide invaluable ecosystem services, such as clean air, water, and rich soils that are fundamental to the livelihood of the local communities and the economy at large.

The agricultural sector is a major component of the region's economy, with approximately 57% of its land dedicated to farming activities. It is noteworthy that about 60% of South Asia's workforce is engaged in agricultural activities, signifying the sector's critical role in livelihood sustenance. The dominant crops in the region include wheat, rice, maize, and soybean, with rice being the most prevalent, and India and Pakistan are among the world's leading rice exporters.

Despite its considerable agricultural output, South Asia confronts the paradox of being the hungriest region worldwide, with a Global Hunger Index score of 30.5. Issues related to food distribution, poverty, and the socio-economic divide contribute significantly to this conundrum. Furthermore, environmental challenges such as deforestation, soil degradation, water scarcity, and climate change pose grave threats to the region's ecosystems and agriculture, exacerbating food security issues.

The region is rich in cultural heritage, boasting centuries-old traditions, languages, religions, and philosophies. This cultural diversity adds another layer of complexity to the region's ecological dynamics as human-nature relationships are deeply embedded in these cultural matrices. The combination of ecological, agricultural, cultural, and socio-economic factors makes South Asia a dynamic and challenging study area.

South Asia's terrestrial ecosystems are continually evolving, influenced by both natural processes and anthropogenic activities. Investigating the estimation of variation in these ecosystems can yield valuable insights into their resilience, adaptability, and vulnerability to ongoing changes, thereby facilitating effective conservation and sustainable development strategies. This area of research is particularly pertinent in the context of escalating environmental challenges and their implications for sustainable livelihoods and regional food security.

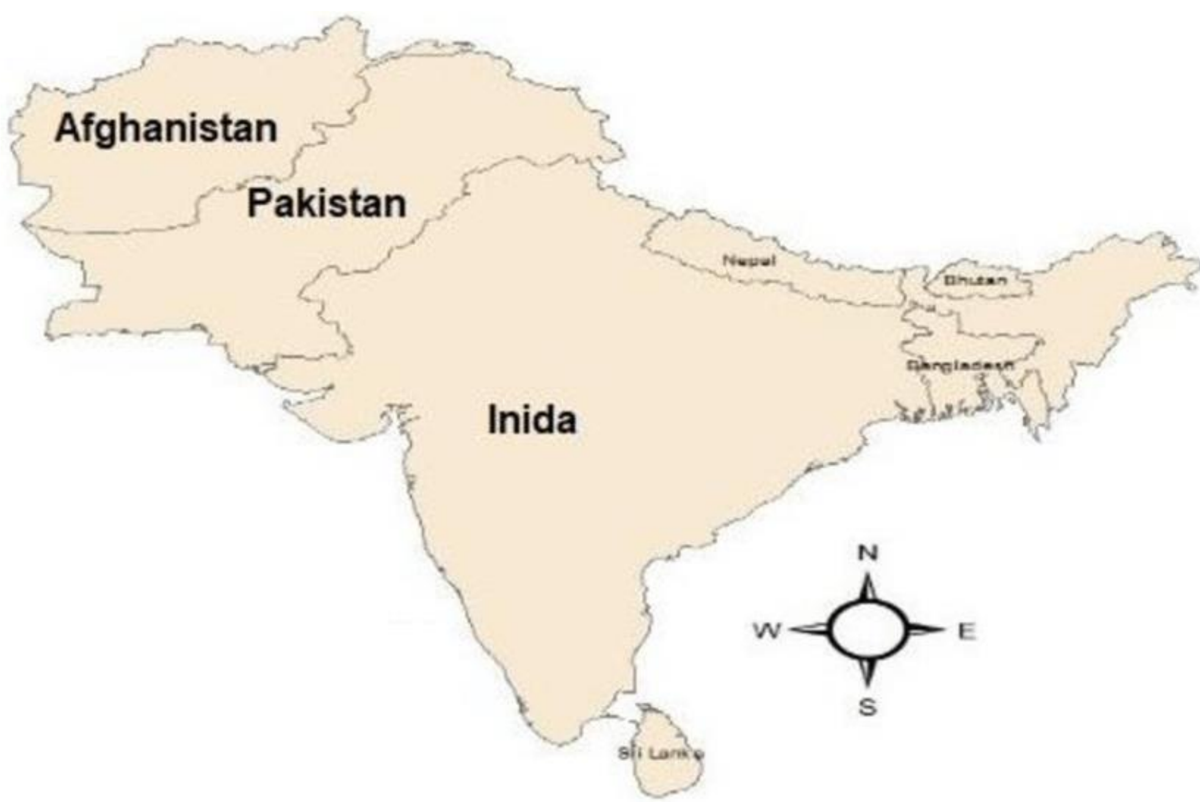


Figure 2: Map of South Asia

3.2 Data Sources and Description

The study utilized various data sources to execute a comprehensive analysis of the terrestrial ecosystems in South Asia and their changes under the influence of climate variations.

Crops Sowing Dates and Harvesting Dates

The data for the sowing and harvesting dates of the crops were acquired from MIRCA2000. These data sets play a significant role in understanding the growing patterns and estimating the productivity of various crops across the regions of South Asia.

Gridlist of South Asia

The study employed the South Asia Gridlist as a primary geographic reference. It provided the geographical boundaries and grid structure for the region of study.

Crops Growing Area

The data for the areas under crop cultivation were also obtained from MIRCA2000. This data provided insights into the spatial distribution of different crop types, which is crucial for evaluating the impacts of climate change on agricultural yield.

N-fertilization Data

Provided by the model developers, N-fertilization data was utilized to assess the effects of nitrogen fertilization on crop productivity and the terrestrial carbon cycle.

Soil Data

Also provided by the model developers, this data set contained information on the soil's physical and chemical properties across the study region. This data was crucial in predicting how soil conditions might affect the region's vegetation growth and carbon sequestration.

CRU and CRU Miscellaneous Data

CRU data sets, which include climate data such as precipitation, temperature, and solar radiation, were used. These factors have a significant impact on ecosystem productivity and hence were crucial for the LPJ-GUESS model's calibration and execution.

CO_2 Data

Data on the atmospheric concentration of CO_2 was used as it directly influences the photosynthetic rates and, consequently, the NPP and NEE of terrestrial ecosystems.

Global Nitrogen Depositions

Data provided by the model developers on global nitrogen depositions was used. Nitrogen deposition is a key factor influencing plant productivity and soil health, making it crucial to estimate changes in vegetation growth and carbon flux.

These comprehensive and multi-source data facilitated a robust analysis and reliable outcomes in studying the variations in South Asian terrestrial ecosystems under climate change.

Chapter 4

Results and Discussion

4.1 Analysis of Crop Yields of Bangladesh

4.1.1 Wheat

The FAO data shows a general increasing trend in wheat yields over the period 1991-2015. While there are small variations, the trend is clearly upward, suggesting improvements in yield over time. The LPJ Guess model data also shows an overall increase in yield. The increase is not as smooth as in the FAO data, with more pronounced year-to-year variations, but the general trend is upward.

Both the FAO data and the LPJ Guess model data show increasing yields over time, indicating some degree of consistency between the two datasets.

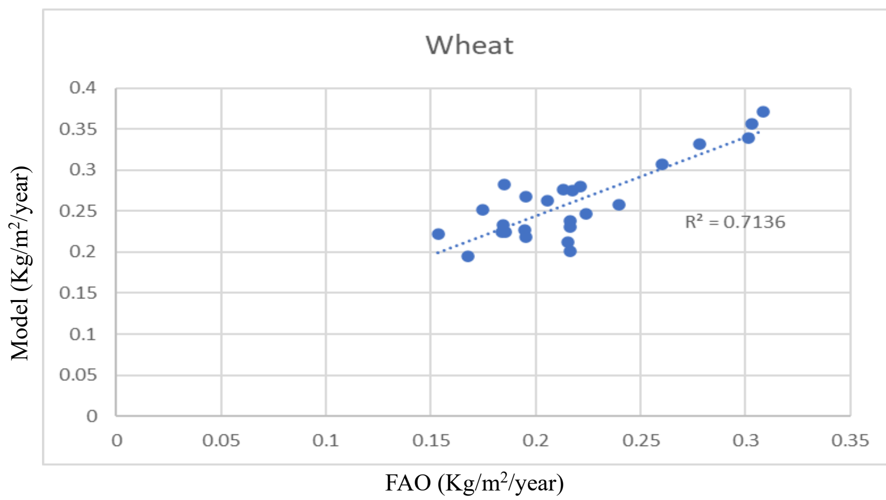


Figure 3: Bangladesh Wheat Yield Scatter Plot

However, The LPJ Guess model's yield estimates are consistently higher than the FAO's values. There is only one instance in 1999 when the LPJ Guess model's estimate is lower than the FAO's. The difference between the FAO and LPJ Guess model data seems to increase over time.

Interestingly, the discrepancy between the LPJ Guess model and FAO data appears to be growing with time. While in the early 1990s, the LPJ Guess model estimates were around 15-30% higher than the FAO's, by 2015 the model's estimates are almost 20% higher.

The results suggest an overall increase in wheat yields in Bangladesh over the period from 1991 to 2015, as reported by both the FAO and the LPJ Guess model.

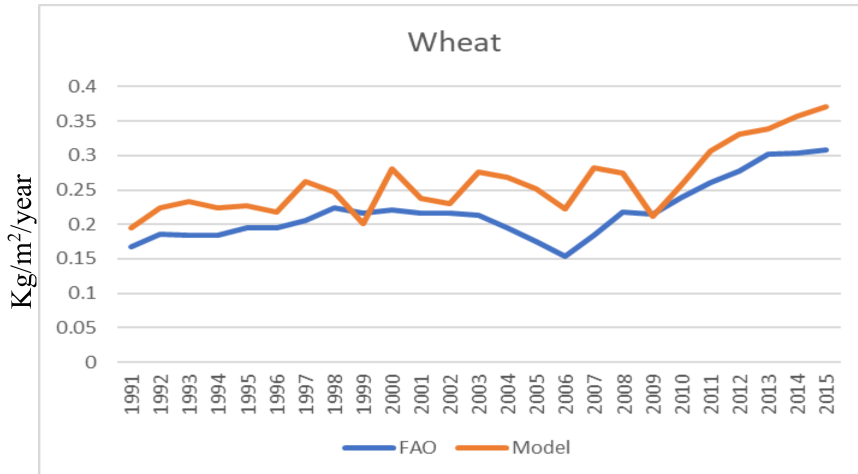


Figure 4: Bangladesh Wheat Yield line Plot

The consistently higher yield estimates from the LPJ Guess model compared to the FAO could indicate that the model might be using data on optimal farming practices or the best available wheat varieties, which could result in higher estimated yields than the actual yields recorded by the FAO.

4.1.2 Maize

The FAO data shows a clear and strong upward trend in maize yields over this time period. There's a particularly notable increase around the turn of the millennium, and the yield has more or less steadily increased since then. LPJ Guess Model data also shows an overall increasing trend over the years. While the increase is not as pronounced or consistent as in the FAO data, the overall pattern is of increasing yield.

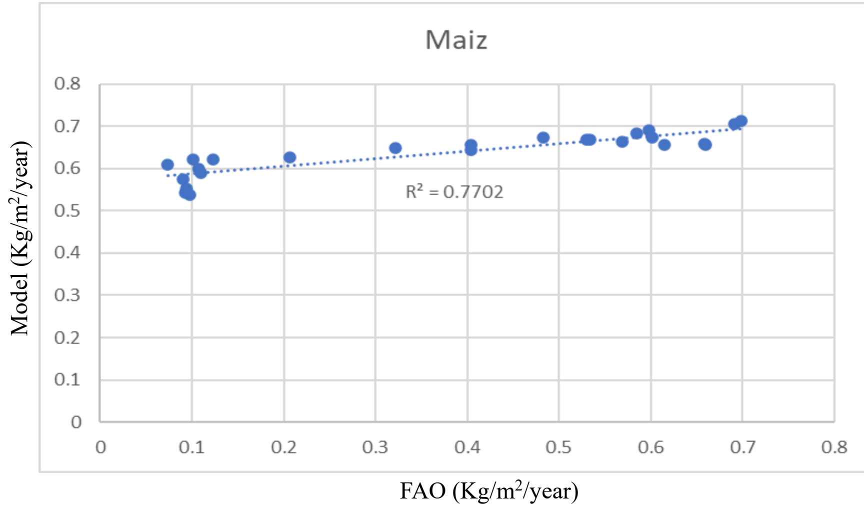


Figure 5: Bangladesh Maize Yield Scatter Plot

Both the FAO data and the LPJ Guess model data show increasing yields over the time period, indicating that both sources agree on the general trend of improving maize production in Bangladesh.

The LPJ Guess model's yield estimates, however, are significantly higher than the FAO's values for every year in the dataset. The discrepancy between the two datasets seems to have remained fairly consistent over time, with the model consistently predicting a much higher yield.

Moreover, the difference between the two datasets is substantial and consistent, with the LPJ Guess model always predicting much higher yields than the FAO. This is despite the fact that both sources show the same general trend of increasing yield.

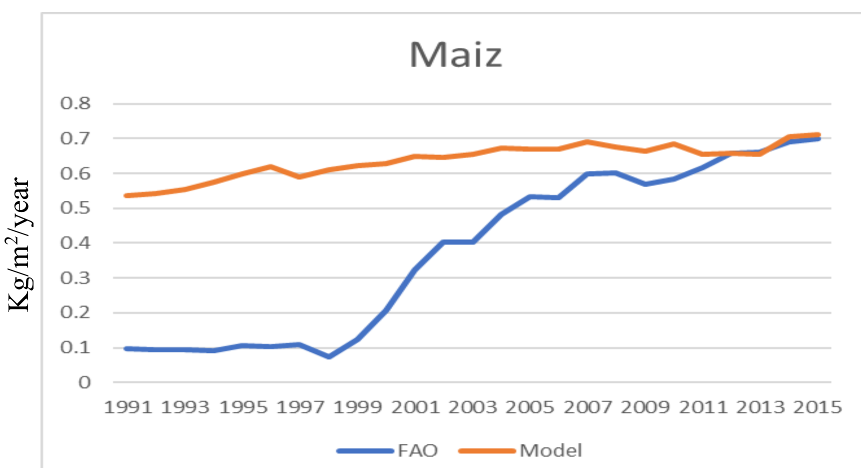


Figure 6: Bangladesh Maize Yield Line Plot

The results suggest an overall increase in maize yields in Bangladesh over the period from 1991 to 2015, as reported by both the FAO and the LPJ Guess model. The consistently higher yield estimates from the LPJ Guess model could indicate that the model is based on optimal or ideal conditions that may not reflect the actual conditions in Bangladesh.

4.1.3 Rice

Both the FAO data and the LPJ GUESS model show an overall increasing trend in the yield of rice crop from 1991 to 2015. This suggests that the productivity of rice has been improving over the years in Bangladesh.

The FAO data consistently shows higher yield values than the LPJ GUESS model for every year in the given period. This indicates that the model tends to underestimate the yield compared to the actual data.

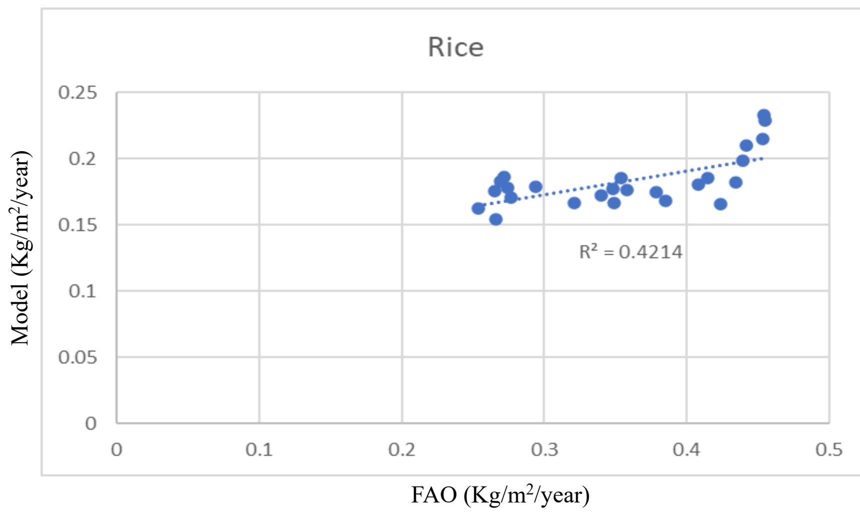


Figure 7: Bangladesh Rice Yield Scatter Plot

The difference between the FAO data and the model data seems to be increasing over time. For instance, the difference in 1991 is about 0.11, while in 2015 it is about 0.23. This suggests that the model's underestimation of the yield is becoming more pronounced over time. Despite the differences in the absolute values, the general trend of increasing yield over time is similar in both the FAO data and the LPJ GUESS model.

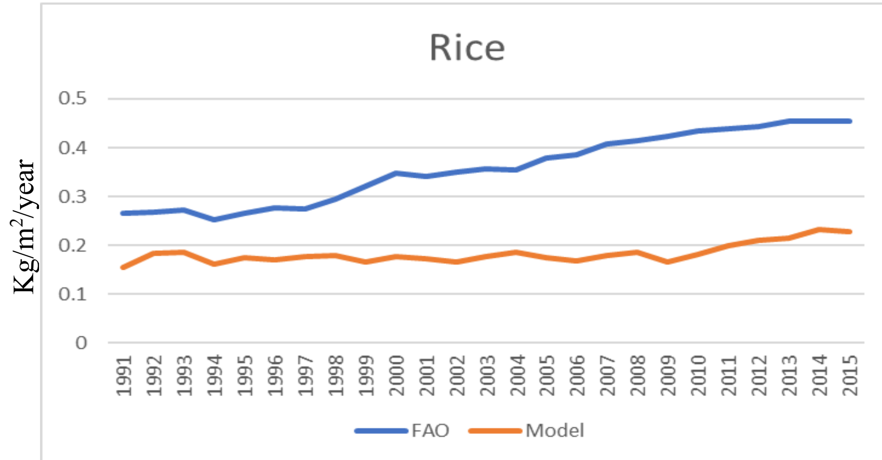


Figure 8: Bangladesh Rice Yield Line Plot

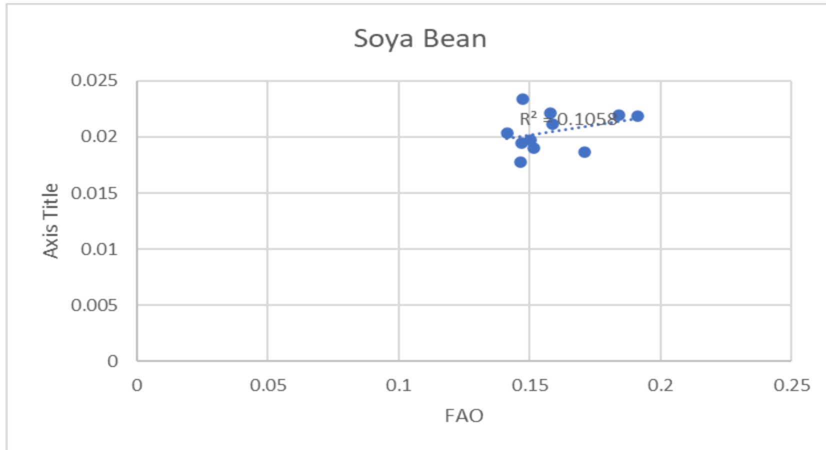
These results suggest that while the LPJ GUESS model is able to capture the overall trend of increasing rice yield in Bangladesh, it consistently underestimates the yield compared to the actual data. The increasing discrepancy over time indicates that the model may not be fully accounting for some factors that have contributed to the increase in yield. These could include improvements in farming practices, use of better-quality seeds, increased use of fertilizers, or changes in climate conditions. Further investigation would be needed to identify the specific factors that the model is not capturing.

4.1.4 Soybean

Both the FAO data and the model data show an overall increasing trend over the years. This suggests that the soybean crop yield in Bangladesh has been improving over the years.

The most significant difference between the two datasets is the magnitude of the values. The FAO data consistently reports higher values than the model data. This could be due to a variety of factors, including differences in data collection methods, differences in the variables considered by the FAO and the model, or inaccuracies in one or both datasets.

Model (Kg/m^2/year)



FAO (Kg/m^2/year)

Figure 9: Bangladesh Soybean Yield Scatter Plot

The year-to-year variations in the two datasets also differ. The FAO data shows more fluctuation, with the yield decreasing in some years (e.g., 2007, 2009, 2013) and increasing in others. The model data, on the other hand, shows a more steady increase over the years, with only minor decreases in some years (e.g., 2006, 2009).

Despite the differences in magnitude and variation, the two datasets show a similar pattern. Both datasets show an increase in yield over the years, suggesting that the model is capturing the overall trend accurately.

Kg/m^2/year

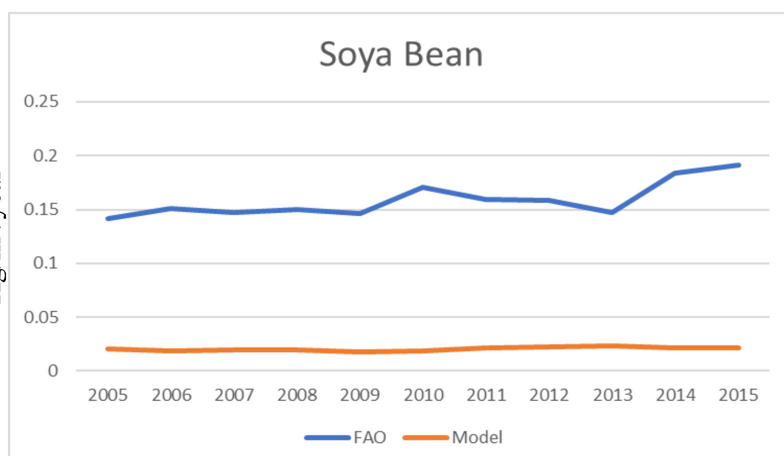


Figure 10: Bangladesh Soybean Yield Scatter Plot

These results suggest that while the LPJ GUESS model is able to capture the overall trend of soybean crop yield in Bangladesh, it consistently underestimates the yield compared to the FAO data. This could be due to the model not considering certain factors that influence yield, or due to inaccuracies in the FAO data. Further investigation would be needed to determine the cause of this discrepancy.

4.1.5 Millet

A general downward trend can be observed in the FAO data from 1991 through 2012, followed by an uptick until 2015. The model data does not clearly reflect this trend. The model data remains relatively stable throughout this period, with a slight upward trend, particularly from 2012 onwards.

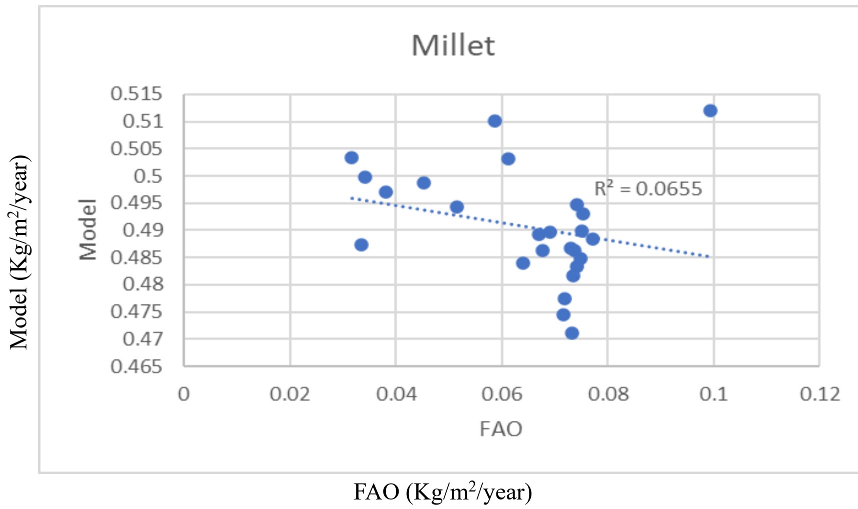


Figure 11: Bangladesh Millet Yield Scatter Plot

The most prominent observation is the persistent difference between the FAO data and the model data. For every year listed, the LPJ GUESS model data yields a higher value than the FAO data. This suggests that the model is consistently overestimating millet crop yields compared to FAO records.

The variations or changes from year to year seem less pronounced in the model data than in the FAO data. The FAO data shows significant fluctuations over time, with a notable decrease observed in 2002 and from 2008 to 2012. Conversely, the model data stays within a much tighter range, with less variation from year to year.

Both datasets show a broad agreement on the relative pattern of crop yield over the years, with ups and downs at similar timeframes. However, the magnitude of these fluctuations is quite different.

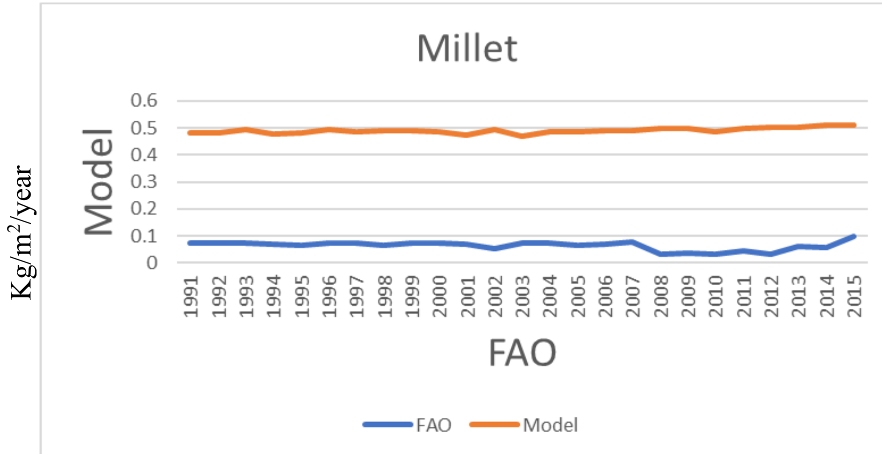


Figure 12: Bangladesh Millet Yield Line Plot

It's noteworthy that the model seems to fail to capture the severe yield reductions seen in the FAO data in 2002 and 2008-2012. This suggests that there may be factors influencing crop yield in those years that the model is not adequately accounting for.

These results suggest that the LPJ GUESS model may need refinement to more accurately represent millet crop yields in Bangladesh. The overestimation by the model across all years suggests that the model's parameters or underlying assumptions may need to be revisited to improve its accuracy. Therefore, further research and refinement of the model are recommended to enhance its predictive power and reliability.

4.2 Analysis of Crop Yields of Bhutan

4.2.1 Wheat

From the FAO data, we observe a general trend of increasing wheat yield over the years from 1991 to 2015. For the LPJ GUESS model, the yield appeared to be relatively stable throughout the years with minor fluctuations.

The FAO data shows more year-on-year variability compared to the LPJ GUESS model. The model seems to underpredict the wheat yield, especially in the years after 2008 where the actual yield (FAO data) has significantly increased. The greatest difference in values is seen in the year 2011, where the FAO reported a yield of 0.26686 while the model predicted a considerably lower yield of 0.093333333.

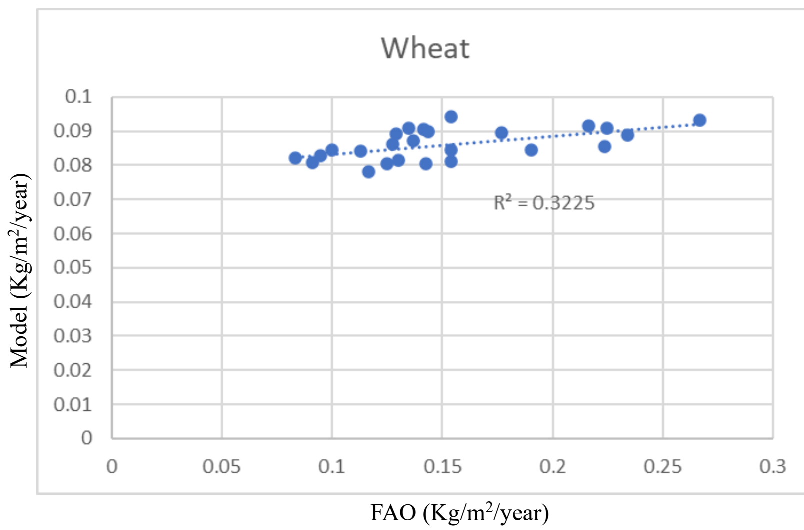


Figure 13: Bhutan Wheat Yield Scatter Plot

Although the values differ, both data sources show some years of increase and decrease, implying that they both might be responding to similar influencing factors, albeit at different magnitudes.

Moreover, a significant surge in the FAO data is noticed starting from 2008, which isn't mirrored in the model data. This could suggest that the model might not be accounting for certain factors that have contributed to the increased yield during these years.

The consistent underestimation of the model suggests that it might be missing some key variables or dynamics that impact wheat yield. This could include factors like advancements in agricultural technology, changes in agricultural practices, government policies, or changes in climate.

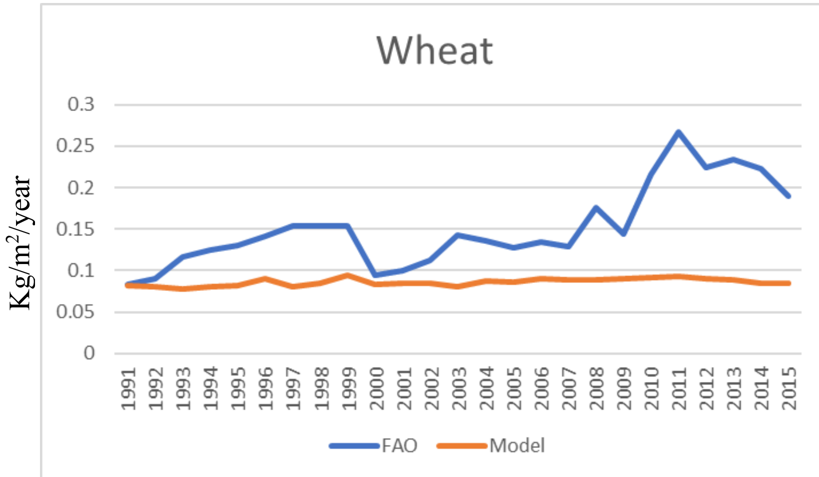


Figure 14: Bhutan Wheat Yield Line Plot

While the LPJ GUESS model provides a consistent yield estimate for wheat in Bhutan across the studied period, it fails to capture the rising trend and year-on-year variations in the actual yield as per FAO data. This could imply the need for further refinement of the model to better align with the ground realities of wheat production in Bhutan.

4.2.2 Maize

There is a general upward trend in the FAO data, with maize yields gradually increasing over the 25-year period from 1991 to 2015. While the model data also shows some fluctuations, the overall trend is more stable, and does not reflect the increasing trend shown by the FAO data.

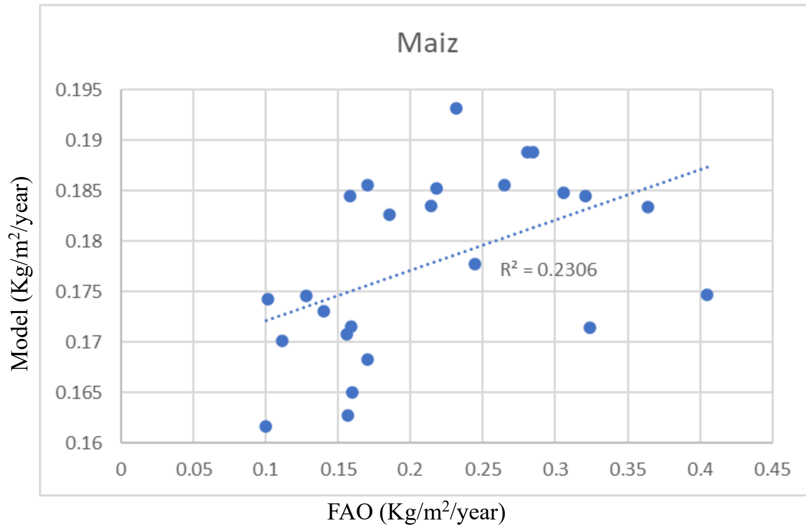


Figure 15: Bhutan Maize Yield Scatter Plot

The LPJ GUESS model generally underestimates the yield compared to the FAO data, with the discrepancy becoming particularly noticeable from 2004 onwards. The largest difference is seen in the year 2004, where the FAO data records a yield of 0.40495, while the model predicts a yield of just 0.174666667.

Both data sets reflect a degree of year-on-year variability in maize yields, suggesting they are responsive to similar influencing factors, although at different magnitudes.

A significant surge in maize yield is seen in the FAO data starting from 2004, which is not captured by the model data. This could imply that there were some changes or events influencing maize production around that time which the model is not accounting for.

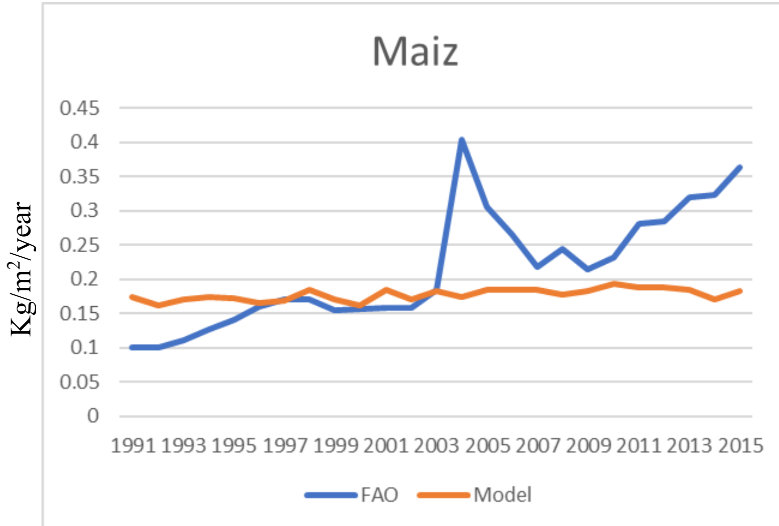


Figure 16: Bhutan Maize Yield Line Plot

The persistent underestimation by the model suggests it may be lacking some key variables or dynamics that influence maize yield. This could include factors like changes in farming practices, technological advancements in agriculture, weather patterns, or policy shifts.

The LPJ GUESS model seems to provide a fairly stable estimate for maize yield in Bhutan across the period under study, but fails to capture the significant upward trend and inter-annual variations in the actual yield as per FAO data. This suggests that the model might need refinement to accurately reflect the realities of maize production in Bhutan.

4.2.3 Rice

The FAO data shows a clear increasing trend in rice yields from 1991 to 2015. The LPJ GUESS model data, on the other hand, is much more stable with slight increase over the years.

The model consistently underestimates the yield compared to the FAO data throughout all years. The discrepancy is especially pronounced from 2008 onwards, with the FAO data showing a significant increase in yield that is not mirrored in the model data. The greatest difference is observed in 2008, where the FAO reported a yield of 0.39983 while the model predicted only 0.050833333.

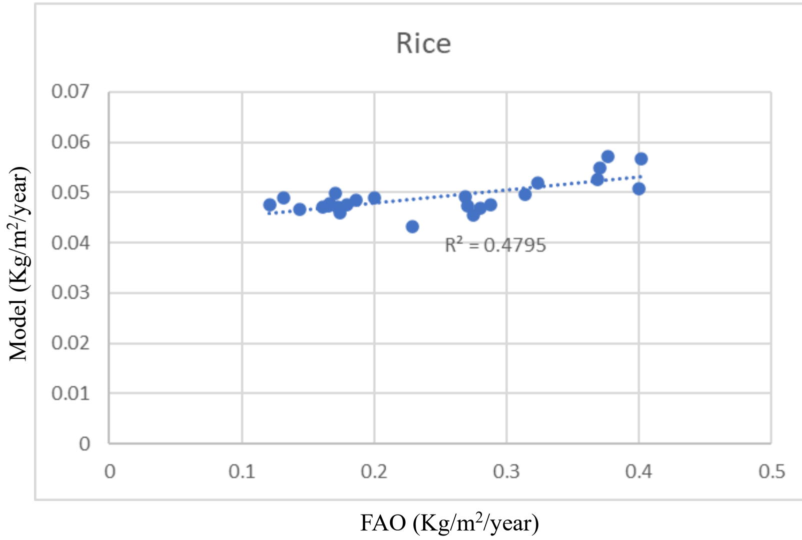


Figure 17: Bhutan Rice Yield Scatter Plot

Both data sets show an upward trend over the years, indicating they may be influenced by similar factors such as climate, but the magnitude of the increase is much larger in the FAO data.

The sharp increase in FAO data from 2008 onwards suggests there may have been factors at play that greatly increased rice yields in Bhutan. This could include advancements in rice cultivation techniques, introduction of higher yielding varieties, or policy changes.

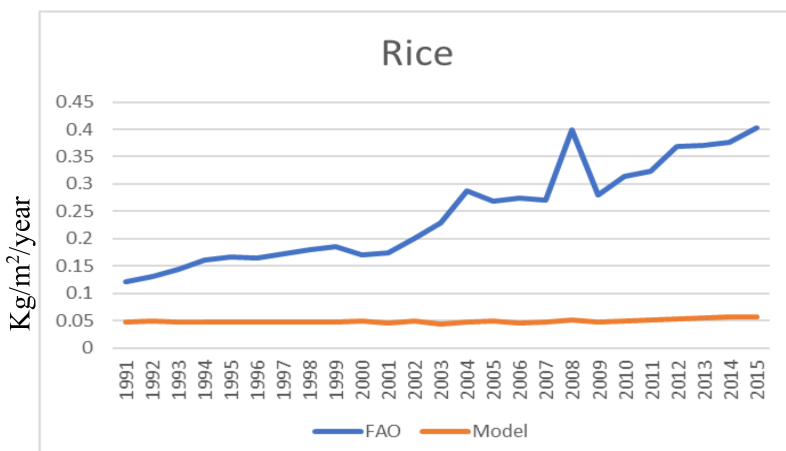


Figure 18: Bhutan Rice Yield Line Plot

While the LPJ GUESS model provides a conservative, stable estimate for rice yield in Bhutan, it fails to capture the significant upward trend in actual yields recorded by the FAO. This indicates a need for refinement of the model, to include additional variables or dynamics that have driven the increase in rice production in Bhutan. Such a refined model could provide a more accurate tool for predicting future rice yields under various scenarios.

4.2.4 Millet

The FAO data shows an upward trend in millet yields from 1991 to 2015, albeit with several fluctuations. On the other hand, the LPJ GUESS model data shows a more stable trend, with slight fluctuations but no clear increase.

While the model consistently overestimates the yield compared to the FAO data from 1991 to 2007, this trend shifts from 2008 onwards, with the FAO data generally reporting higher yields. The highest discrepancy occurs in 2014, where the FAO reported a yield of 0.28706 while the model predicted a significantly lower yield of 0.200083333.

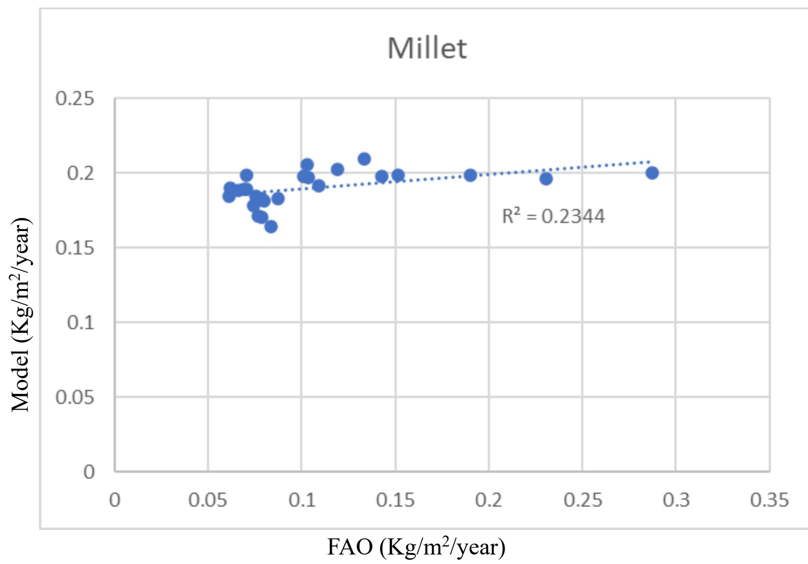


Figure 19: Bhutan Millet Yield Scatter Plot

Despite the different magnitudes, both data sets show year-on-year fluctuations, suggesting they respond to similar influencing factors.

Moreover, the FAO data shows a sharp increase in yield from 2008 to 2014, which is not captured by the model. This could indicate that there were significant advancements or changes in millet farming practices during this period that are not accounted for in the model.

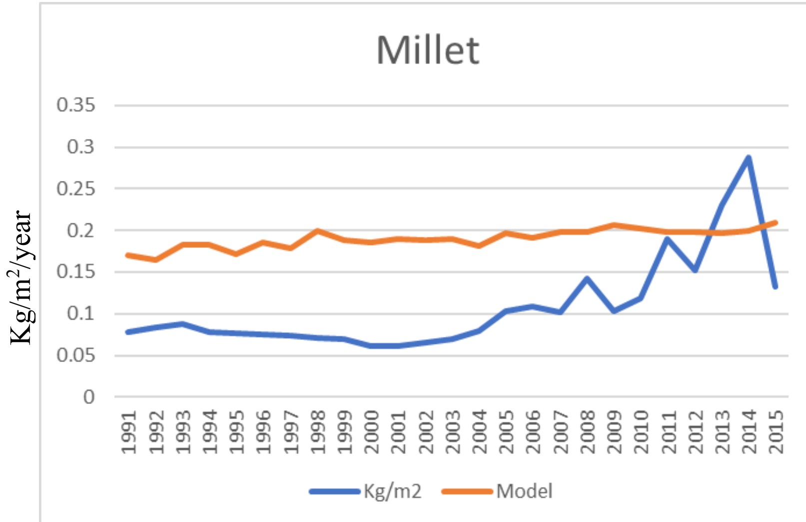


Figure 20: Bhutan Millet Yield Line Plot

The divergence in trends from 2008 onwards indicates that the model may not accurately represent all factors influencing millet yield in Bhutan, especially any changes or improvements introduced around 2008.

While the LPJ GUESS model provides a relatively consistent estimate for millet yield in Bhutan, it does not accurately reflect the upward trend and fluctuations in the FAO data, especially after 2008. This suggests the need for further refinement of the model to include any factors or dynamics that have influenced the increase in millet yields in Bhutan, which could improve the model's accuracy in future yield predictions.

4.3 Analysis of Crop Yields of India

4.3.1 Wheat

Both the FAO data and the LPJ GUESS model data show an overall upward trend in wheat yields from 1991 to 2015, indicating improving productivity over this period.

The LPJ GUESS model consistently underestimates the wheat yield compared to the FAO data throughout the observed period. The difference between the two data sets gradually narrows down over time but remains significant, with the largest gap occurring in 1991 (0.22814 FAO vs 0.108380953 Model) and the smallest in 2015 (0.27496 FAO vs 0.179126685 Model).

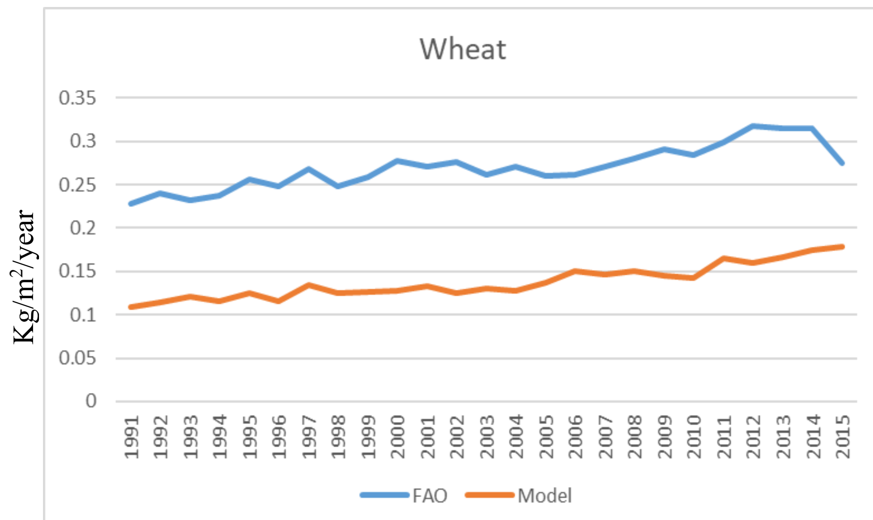


Figure 21: India Wheat Yield Line Plot

Both data sets reflect a similar pattern of fluctuations, suggesting that they respond to the same influencing factors, such as seasonal variations, climate conditions, or changes in farming practices.

Furthermore, from 2006 onwards, the model data shows a significant increase in yield, which is more in line with the upward trend observed in the FAO data. This may suggest improvements in the model's alignment with actual yield factors during this period.

The consistent underestimation of the wheat yield by the model suggests that it may not fully account for certain influential factors contributing to wheat productivity in India, such as advancements in agricultural technology, improved irrigation methods, or the use of high-yield varieties.

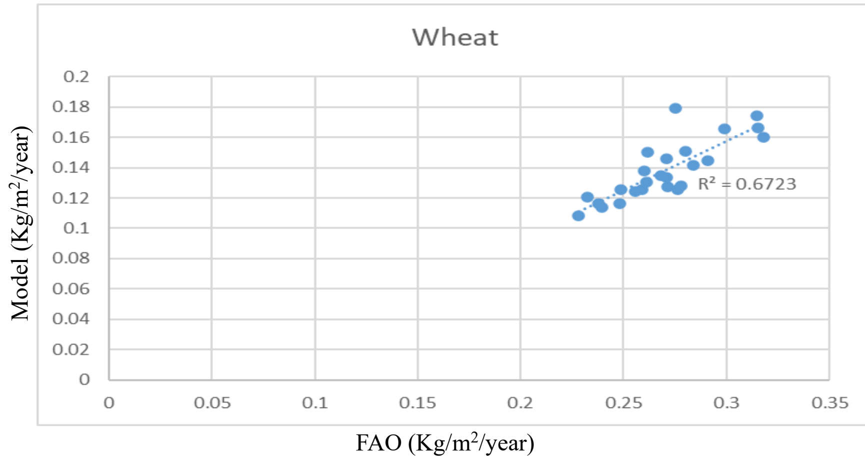


Figure 22: India Wheat Yield Scatter Line Plot

While the LPJ GUESS model provides a decent trend representation for wheat yield in India, it consistently underestimates the actual yield as per the FAO data. This indicates a need for further refinement of the model to include all potential factors influencing wheat productivity in India. Nonetheless, the model seems to be progressively improving, as seen by the narrowing gap between the model and FAO data in later years.

4.3.2 Maize

Both the FAO data and the LPJ GUESS model data show an upward trend in maize yields from 1991 to 2015, suggesting an increase in productivity over time.

Unlike the previous analysis for wheat, the LPJ GUESS model consistently overestimates the maize yield compared to the FAO data throughout the observed period. The difference between the two datasets, while significant, does not seem to be decreasing or increasing consistently over time.

Both data sets show similar fluctuation patterns, suggesting that they respond to the same influencing factors. Notably, both datasets show a dip in yield in 2002 and a peak in 2011.

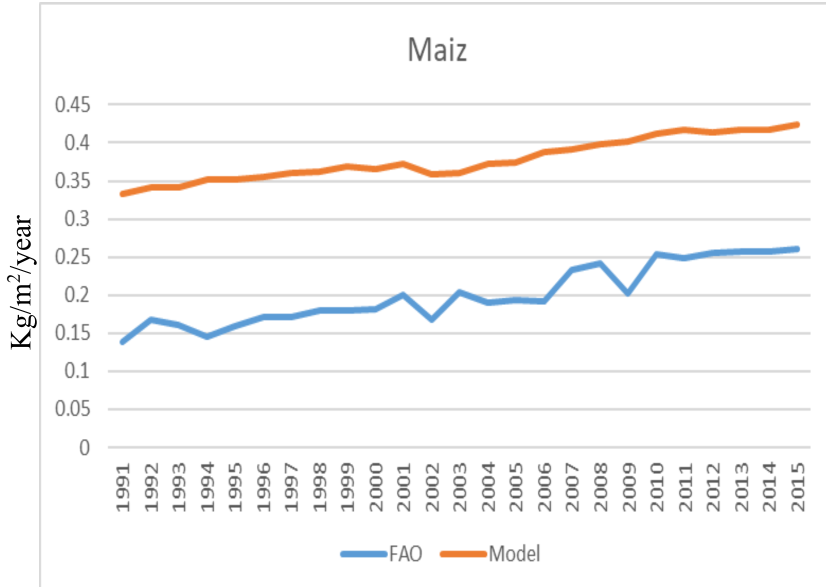


Figure 23: India Maize Yield Line Plot

Even though the model overestimates the yield, it accurately captures the relative ups and downs in the FAO data. This suggests that the model is likely capturing the correct factors influencing yield but perhaps not accurately capturing the magnitude of these factors.

The consistent overestimation of the maize yield by the model indicates it may not fully account for some constraints on maize production in India.

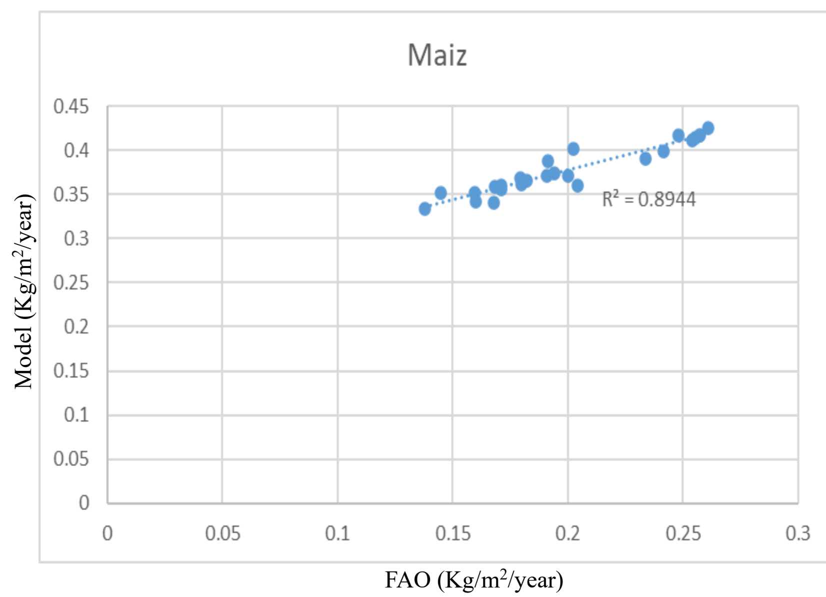


Figure 24: India Maize Yield Scatter Plot

While the LPJ GUESS model captures the trend and fluctuations in maize yield in India reasonably well, it consistently overestimates the yield as per the FAO data. This indicates that the model may need refinement to better account for factors that limit maize production in India. However, the model's ability to reflect the relative changes in yield over time suggests that it captures the primary influences on maize yield.

4.3.3 Rice

Both FAO and the LPJ GUESS model show an increasing trend in rice yield from 1991 to 2015, which indicates that rice productivity in India has generally improved over the years.

The LPJ GUESS model consistently underestimates the rice yield when compared with the FAO data for the entire period from 1991 to 2015. The gap between the model's output and the FAO data does not show a clear pattern of increase or decrease, and the underestimation remains consistent across the years.

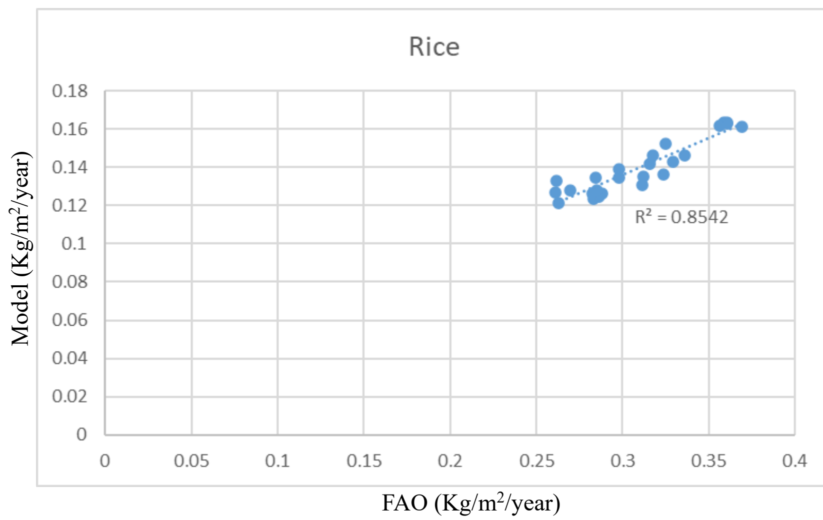


Figure 25: India Rice Yield Scatter Plot

Despite the difference in the values, both the model output and the FAO data follow a similar pattern, showing rises and falls in the yield in the same years. This similarity suggests that the model captures the influencing factors impacting the rice yield well.

Both the FAO data and the model's output depict a dip in the yield in 2002, followed by an increasing trend. This similarity further strengthens the observation that the model is able to capture significant changes in the yield, though it may not predict the actual yield values accurately.

The consistent underestimation of the rice yield by the LPJ GUESS model could indicate a limitation in the model's ability to fully capture the factors contributing to rice production in India.

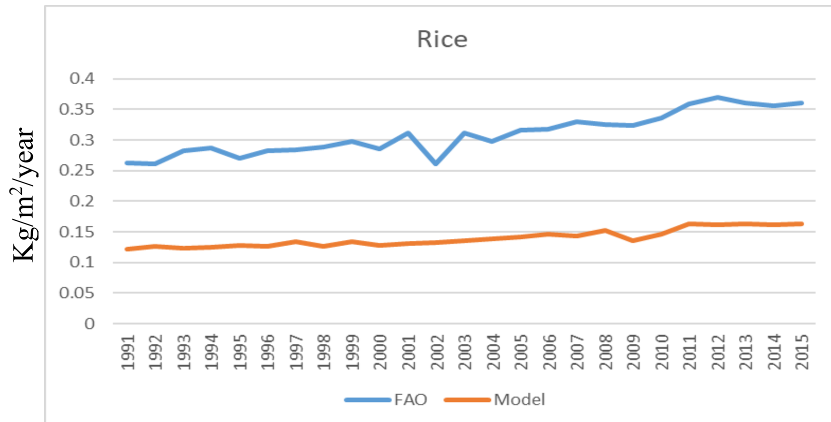


Figure 26: India Rice Yield Line Plot

While the LPJ GUESS model effectively captures the general trend and fluctuations in rice yield in India, it consistently underestimates the yield compared to the FAO data. This might necessitate further calibration or refinement of the model to enhance its predictive accuracy. Despite this, the model's overall performance in reflecting changes in yield suggests it captures the primary influences on rice yield, which can be valuable in simulating future scenarios.

4.3.4 Soybean

The FAO data shows a somewhat variable, but overall increasing trend in soybean yield from 1991 to 2015, except for a decline in the last few years. The model data, in contrast, consistently increases over the years, without showing a clear decline towards the end.

The LPJ GUESS model tends to underestimate the soybean yield when compared with FAO data across all years, with a constant gap that does not exhibit a clear trend of increase or decrease.

Despite the differences in the values, both datasets show a general upward trend, with both indicating similar years of higher and lower yield, indicating that the model is able to capture some of the main influencing factors affecting soybean yield.

The FAO data shows a significant decline in soybean yield from 2012 to 2015, which is not reflected in the model's output. This could indicate that the model might not be capturing certain significant factors affecting soybean yield in recent years.

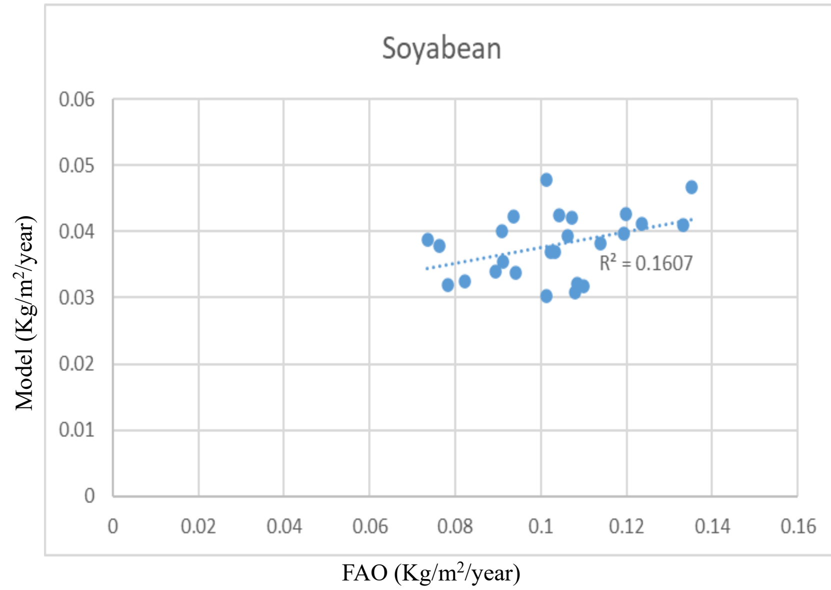


Figure 27: India Soybean Yield Scatter Plot

The constant underestimation of the yield by the model suggests it may not capture all relevant variables influencing soybean production in India. Although the LPJ GUESS model generally captures the trend in soybean yield in India, it systematically underestimates the yield when compared to the FAO data. This indicates a potential need for further refinement or calibration of the model.

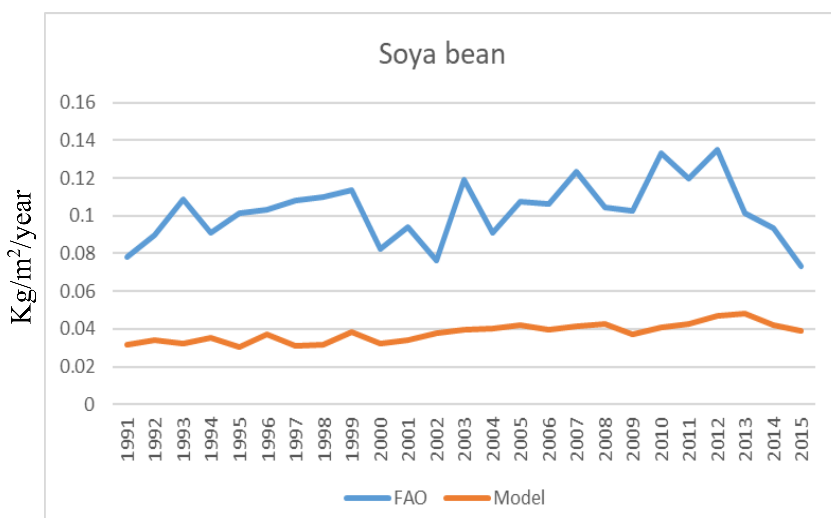


Figure 28: India Soybean Yield Line Plot

The divergence between FAO data and the model output towards the last few years further emphasizes this need. Despite these shortcomings, the overall trend captured by the model could still be useful for understanding the broad patterns in soybean yield over time.

4.3.5 Millet

Both the FAO data and the LPJ GUESS model output indicate a general upward trend in millet yield over the years.

The LPJ GUESS model significantly overestimates the yield of millet as compared to the FAO data for all the years. The discrepancy between the two datasets seems to be increasing over time, suggesting that the model's assumptions might be increasingly divergent from actual conditions.

Despite the differences in yield levels, the two datasets present similar fluctuation patterns, with both the FAO data and the model's output showing some years with dips followed by recovery.

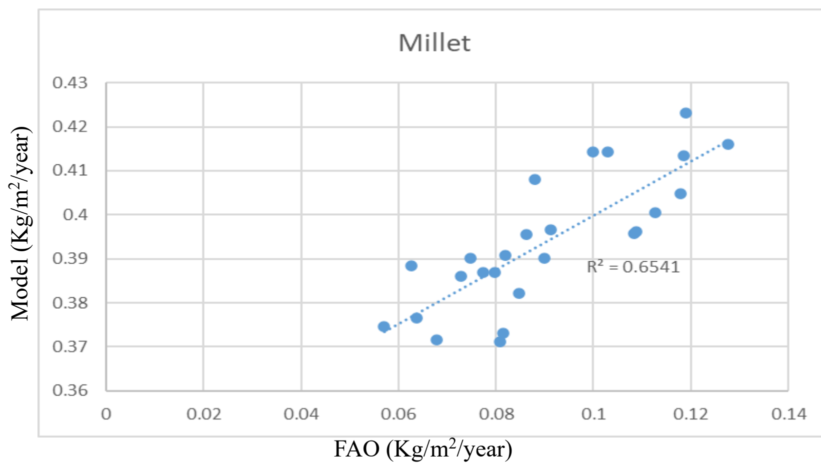


Figure 29: India Millet Yield Scatter Plot

There are significant dips in the FAO data in 1993, 2002, and 2009, which the model does not capture. This suggests that the model might not be adequately considering some factors that can drastically reduce yield in some years.

The constant overestimation of yield by the model suggests it might not be capturing some critical constraints in millet production in India. It could be missing some important factors, such as the effects of pests, diseases, or extreme weather events.

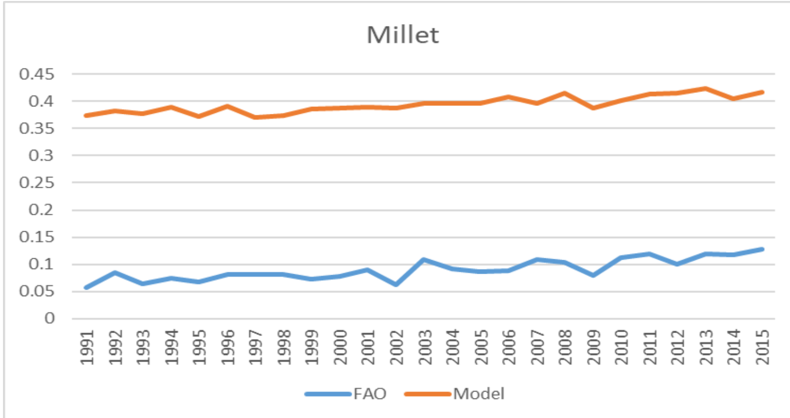


Figure 30: India Millet Yield Line Plot

The LPJ GUESS model seems to capture the general trend in millet yield in India but consistently overestimates the yield compared to the FAO data. This indicates a need to refine the model to more accurately predict millet yield in India. The model's inability to capture significant yield reductions in certain years further emphasizes this need. Despite these limitations, the model's output could still provide valuable insights into the general patterns of millet yield over time.

4.4 Analysis of Crop Yields of Nepal

4.4.1 Wheat

The dataset presented compares the yield of wheat in Nepal as per the Food and Agriculture Organization (FAO) data and the LPJ GUESS model predictions from 1991 to 2015.

Both the FAO data and the LPJ GUESS model output indicate an overall upward trend in wheat yield over the years.

The LPJ GUESS model consistently underestimates the yield of wheat as compared to the FAO data for all the years. The gap between the FAO data and the model's estimates appears to be growing over time, suggesting that the model may not fully capture the factors contributing to wheat yield increases.

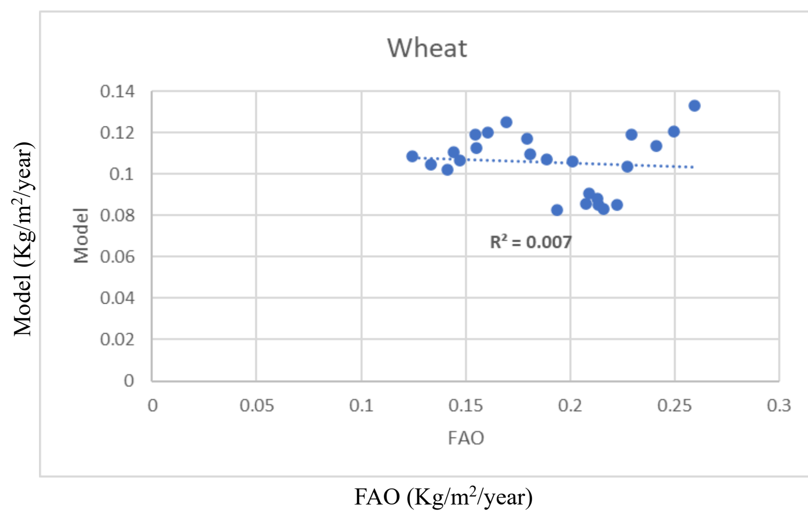


Figure 31: Nepal Wheat Yield Scatter Plot

Despite the differences in yield levels, both present similar patterns of fluctuations. Both the FAO data and the model's output show increases and decreases in yield from year to year, indicating that the model is able to capture the general trend in wheat yield, even if it underestimates the actual values.

Moreover, there is a significant dip in FAO data in 2009, which the model does not capture as sharply. This suggests that the model might not be adequately considering some factors that can drastically reduce yield in some years.

The constant underestimation of yield by the model suggests it might not be capturing some key facilitators in wheat production in Nepal. It could be missing factors such as advancements in farming techniques, improved seed quality, better pest management, etc.

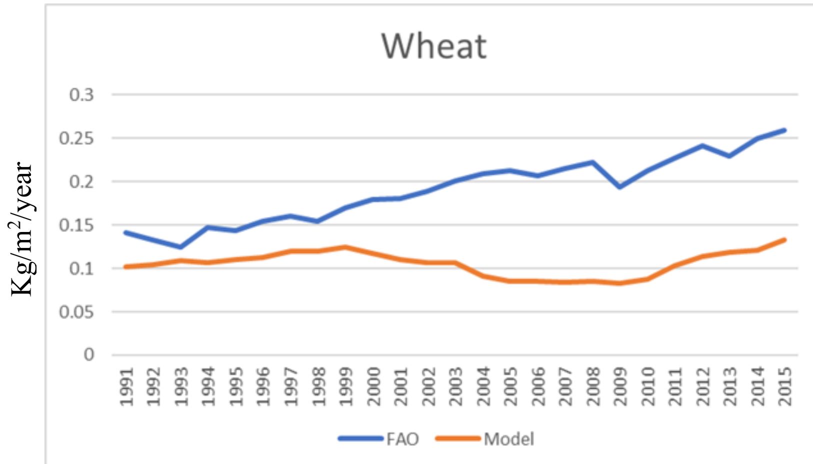


Figure 32: Nepal Wheat Yield Line Plot

While the LPJ GUESS model appears to capture the general trend in wheat yield in Nepal, it consistently underestimates the yield compared to FAO data. This suggests the need for refining the model to accurately predict wheat yield in Nepal. Despite these limitations, the model's output can still provide valuable insights into the general trends and fluctuations in wheat yield over time.

4.4.2 Maize

Both FAO data and the LPJ GUESS model show an upward trend in maize yield over the years, indicating improvements in production over time.

The LPJ GUESS model tends to underestimate maize yield compared to FAO data, albeit the gap is narrower compared to some previous crops discussed. Particularly from the year 2010 onward, the model's predictions get closer to the FAO figures.

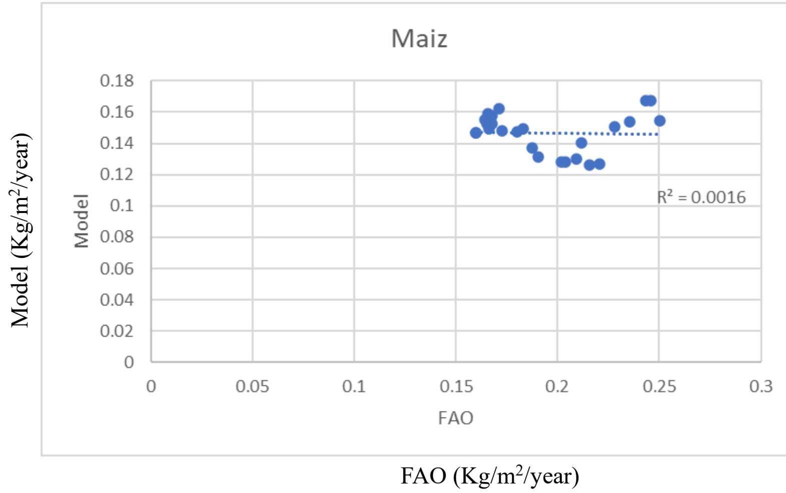


Figure 33: Nepal Maize Yield Scatter Plot

Despite differences in specific yield values, both datasets show similar patterns of year-to-year fluctuations, indicating that the model generally follows the same trend as the FAO data.

The gradually decreasing discrepancy between the model and FAO data suggests the model might be improving in capturing factors influencing maize production in Nepal.

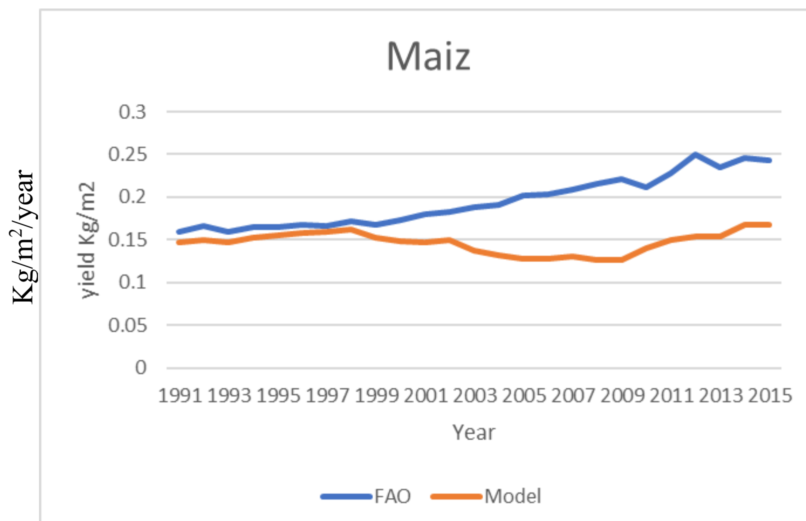


Figure 34: Nepal Maize Yield Line Plot

The LPJ GUESS model for maize in Nepal seems to capture the general upward trend in yield over time and does a comparatively better job than for previous crops, particularly in later years. However, consistent underestimation suggests room for further refinement. These insights can guide future model adjustments to enhance their predictive accuracy for maize yield in Nepal.

4.4.3 Rice

Both the FAO data and the LPJ GUESS model demonstrate an upward trend in rice yield over the years, indicating a general increase in productivity.

Throughout the entire period, the LPJ GUESS model tends to underestimate the rice yield compared to the FAO data. While the model's predictions also show an increasing trend, they are consistently lower than the FAO figures.

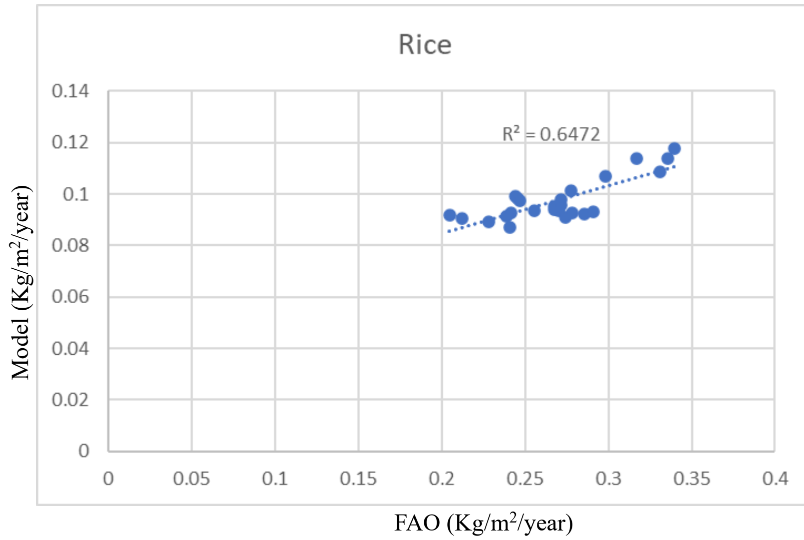


Figure 35: Nepal Rice Yield Scatter Plot

However, despite discrepancies in actual yield values, both datasets show similar year-to-year fluctuations, indicating that the model generally captures the same trends as the FAO data. Moreover, In the last five years of the dataset (2011-2015), the model's predictions seem to be getting closer to the FAO data, suggesting possible improvements in the model's predictive capabilities over time.

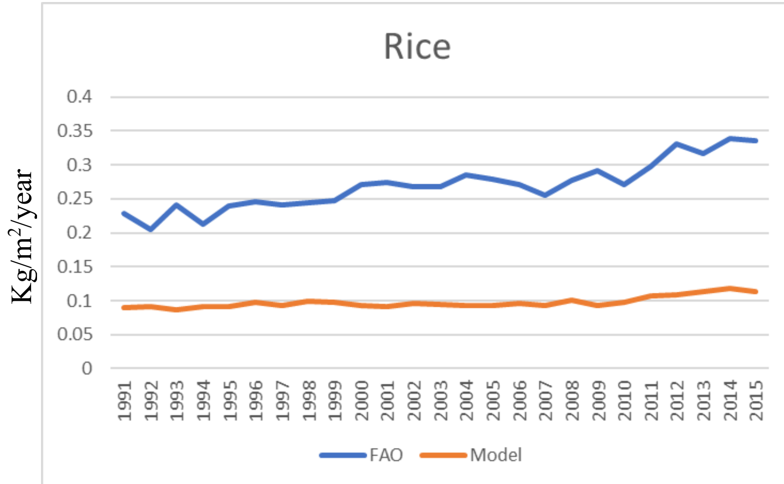


Figure 36: Nepal Rice Yield Line Plot

Despite the general underestimation, the convergence of the model's predictions to the FAO data in recent years might indicate a learning curve or an adjustment of the model's parameters that are more suitable for predicting rice yield in Nepal.

The LPJ GUESS model for rice in Nepal appears to capture the overall upward trend in yield, despite its consistent underestimation. Particularly in the later years, the model seems to be improving, suggesting potential refinements in the model. However, the consistent underestimation throughout most of the observed period indicates a need for further improvement. Future adjustments to the model should take these insights into account to enhance its predictive accuracy for rice yield in Nepal.

4.4.4 Millet

The FAO data show a slight upward trend in millet yield over the years, while the LPJ GUESS model suggests a generally stable yield with minor fluctuations.

The model consistently overestimates the millet yield compared to the FAO data. This disparity might be due to the model's parameters or underlying assumptions which could be overestimating the productivity of millet in Nepal.

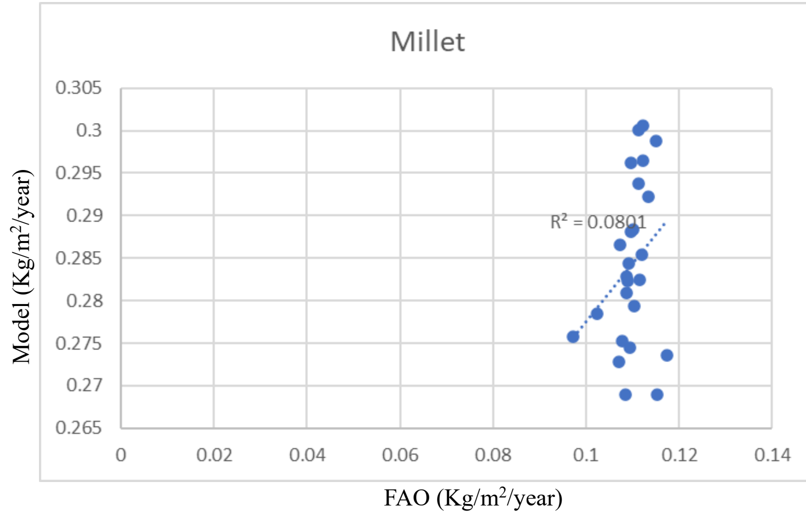


Figure 37: Nepal Millet Yield Scatter Plot

While the LPJ GUESS model's yield predictions are consistently higher, they tend to move parallel to the FAO data, reflecting a similar year-to-year variation pattern.

Despite the consistent overestimation, the relative stability in the model's predictions compared to the slight upward trend in the FAO data suggests that the model might not be fully capturing the factors contributing to the increase in yield observed in the FAO data.

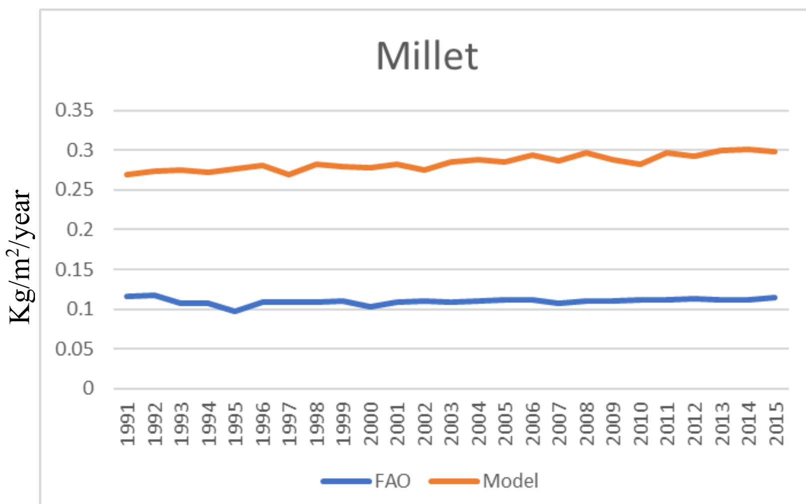


Figure 38: Nepal Millet Yield Line Plot

While the LPJ GUESS model for millet in Nepal reflects the year-to-year fluctuations similar to the FAO data, it consistently overestimates the yield and fails to capture the slight upward trend shown in the FAO data. This suggests that the model might require further refinement to improve its predictive accuracy for millet yield in Nepal.

4.5 Analysis of Crop Yields of Pakistan

4.5.1 Wheat

Both FAO and Model data show an upward trend over time, which indicates that wheat production or yield in Pakistan is generally increasing.

The LPJ GUESS model consistently predicts lower values than the FAO data. However, the discrepancy appears to be less pronounced, suggesting that the model might be more accurate for wheat crop in Pakistan.

Both datasets show variations, and the patterns of fluctuation appear quite similar. An increase or decrease in FAO data is typically mirrored in the model data.

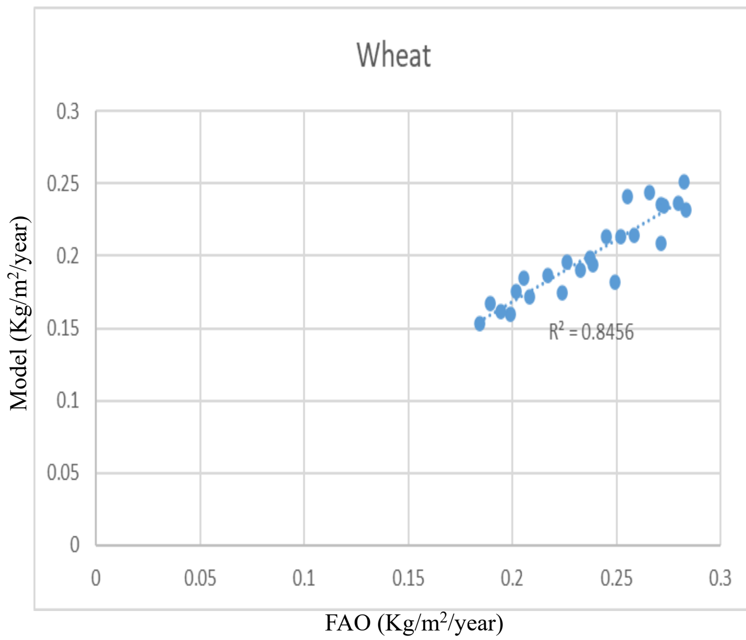


Figure 39: Pakistan Wheat Yield Scatter Plot

Both data series rise and fall in a similar pattern. The overall similarity in the patterns of fluctuation between the two sets indicates that the model is capturing the fundamental dynamics of wheat production in Pakistan, though it underestimates the values.

Around the year 2008, the model data shows a significant increase that is close to the actual FAO data. This suggests that the model is becoming more accurate over time, or it might be more capable of capturing certain factors or conditions related to wheat production during these years.

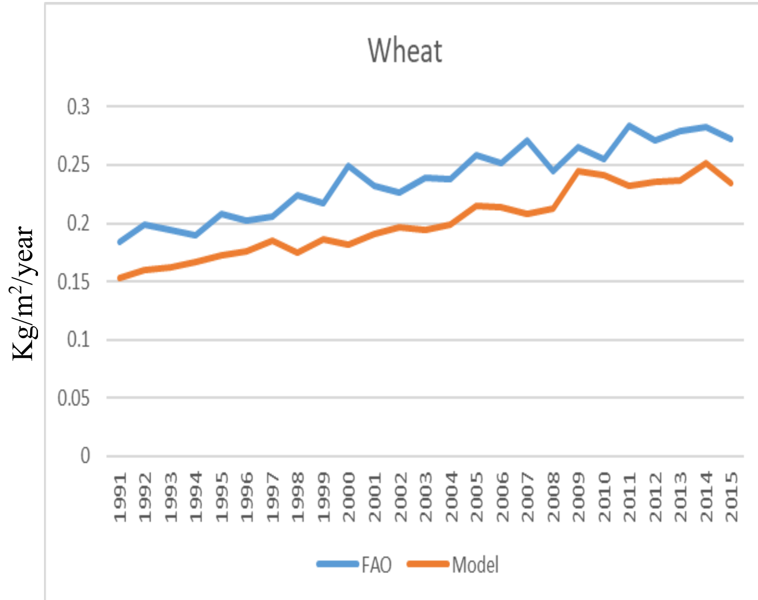


Figure 40: Pakistan Wheat Yield Line Plot

These results suggest that the LPJ GUESS model, while underestimating wheat yields in Pakistan, is capturing the general upward trend and fluctuation patterns well. The reduced discrepancy in later years indicates that the model might be improving in accuracy over time or is more suited to capturing the conditions of these particular years.

4.5.2 Maize

From a broad perspective, both FAO and Model data show an upward trend over time, implying that Maize production or yield in Pakistan is generally increasing. The LPJ GUESS model consistently predicts lower values than the actual FAO data. This implies that the model might be underestimating Maize yields for Pakistan.

Both datasets show variations, but it's worth noting that the variance in the FAO data seems to be larger than in the model data, particularly in later years. The FAO data exhibits a more pronounced increase, especially notable from the 14th data point onward.

Despite the model's consistent underestimation, the overall patterns in both datasets are quite similar. Both data series rise and seem to fluctuate in tandem. When the FAO data increases or decreases, the LPJ GUESS model data does too, though to a lesser extent.

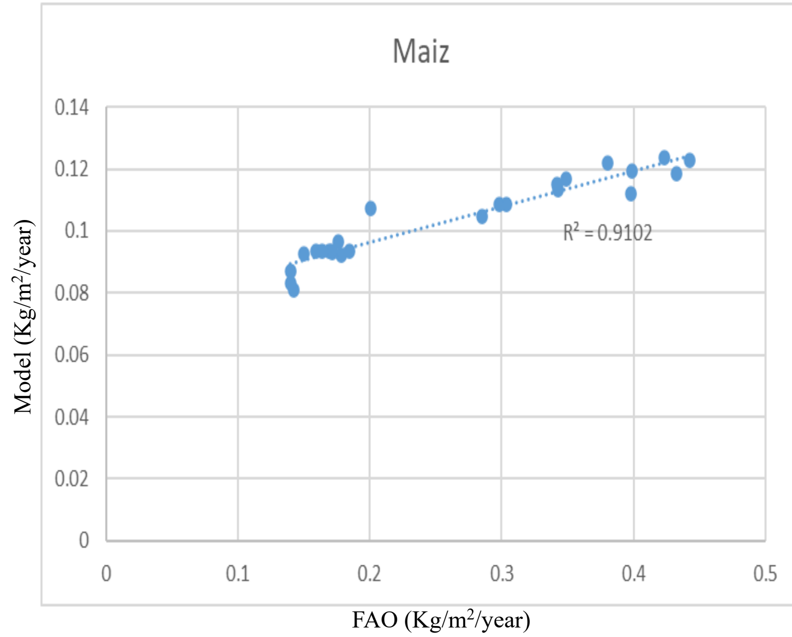


Figure 41: Pakistan Maize Yield Scatter Plot

Moreover, From the 2003 onward, there is a significant rise in the FAO data, which the model does not fully capture. This could be a point of interest for further investigation. Why is the model not capturing this increased yield? This might be indicative of the increased adoption/cultivation of spring maize during that period, especially due to the active involvement of multinationals in Pakistan (Tariq & Iqbal, 2010).

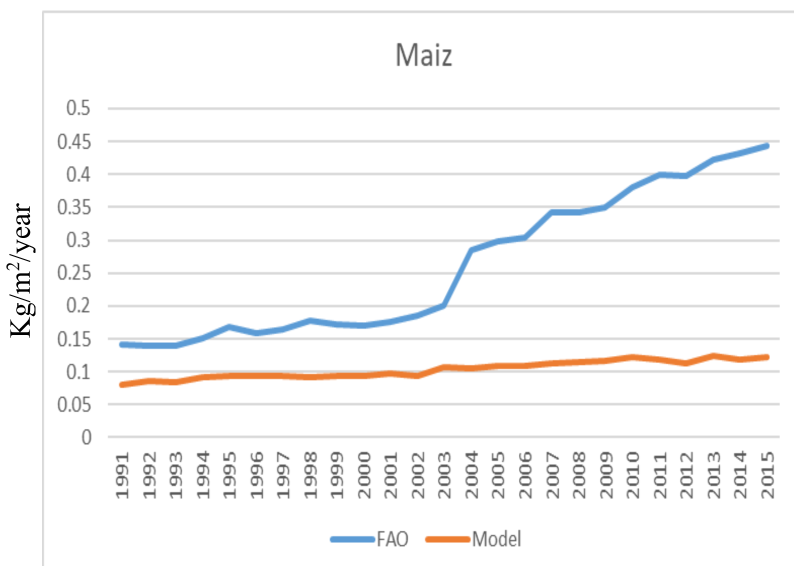


Figure 42: Pakistan Maize Yield Line Plot

These results suggest that while the LPJ GUESS model captures the overall upward trend and some fluctuations in Maize yields in Pakistan, it consistently underestimates the yields. The model's inability to capture the more significant increases in yield suggests that there might be factors at play not currently incorporated in the model.

4.5.3 Rice

Both FAO and Model data show an overall increasing trend over time, implying that Rice yield in Pakistan is generally improving.

Similar to the Maize data, the LPJ GUESS model consistently predicts lower values than the actual FAO data. This could indicate that the model systematically underestimates Rice yields in Pakistan.

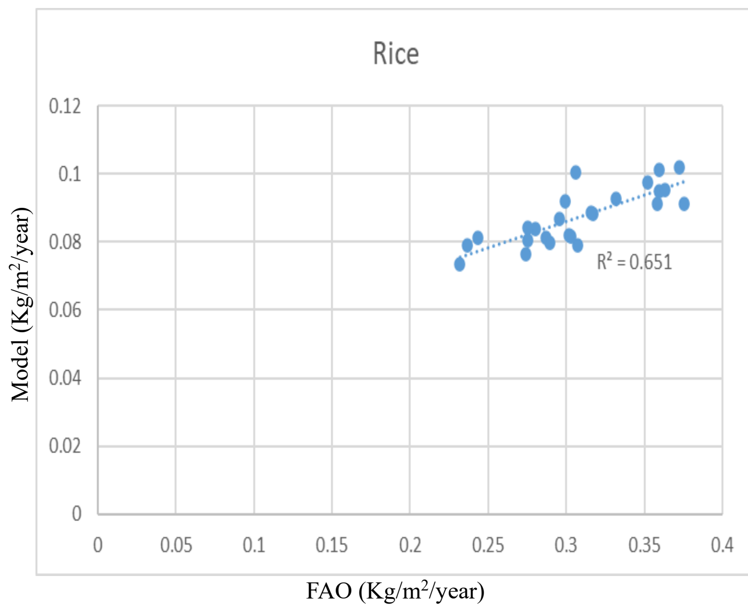


Figure 43: Pakistan Rice Yield Scatter Plot

Both datasets show fluctuations, but the variance in the FAO data is larger than in the model data. Some of these variations do not appear to be fully captured by the model.

Despite the model's consistent underestimation, it does reflect the overall patterns seen in the FAO data. When the FAO data increases or decreases, the LPJ GUESS model data follows a similar pattern, although to a lesser extent.

The difference between the FAO and model data seems to widen in later years. The model's predictions do not increase at the same rate as the FAO data, indicating that the model might be missing some key factors affecting rice yields in these years.

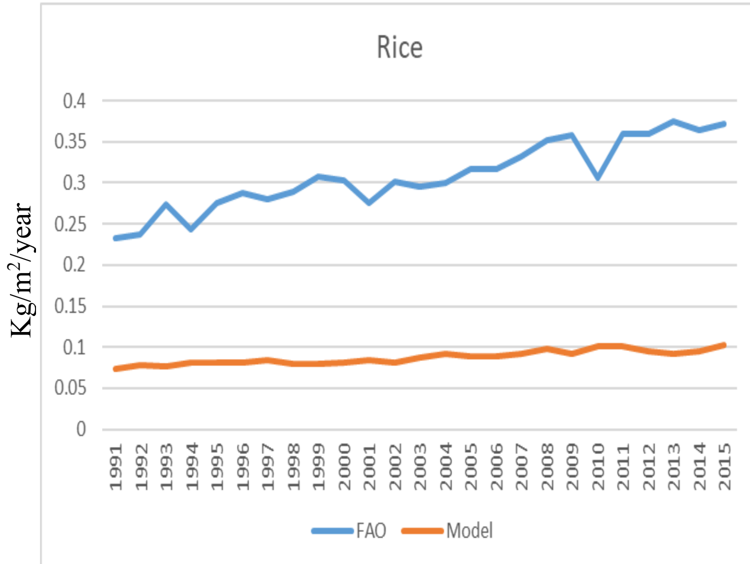


Figure 44: Pakistan Rice Yield Line Plot

The results suggest that while the LPJ GUESS model captures the general upward trend and certain fluctuations in Rice yields in Pakistan, it consistently underestimates the yields. The widening gap in later years suggests that the model is likely not accounting for certain factors that have positively impacted rice yields.

4.5.4 Millet

The FAO data shows a gradual increasing trend in millet yields over the years. The increase is not linear, with some years seeing a decline, but overall, the trend is upwards. The LPJ Guess model data also displays a general increasing trend. Although there are some minor fluctuations, the model shows an upward trend over the years. Both data sets show an overall increase in yield over time, although the rates and exact year-to-year values differ.

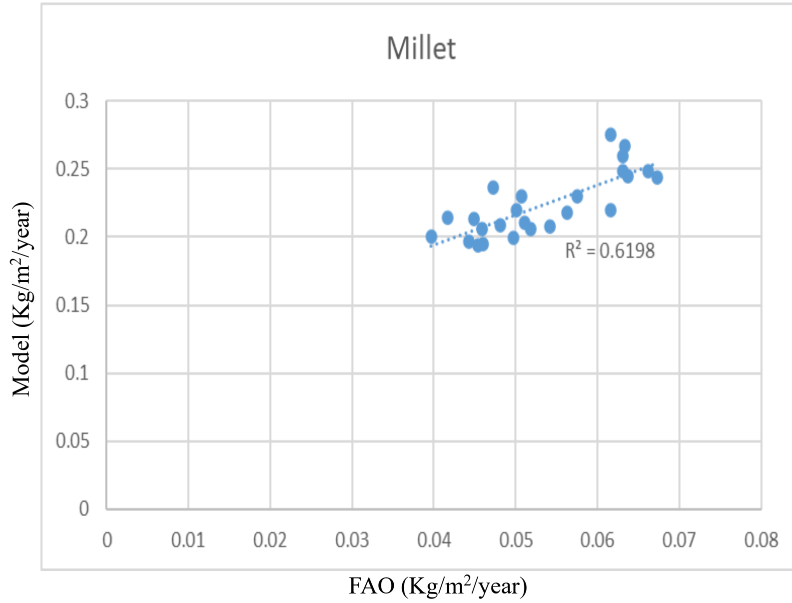


Figure 45: Pakistan Millet Yield Scatter Plot

The results suggest that both the FAO and the LPJ Guess model have observed an increase in millet yield over the years, potentially due to improvements in farming practices, use of improved varieties, or other factors.

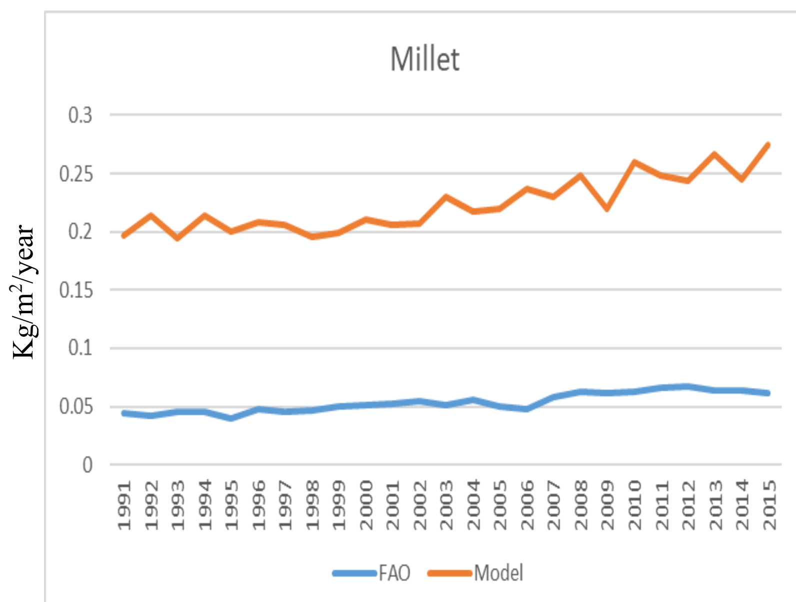


Figure 46: Pakistan Millet Yield Line Plot

However, the substantial difference in absolute yield values suggests that the LPJ Guess model might be overestimating millet yields in Pakistan or the FAO might be underreporting them. The reasons for this could include differences in underlying assumptions, data collection and calculation methods, or inaccuracies in the input data used by the model or reported to the FAO. Further investigation would be needed to identify the reasons for the discrepancy and to improve the accuracy of both yield estimates and predictions.

4.6 Analysis of Crop Yields of Siri Lanka

4.6.1 Rice

Both the FAO data and the LPJ GUESS model show an overall increase in rice yield during the observed period. However, the FAO data suggests a higher rate of increase compared to the model.

The LPJ GUESS model consistently underestimates the rice yield in Sri Lanka compared to the FAO data. The discrepancy between the two datasets seems to be growing larger with time, suggesting that the model is not completely capturing the factors contributing to the increased yield over time.

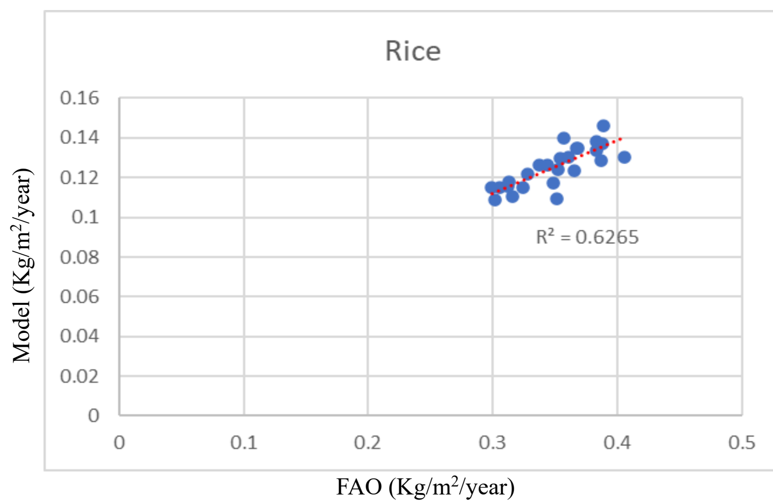


Figure 47: Sri Lanka Rice Yield Scatter Plot

The model generally tracks the year-on-year fluctuations in yield as reported by the FAO. For example, the dip in yield in 1994 and the subsequent recovery are mirrored in both datasets.

There is a significant difference in the overall yield values between the FAO data and the LPJ GUESS model. This could be a result of factors not accounted for in the model, such as advancements in farming practices, changes in the use of fertilizers, or other local conditions affecting rice growth in Sri Lanka.

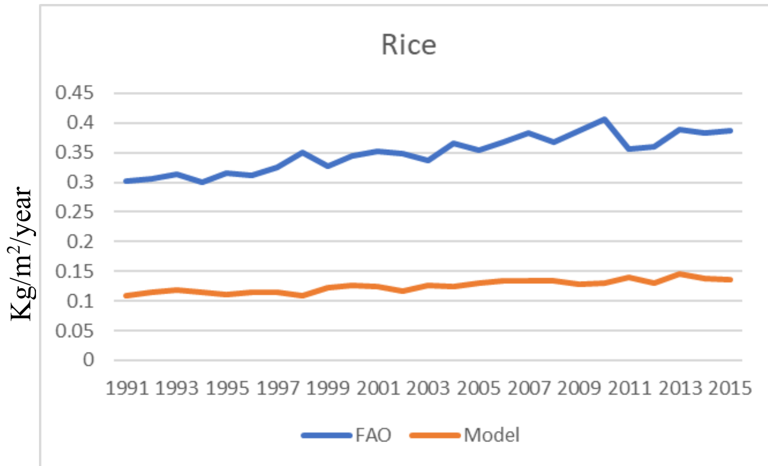


Figure 48: Sri Lanka Rice Yield Line Plot

While the LPJ GUESS model for rice in Sri Lanka reflects the year-to-year fluctuations in the FAO data, it consistently underestimates the yield and fails to match the upward trend in yield as seen in the FAO data. This indicates that the model might require calibration or inclusion of additional parameters to improve its predictive accuracy for rice yield in Sri Lanka.

4.7 Analysis of Net Primary Productivity (NPP) of South Asia

Net Primary Productivity (NPP) refers to the rate at which photosynthetic organisms, primarily plants, produce organic matter in an ecosystem, subtracting the energy expended during respiration. It serves as a critical metric for understanding energy flow and biomass accumulation in ecological systems. NPP is commonly expressed in units of mass or energy per unit area over a specific time period. Variation in NPP estimated in this study are depicted in figure 49 and figure 50.

4.7.1 Temporal Mean Plot

Figure 49 presents the changes in temporal mean of Net Primary Productivity (NPP) for various crops—specifically, wheat (Tewwi), maize (TeCsi), soybean (TeSoi), rice (TrRii), and millet (TrMii)—across South Asia during the period from 1991 to 2015.

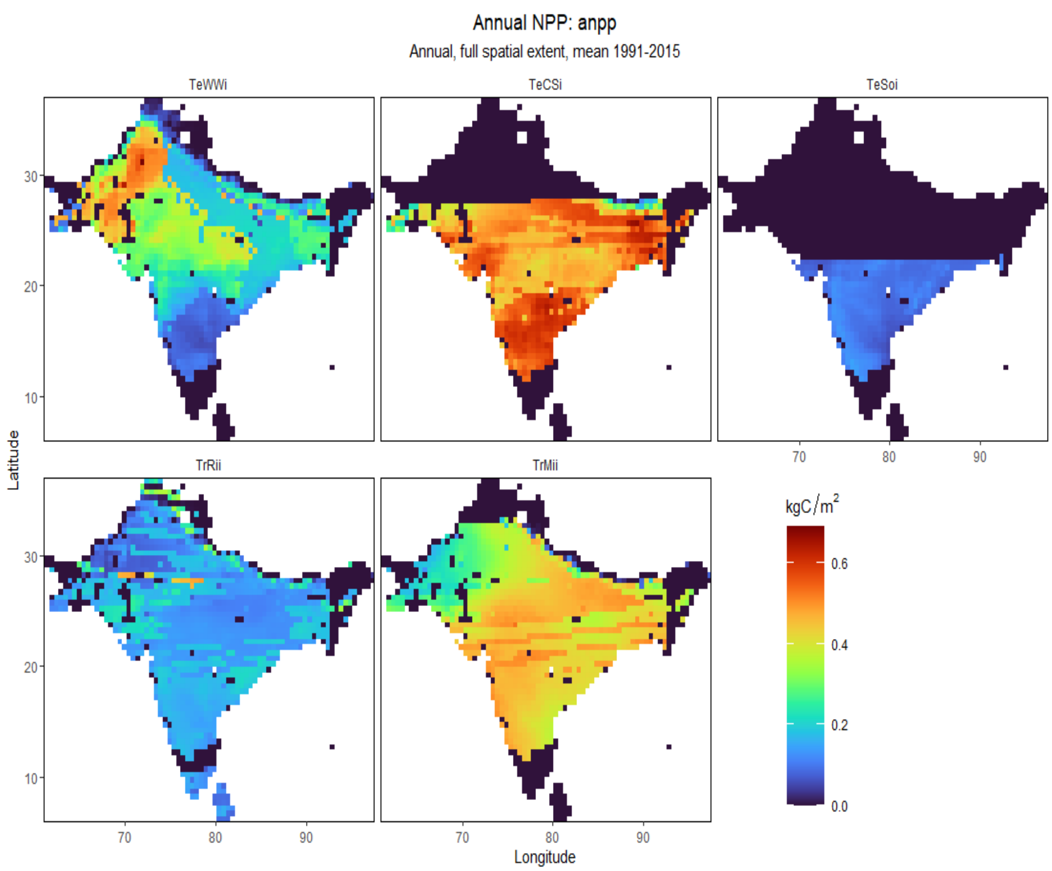


Figure 49: NPP Temporal Mean Plot

Wheat

The highest productivity (0.4-0.6 Kg C/m²/yr) is seen in Punjab and Sindh of Pakistan and parts of KP and Baluchistan, which could be attributed to the fertile soil and favorable climate conditions for wheat in these areas. In India, parts of Rajasthan, Gujarat, Maharashtra, Chhattisgarh, and Telangana have moderate productivity (0.2-0.4 Kg C/m²/yr). The Madhya Pradesh region, a major wheat-growing area in India, has a mix of moderate and higher productivity. Punjab and UP, known for their wheat production, show a mixture of lower to moderate productivity which may seem a bit off as these are major wheat-producing regions in India. The lower productivity in Southern India and countries like Sri Lanka, Nepal, Bhutan could be due to their hotter and more humid climates which are not as suitable for wheat cultivation.

Maize

Pakistan shows very low productivity for maize, which might be accurate as maize is not the major crop in Pakistan. For India, Rajasthan, UP, Bihar, Punjab, Haryana, and Uttarakhand show very low productivity as well. These areas are known more for their wheat and rice production than maize. However, seeing other regions of India with moderate to high productivity is a bit unexpected as maize is typically grown in cooler regions of India. Therefore, the model might be slightly off for India in the case of maize.

Rice

Punjab and Sindh of Pakistan show higher productivity for rice, which makes sense as these areas have extensive irrigation networks suitable for rice cultivation. Most of India shows lower to moderate productivity except for Madhya Pradesh, which appears as a major rice-producing area according to the model. This is a bit surprising because traditionally, states like West Bengal, Punjab, UP, and Andhra Pradesh are the major rice-producing areas in India. These areas are not depicted as high productivity in the model, suggesting the model might not be entirely accurate for rice production.

Soybean

According to the model, soybean production across South Asia is very low. In India, moderate productivity is shown in Karnataka, Andhra Pradesh, Telangana, Maharashtra, and parts of Chhattisgarh and Gujarat. This seems accurate because Madhya Pradesh, Maharashtra, and Rajasthan are the major soybean-producing states in India. But the absence of Madhya Pradesh and Rajasthan in moderate productivity could indicate that the model is not completely accurate for soybean production.

Millet

The model shows higher productivity for millet across most of India and Pakistan, which is accurate as millet is a hardy crop that can grow well in dry and high-temperature regions, common conditions in these countries. South India, Sri Lanka, and Nepal show very low productivity, which might be due to the higher rainfall and humidity in these regions not being suitable for millet cultivation.

Spatial Mean Plot

Figure 50 illustrates the variations in Spatial mean of Net Primary Productivity (NPP) for various crops—namely, wheat (Tewwi), maize (TeCsi), soybean (TeSoi), rice (TrRii), and millet (TrMii)—across South Asia during the period from 1991 to 2015.

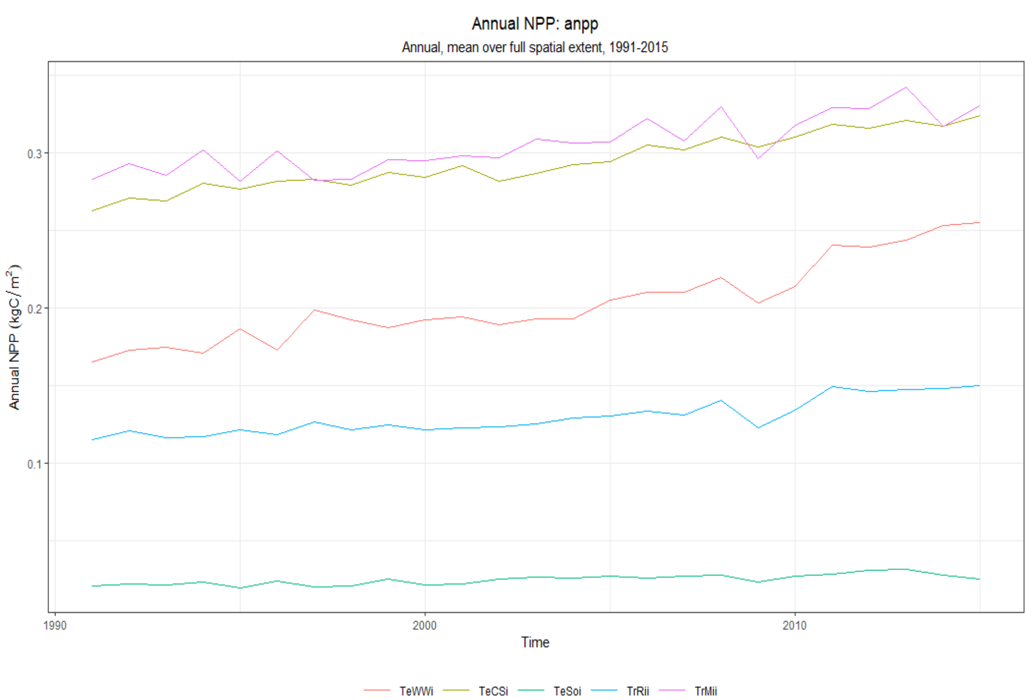


Figure 50: NPP Spatial Mean Plot

Soybean

Soybean shows the lowest NPP, starting from 0.02 and ending at 0.03 Kg C/m²/yr. There are minor fluctuations over the years, but overall, the NPP for soybean seems to be stable.

Given soybean's preference for specific climates and soil conditions, the lower NPP might be expected. However, one needs to take into account the expansion of soybean cultivation due to its increasing demand, which might not be reflected in the model.

Rice

Rice shows a slightly higher NPP than soybeans, starting from 0.12 and ending at 0.15 Kg C/m²/yr. The fluctuations indicate variations in annual productivity, which could be due to yearly changes in weather conditions, irrigation availability, and other factors. The overall increase could suggest improved farming practices, expanded irrigation, or climate changes favoring rice cultivation.

Wheat

The wheat line starts from 0.17 and ends at 0.25 Kg C/m²/yr, indicating an overall increase in NPP over the 25 years. The rise in NPP could be due to improved farming practices, the introduction of new high-yield varieties, increased use of fertilizers, and expansion of wheat cultivation areas.

Maize

Maize shows a higher NPP, starting from 0.26 and ending around 0.325 Kg C/m²/yr. The gradual increase over the years could be due to similar reasons as wheat - the adoption of modern farming practices, increased use of fertilizers, and possibly an expansion of cultivated areas.

Millet

Millet has the highest NPP, starting from 0.28 and ending around 0.33 Kg C/m²/yr. The overall increase in NPP could be due to the expansion of millet cultivation in arid and semi-arid regions, and the increased use of hybrid varieties that are high yielding and more resistant to drought and pests.

4.8 Analysis of Net Ecosystem Exchange (NEE) of South Asia

Net Ecosystem Exchange (NEE) is a measure of the net flux of carbon dioxide between an ecosystem and the atmosphere, accounting for both carbon assimilation through photosynthesis and carbon release via ecosystem respiration. It serves as an integral indicator for assessing an ecosystem's role as a carbon sink or source. NEE is usually quantified in units of mass of carbon per unit area per unit time. Variation in NEE estimated in this study are depicted in figure 51 and figure 52.

4.8.1 Temporal Mean of NEE

The Temporal Mean of NEE represents the average NEE values at each location over the time period from 1990 to 2015. The colors provide an indication of whether a region is, on average, a carbon sink or a source over that period. Regions in blue are carbon sinks (more carbon is absorbed than released), while yellow regions are carbon sources (more carbon is released than absorbed). Green regions are close to carbon neutral.

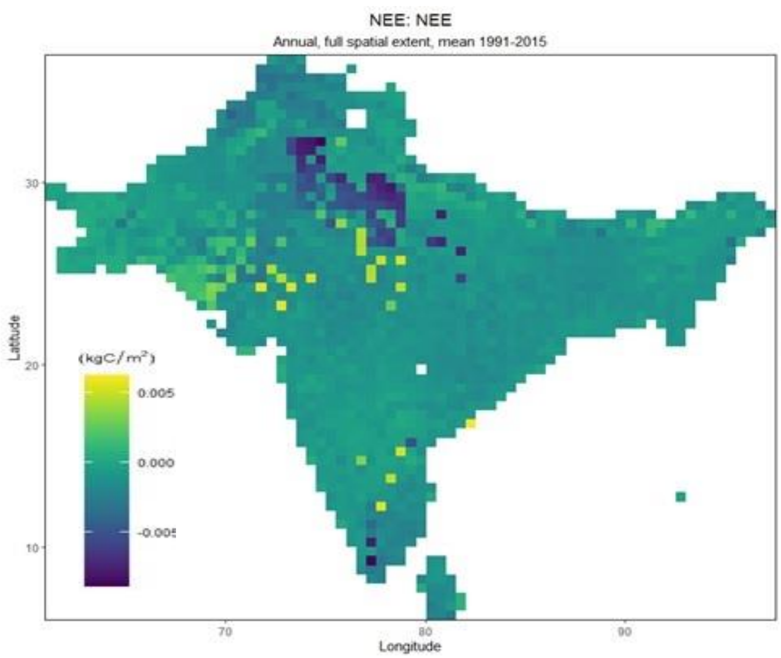


Figure 51: NEE Temporal Mean Plot

Most of South Asia is light or dark green, suggesting that these regions are close to carbon neutral on average, with their carbon uptake roughly equal to their carbon output.

Dark blue spots in the Punjab and Khyber Pakhtunkhwa regions of Pakistan, and in Uttar Pradesh, Himachal Pradesh, and some southern regions of India indicate stronger carbon sinks. These could be areas with significant vegetation cover, such as forests, that are absorbing and storing carbon at a higher rate. The presence of forests, healthy agricultural lands, and other ecosystems with high carbon sequestration capacity explain these observations.

The yellow spots in Gujarat, Rajasthan, Madhya Pradesh, Andhra Pradesh, and Karnataka suggest these areas are carbon sources. These areas are releasing more carbon into the atmosphere than they are absorbing. This could be due to a variety of reasons: land degradation, deforestation, or intensive agriculture can all lead to the release of stored carbon. Also, these regions include arid and semi-arid regions (like Rajasthan and parts of Gujarat), where vegetation cover might be sparse leading to less carbon absorption.

4.8.2 Spatial Mean of NEE

The Spatial Mean plot represents the average NEE across all of South Asia for each year from 1990 to 2015. This plot shows how the carbon balance of the entire region has fluctuated over time.

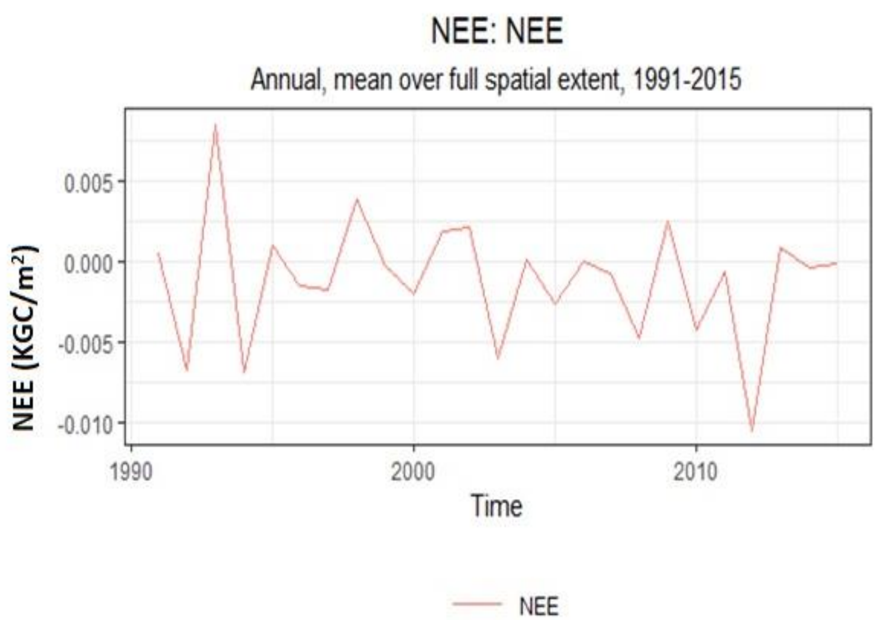


Figure 52: NEE Spatial Mean Plot

The pattern, with the line rising and falling, suggests that the net carbon balance of South Asia has been fluctuating significantly from year to year. When the line is above zero, South Asia as a whole is a net carbon source, and when it's below zero, it's a net carbon sink.

The rapid fluctuations could be due to a variety of factors. Changes in land use, such as deforestation or the conversion of natural ecosystems to agriculture, can alter the carbon balance. For instance, wetter years could lead to more plant growth and hence more carbon absorption, whereas drought years could lead to increased respiration and less carbon absorption.

4.9 Analysis of Carbon Pool of South Asia

A carbon pool refers to a reservoir within the Earth system that has the capacity to accumulate, store, and release carbon in various forms such as organic matter, inorganic carbonates, or carbon dioxide. These pools play a pivotal role in the global carbon cycle, influencing the concentration of atmospheric greenhouse gases. Common examples include forests, soils, oceans, and the atmosphere.

4.9.1 Temporal Mean Analysis

The figure 53 primarily dominated by light and dark blue suggests that much of South Asia had relatively low Cpool values, specifically between 0 to 0.05 KgC/m2, and 0.05 to 0.10 KgC/m2. This could be due to a range of factors, including population density, agricultural practices, and the predominance of certain types of land use that might not contribute significantly to carbon sequestration.

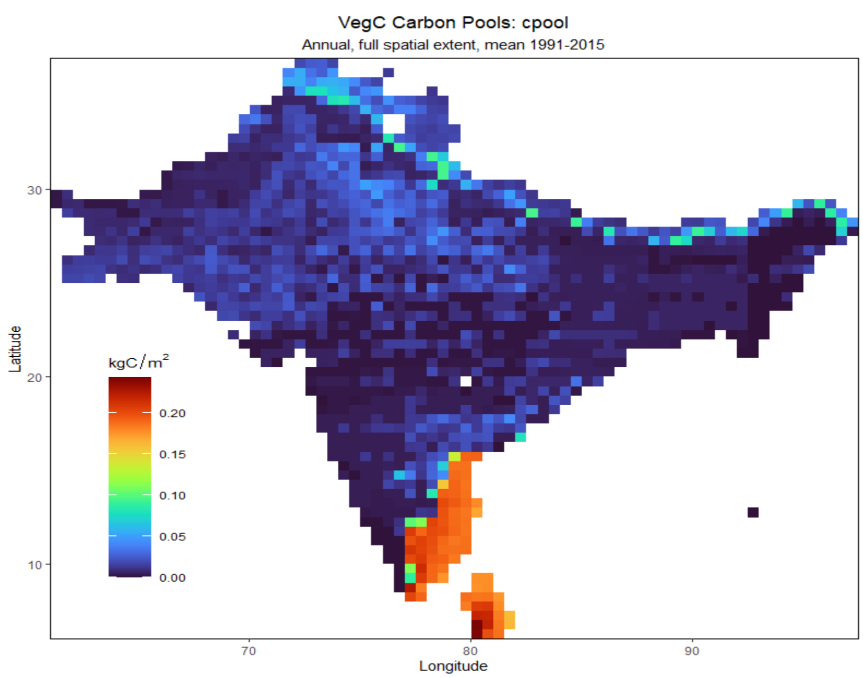


Figure 53: Cpool Temporal Mean Plot

The greenish regions in the northern parts of Pakistan and India, as well as some parts of southern India, indicate Cpool values in the range of 0.10-0.15 KgC/m2. This could be attributed to the presence of dense forested areas, which are known to sequester more carbon due to high biomass.

The Tamil Nadu region of India and Sri Lanka, shaded orangish, signify even higher Cpool values of 0.15 to 0.2 KgC/m2. This could be a result of the presence of diverse vegetation types, including forests and mangroves, that store substantial amounts of carbon.

Higher value of Cpool in Bhutan can be attributed to their extensive forest cover and vegetation. Whereas Nepal, and Bangladesh, being bluish in color, seem to have lower carbon pool values. For Nepal, despite their forest cover, the rugged mountainous terrain might limit vegetation growth, thereby resulting in a lower carbon pool. As for Bangladesh, rapid urbanization might be the contributing factor.

4.9.2 Spatial Mean Analysis

The fluctuating line plot representing spatial mean Cpool values from 1990 to 2015 suggests variability in vegetation carbon sequestration over time. This could be due to continuous and spontaneous changes taking place in South Asia such as changes in land use, climatic variations, natural disasters, or human activities.

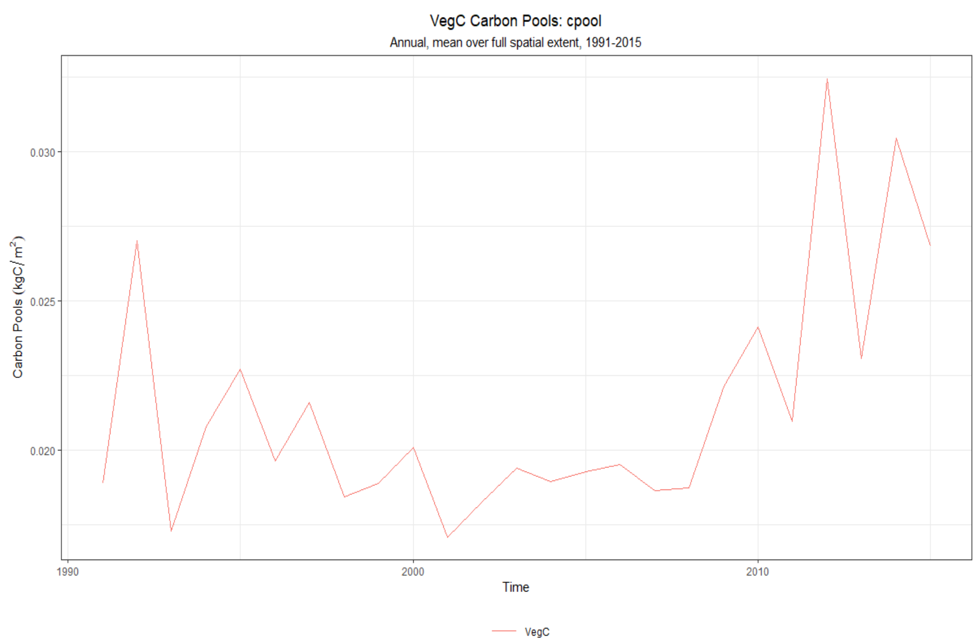


Figure 54: Cpool Spatial Mean Plot

The steep rise in the carbon pool in 2012 suggests a significant increase in carbon sequestration that year. This could be due to large-scale afforestation programs, an unusually high growth period for vegetation due to favorable weather conditions, or a decrease in activities that release carbon, such as reduced deforestation.

The fact that the line ends at around 0.027 Kg C/m²/yr in 2015 suggests that the carbon pool at the end of the period is larger than it was at the beginning. This would suggest an overall net increase in the carbon pool over the period.

4.10 Analysis of Carbon Flux of South Asia

4.10.1 Temporal Mean of Vegetative Cflux

The different colors on the map represent different values of carbon flux in the regions of South Asia. Since most of the color shades are negative, this suggests that, on average, most regions were net absorbers of carbon over this time period - they were sequestering more carbon than they were emitting.

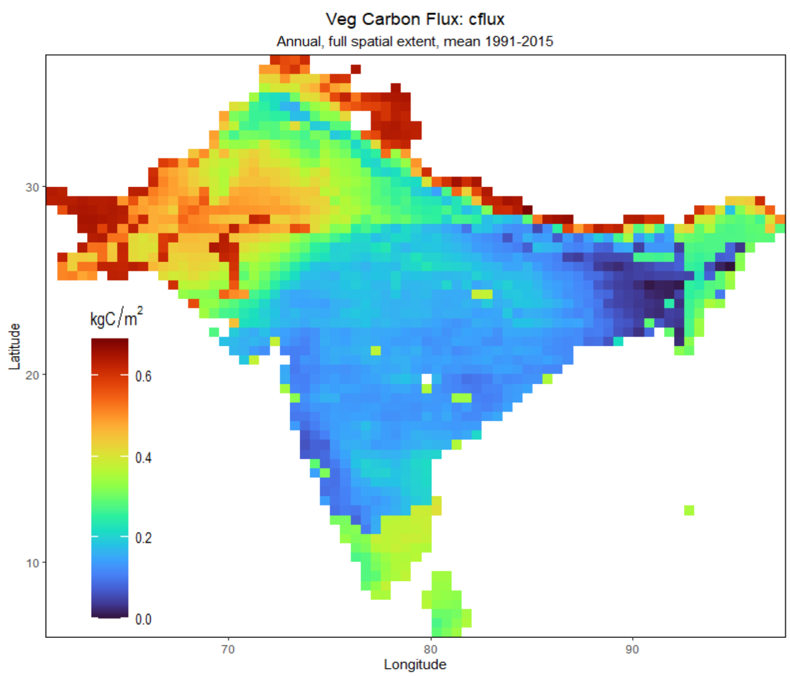


Figure 55: Cflux Temporal Mean Plot

Regions like most of Pakistan, major parts of India, Sri Lanka, and Bangladesh, which are shaded in shades of blue and green, are associated with higher carbon sequestration (lower values of Cflux between -0.5 and -0.2 KgC/m^2). This may suggest these regions had healthy vegetation growth, possibly due to favorable conditions for photosynthesis such as adequate rainfall and temperature, which in turn led to a greater intake of CO_2 from the atmosphere. In the context of the carbon cycle, these regions can be considered as "carbon sinks".

Conversely, areas that are shaded orange, like most of Baluchistan, northern regions of Pakistan and India, and the countries of Nepal and Bhutan, have less negative Cflux values, approaching 0 KgC/m^2. This could suggest that these regions had lower rates of carbon sequestration, potentially due to factors like lower plant growth, greater amount of soil respiration, or human activities like deforestation, land-use changes, and burning of biomass.

4.10.2 Spatial Mean of Vegetative Cflux

The Spatial mean of Cflux across the South Asian region shows a generally declining trend from around -0.24 to -0.30 KgC/m²/yr from 1990 to 2015, albeit with fluctuations. The negative values suggest that overall, the region was a net absorber of carbon during this period.

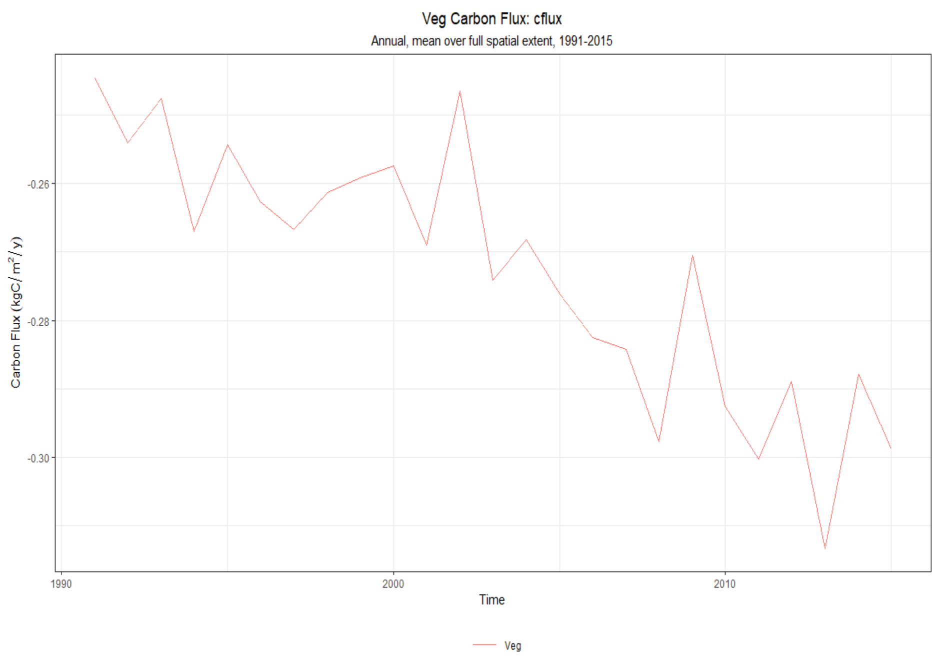


Figure 56: Cflux Spatial Mean Plot

The trend of decreasing Cflux (more negative) indicates that the region's ability to sequester carbon may have increased over this period. This could be due to factors like increased forest growth or changes in land management practices that increased the carbon sequestration potential of the region. The fluctuations could reflect variability in factors influencing carbon sequestration, such as changes in climate, land use, and human activities.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

This Study has provided valuable insights into agricultural productivity, carbon dynamics, and crop yields in South Asia from 1990-2015. The analysis integrated multiple data sources including satellite observations, process-based models, and ground-collected statistics.

The NPP analysis revealed regional variations in productivity of key crops across South Asia. Wheat exhibited high productivity in parts of Pakistan and India, while rice thrived in irrigated areas of India and Pakistan. Maize showed overall low productivity except in limited Indian regions. Soybean productivity was bleak across most of South Asia, with pockets of moderate productivity in central and south India. Millet demonstrated resilience, with high productivity across arid parts of India and Pakistan.

Temporal NPP trends indicated increasing crop productivity from 1990-2015 for most crops, although fluctuations occurred due to climate variability and other factors. Carbon dynamics were complex - some areas acted as carbon sinks while others were sources, depending on region and time period. Vegetation carbon pools showed increases over time in many regions.

Comparisons between process-based model estimates (LPJ-GUESS) and FAO statistics for country-level crop yields revealed that while models could capture general trends, discrepancies existed between reported and modeled yields. This highlights the need for continual refinement and validation of models against ground data. However, models remain useful tools for yield projections and scenario analyses, if their limitations are considered.

There is immense potential for further work to build on the approaches demonstrated in this study. Integrating ground data, satellite observations and process-based models provides a powerful methodology. Future studies could apply these methods to analyze agricultural sustainability, food security dynamics, and environmental impacts of agriculture in South Asia. The results could support evidence-based policies for sustainable development in the region.

The study has highlighted the value of using multiple data sources to gain nuanced insights into agricultural productivity, carbon cycling, and crop yields in South Asia. It has revealed spatial and temporal patterns that can inform policies. There is tremendous scope for extending these integrated approaches to provide robust evidence to tackle food security and sustainability challenges in the region.

5.2 Recommendations

This study underscores the importance of advancing research in several pivotal domains related to climate change and its impact on vegetation growth.

Firstly, it is paramount not just to replicate but also to augment the scope of this research in diverse geographies. By conducting this research across varied regions, we can assimilate data on a macro level, painting a more holistic and global picture of climate change's influence on vegetation dynamics. Such extended studies will pave the way for intricate comparisons, allowing us to juxtapose results from divergent ecological settings and climatic backgrounds, thereby enhancing the robustness and universality of our findings.

Secondly, the research community should venture into the utilization of an array of dynamic global vegetation models. While the LPJ-GUESS model has provided insightful data for this study, incorporating alternative models will invariably broaden our horizons. It will not only validate or challenge the findings from the LPJ-GUESS model but will also furnish a multifaceted view of how climate change could variably impact vegetation growth, pushing the envelope of our existing knowledge.

Thirdly, to truly delve into the ramifications of shifting vegetation patterns, an integrative, interdisciplinary methodology is of the essence. Pooling expertise from various sectors – be it social scientists who can evaluate societal implications, agronomists who delve deep into agricultural dynamics, economists who can forecast economic repercussions, or urban planners who can provide insights into changing urban landscapes – will ensure a more rounded understanding. This interdisciplinary lens becomes increasingly crucial in discerning the nuanced effects on key sectors such as livelihoods, food accessibility, and urban evolution, especially considering the backdrop of soaring population metrics.

Lastly, there is a pressing need for institutionalizing a longitudinal monitoring mechanism, specifically targeting the vegetation dynamics in South Asia. By establishing a framework that continually assesses and reports on changes, we can garner a treasure trove of real-time data. This, in turn, will significantly elevate our capacity to preempt, navigate, and adapt to the swift and often unpredictable alterations brought about by climate change, thereby fortifying our resilience and strategizing capacity in the face of these global challenges.

Chapter 6

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