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Increasing crop yields under climate change scenarios in Nigeria

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Increasing crop yields under climate change scenarios in Nigeria.

Imogen Grace O'Keefe

Master thesis, 30 credits, in *Atmospheric Science and Biogeochemical Science*

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Abstract

Climate change is projected to cause unprecedented levels of global change and it will alter the ways in which humans currently rely on getting essential resources such as food (IPCC, 2019). Africa is considered to be the most vulnerable continent to this change, with many countries that have low economic stability and insecure food sources a change to the way resources can be accessed could be detrimental to the population (Eze, 2018). One such example of this is agriculture: with the population expected to continue to rise stable sources of food will be needed, but climate change is making the production of high crop yields more difficult. This research studied the impact climate change will have on crop yields in Nigeria under the RCP 4.5 and the RCP 8.5 emissions scenarios from 1986 to 2100 using the LPJ-GUESS model. It showed that the average crop yields in Nigeria for maize, sorghum, wheat and pulses are likely to increase; even more so under the RCP 8.5 scenario due to higher estimated CO_2 fertilization effects. Different management strategies to increase this further were then modelled which illustrated that when cover crops, irrigation or additional nitrogen were used, crop yields increased further, where the latter management strategy was most effective. Of the different crops, maize and sorghum produced the highest yields and were most robust to climate change. In general, crop yields were highest in the north and lowest in the south of Nigeria, with the exception of pulse crops where the opposite was true. Overall, this research highlights the importance of using management strategies to increase food production for Nigeria in the face of climate change.

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Abbreviations

LPJ-GUESS	*Lunds-Potsdam-Jena General Ecosystem Simulator*
MPI-ESM	The Max-Planck-Institute Earth System Model
SDG	Sustainable Development Goals
GCM	General Circulation Model
DGVM	Dynamic global vegetation model
PFT	plant functional type
FAO	The Food and Agricultural Organisation for the United Nations
EWEA	Early Warning Early Action
SRES	Special Report on Emissions Scenarios
TeCo	Maize
TeSW	Wheat
TrMi	Sorghum
TeFb	Pulses

Research Questions

1. How will crop yields in Nigeria change by the year 2100 under the RCP 4.5 and RCP 8.5 emissions scenarios?
2. How can altering agricultural management strategies improve these yields both spatially and temporally?

1. Introduction

Climate change has been gaining traction within the scientific community for decades, as has the understanding that it is drastically altering Earth's ecosystems and cycles beyond merely warming the planet (IPCC, 2019). Twelve to fourteen percent of ice-free land surface now lends its use to croplands, reducing global biodiversity by a similar percentage (IPCC, 2019). Global warming is defined as a gradual increase in the average temperature of the Earth's atmosphere and the oceans and is a symptom of increased concentrations of atmospheric carbon dioxide (Olaniyi, Olutimehin, and Funmilayo, 2019). The major shift in climate and a global warming greater than 1˚C, above pre-industrial levels, is not only a cause for concern but a call to action for scientists to understand how this will impact the future of human life and food security (IPCC, 2018). The United Nations (UN) outlined seventeen Sustainable Development Goals (SDGs), which were adopted by all member states in 2015, to achieve a better future by 2030 (United Nations, 2020b). Climate change directly threatens many of these goals; via extreme weather events, by destabilising food systems and through disrupting economies, leaving the poorest nations highly vulnerable to its impacts (United Nations, 2020a). It is therefore imperative that action against the impacts of climate change are taken to both mitigate harm caused by it and to adapt to the changes which will undoubtedly take place as a consequence of actions already taken. The vast disturbance of Earth's systems has caused a major shift in climate, causing global warming greater than 1˚C above pre-industrial levels (IPCC, 2018). One such consequence of global temperatures rising is the effect on reducing agricultural productivity (such as maize, sorghum and wheat) in semi-arid and sub-humid regions of Africa (IPCC, 2019; McCarthy and Vlek, 2012). Without large-scale mitigation, food supply from such crops is at great risk and it is highly likely that even with mitigation, adaptation of lifestyle and agricultural practice will be necessary to maintain food production in certain regions (IPCC, 2019). Large-scale changes in land-use configurations, including crop choice, will be needed to meet future food needs and maintain steady production (Pugh *et al.,* 2016). Adaptation strategies are especially necessary in developing countries where the risks from the changing climate are high and the resources in place to cope with it are low (Eze, 2018). Africa is considered to be the most susceptible continent to climate change, attributing to its tropical locality, and therefore a more thorough understanding of the changes taking place there, paired with response strategies to this are necessary (Eze, 2018). This report aims to simulate future attainable crop yields in Nigeria under potential future climate scenarios, using Lunds-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) version 4.1 paired with the MPI-ESM climate model (Portmann *et al.,* 2010; Olin *et al.,* 2015; Smith *et al*., 2014). From this, adaptation strategies, based on the premise of altering management practices in areas of lower crop-yields, will then be formed.

2. Study Area

This report details a country-wide study of climate change impacts on croplands in Nigeria, Fig.1. The country is covered by 302 LPJ-GUESS grid cells (0.5º x 0.5º cell size) and covers several distinct agroecological zones. Nigeria borders Cameroon, Benin, Chad and Niger.

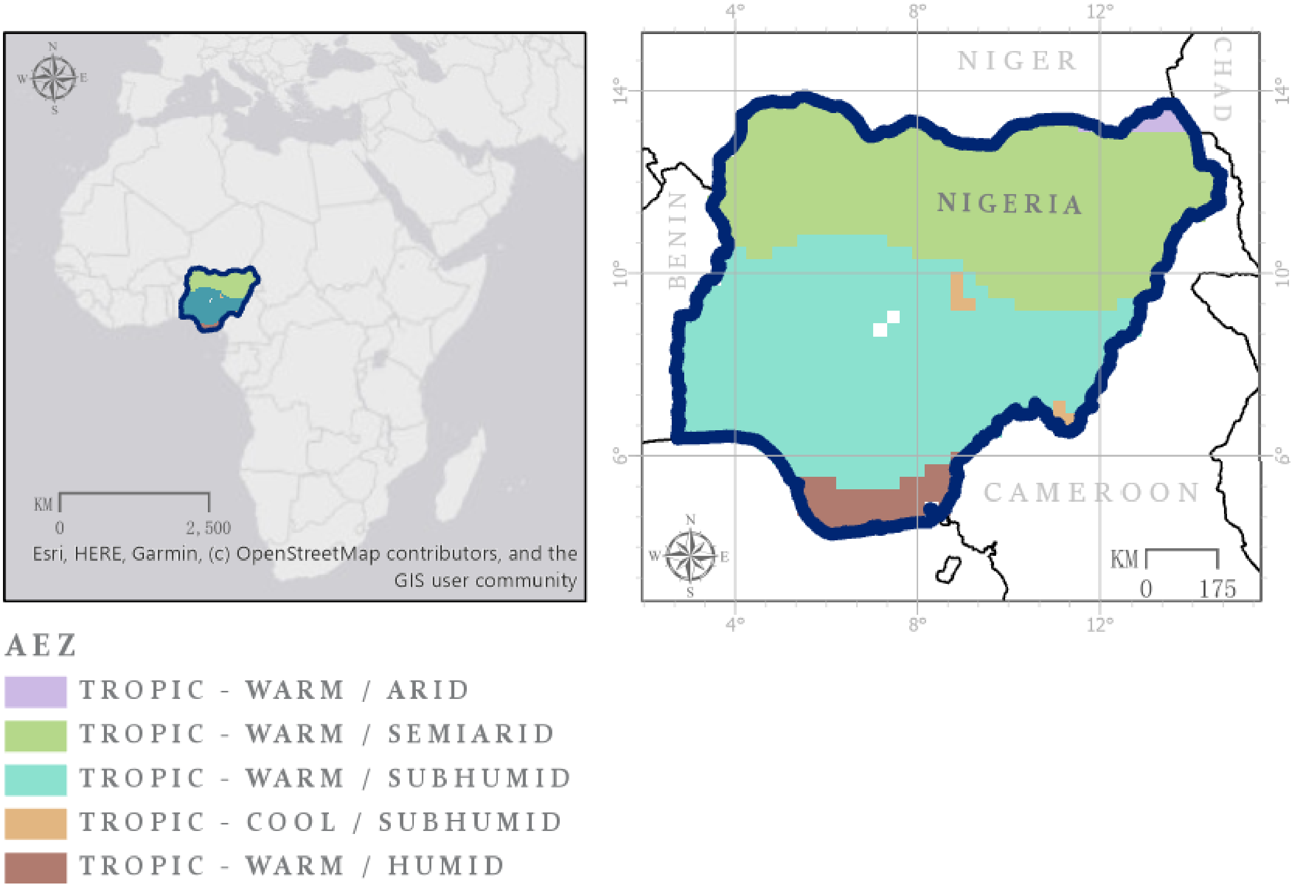


Figure 1: A map illustrating the study area of Nigeria. Nigeria has five agroecological zones which affect the productivity of agriculture across the country. This map was created in ArcGIS Pro using a pre-loaded base-map and an AEZ raster shapefile from HarvestChoice (2010). The spatial reference used is GCS WGS 1984.

Agriculture is the main economic activity in Nigeria, and therefore stable and high crop yields are not only vital to peoples' livelihoods but also to the country's economy (FAO, 2005; FAO, 2006; FAO, 2017). Agriculture in Nigeria is predominantly rainfed, subsistence farming where often the demand for food outweighs production and the main food crops are maize and sorghum (FAO, 2020a). Furthermore, there is little irrigation in the region and the amount of fertiliser required for maintaining high crop yields is not always available (FAO, 2020a). Sustainable levels of crop yields should meet the needs of the present population, without compromising the ability of future generations to also meet those needs (Smit and Smithers, 1993). It is not always possible to obtain yields which can achieve sustainable levels of crop production in Nigeria as a result of economic and practical constraints, such as access to irrigation or fertiliser, but also unsustainable agricultural intensification could quickly reduce essential nutrients from the soil making them unusable in the future (Smit and Smithers, 1993). There are large similarities in the farming practices in this region of Africa: rainfed agriculture with cover crops grown between seasons and little to no fertiliser (FAO, 2017; Thomas, 2003). As such, the conclusions drawn from this study may be applicable across West Africa as a whole (Adaptation Fund, 2019).

Adapted management practices are needed to reduce vulnerability to climate variability in Nigeria. This is especially true for smallholder farmers in the region, given the predicted rise in population and subsequent demand for food (Douxchamps *et al.,* 2016). The Food and Agricultural Organisation for the United Nations (FAO) has identified Nigeria as being a high-risk Early Warning Early Action (EWEA) country, alongside its neighbouring countries such as Niger and Burkina Faso (FAO, 2020b). EWEA countries are those where there is a high probability of disaster relating to agriculture and food security (FAO, 2020b). The FAO has also defined food security in Nigeria as a critical area to be addressed as part of its five-year strategic plan to improve agriculture in the country (FAO, 2019b). Thus, this study area has been chosen to represent a transect of areas which are highly vulnerable to the effects of climate change and that should therefore be a high priority for adaptation strategies and for scientific analysis. Within the arid zone, climate change is an unprecedented threat to food security; the arid and the semi-arid areas in Nigeria become drier every year with worsening droughts whilst the south becomes wetter (Olaniyi, Olutimehin, and Funmilayo, 2019). Both the frequency and intensity of floods and droughts within Nigeria will increase, creating the need for intense adaptations to these new climate conditions (Olorunfemi, 2011). Modifications to agricultural practices are one method by which the impact of climate change can be mitigated, especially the threat posed to crop yields and declining agricultural productivity (Olaniyi, Olutimehin, and Funmilayo, 2019).

2.1 Agroecological Zones

Agroecological zones (AEZs) are defined based on regional rainfall, temperature, seasonality, and latitude (HarvestChoice, 2010; Sebastian, 2014). AEZs are categorised by their ability to enable rainfed agriculture, as influenced by climate conditions and geographical area, and they have three main components – climate zones, moisture zones and highland/lowland elevation (HarvestChoice, 2010; Sebastian, 2014). The proposed study area covers five distinct AEZs, Fig.1., all of which are tropical lowland areas (i.e. mean monthly temperature >18^{o}C for all months and an elevation of 50-

800m) however they have distinct moisture zone classes defined by length of growing period (LGP) (HarvestChoice, 2010; Sebastian, 2014). For the tropical warm semi-arid zone, the LGP is 10-180 days and for the sub-humid zone the LGP is 180-270 days (HarvestChoice, 2010; Sebastian, 2014). Consequently, this causes a difference in irrigation required for crop-growth; the former AEZ relies on irrigation to compensate for unreliable rainfall, whereas the latter only requires irrigation throughout the dry season (Brouwer and Heibloem, 1986). The same is true for the arid region, although it experiences even less rainfall (Frenken, 2005). The north of Nigeria forms part of the Sahel, an area vulnerable to future climate change, and a region already facing acute food insecurity (Eze, 2018; FAO, 2018). Whilst the Sahel will experience the most severe impacts of climate change, it is also important to consider all AEZ zones when studying agriculture maintaining crop yields is still a country-wide issue (Eze, 2018). The humid and sub-humid regions, in the south of Nigeria, have more prolonged growing periods as a consequence of higher rainfall, when compared to the semi-arid regions, explaining the higher yields than in the more northern grid-cells (Erenstein, 2003). Irrigation is therefore more common in the semi-arid AEZ where water is a more prominent limiting factor, however water is still an expensive commodity and not widely used as a management practice (Muimba-Kankolongo, 2018).

Conversely, the semi-arid region has a better climate for the use of fertiliser because the heavy rainfall in the sub-humid region increases nutrient losses (Deckers, 1993; Erenstein, 2003; Stigter, 1984). Presently, in the sub-humid and semi-arid zones, only very low levels of fertiliser, or any plant-care products, are used to enhance crop yields and the practice is not widespread (Muimba-Kankolongo, 2018). The warm-arid and cool sub-humid zones cover only a slight area of Nigeria and thus are unlikely to have a major impact on the overall yields shown, however they may still affect the spatial distribution of crop yields. The southern-most warm-humid area shows variable rainfall from east to west and has the longest rainy season of the five AEZs found in Nigeria (Udoh, Cardwell and Ikotun, 2000). This region has adequate water supply and does not need irrigation to supplement the rainfall but similarly to the warm sub-humid region, it is subjected to erosion and leached soils (Udoh, Cardwell and Ikotun, 2000). The main food crops grown in Nigeria are roots and tubers, maize, sorghum, and pulses (Jalloh, Roy-Macauley and Sereme, 2012; Baudron *et al.,* 2012). This varies north to south, with the south-most humid zone producing cash crops such as oil palm, cocoa and rubber, the sub-humid zone producing food crops such as cassava, yam, plantain, sorghum and maize and the semi-arid zone also producing food crops where sorghum, millet and maize are the most important (Frenken, 2005).

The sub-humid AEZ might be a suitable area to consider increasing crop yields as small-holder farmers consider their farm size to be the biggest limitation to crop yield, in contrast to those in the semi-arid region where rainfall and perceived climatic change is considered to be the biggest reason for low yields (Kalungu and Harris, 2013). This would also suggest that those farmers in the semi-arid region should focus on climate adaptation i.e. crops more suitable to the warming climate and reduced rainfall (Kalungu and Harris, 2013). Whilst these are only perceptions gathered qualitatively, local farmers have an in-depth working knowledge of their land and thus their opinions shape the success of agriculture (Kalungu and Harris, 2013). Soil quality and water availability are highly variable in this region; this includes within the borders of a country and across individual AEZs therefore this study assesses the variability not only across time but also on a cell by cell basis. This enables management practices to be assessed on both a smaller and larger scale. Furthermore, there is a clear disparity between yields found in the sub-humid AEZ compared to those found in the semi-arid AEZ and bridging this this gap is a pertinent issue for food security (Kalungu and Harris, 2013).

2.2. Climate Change

Nigeria is highly vulnerable to climate change, where previous research suggests that increased temperatures could lead to sharp declines in crop yields (Douxchamps *et al.*, 2016; IPCC, 2019). The first annex of the IPCC (2013a) report, *Annex I: Atlas of Global and Regional Climate Projections*, details region specific climate projections for different seasons, including West and East Africa, Fig. 2., which demonstrate the projected rise in temperature for this region using RCP scenarios for the 50th percentile i.e. the median temperature change for the region. For both the RCP 8.5 (a “business as usual”, higher emissions scenario) and the RCP 4.5 (a lower emissions scenario) (IPCC, 2013a). In these projections, warming exceeds 1.5^{o}C above pre-industrial levels, reaching at least 2^{o}C of warming and increasing the risks of drought and precipitation deficits (IPCC, 2013a; IPCC 2018; Roy *et al.*, 2018). Furthermore, at warming of 2^{o}C, food availability is projected to decrease in Africa (IPCC, 2018). Climate change is altering crop yields in this region, and despite the positive effect of CO_2 fertilisation on plant growth, yields may still fall short of their maximum potential (IPCC, 2019).

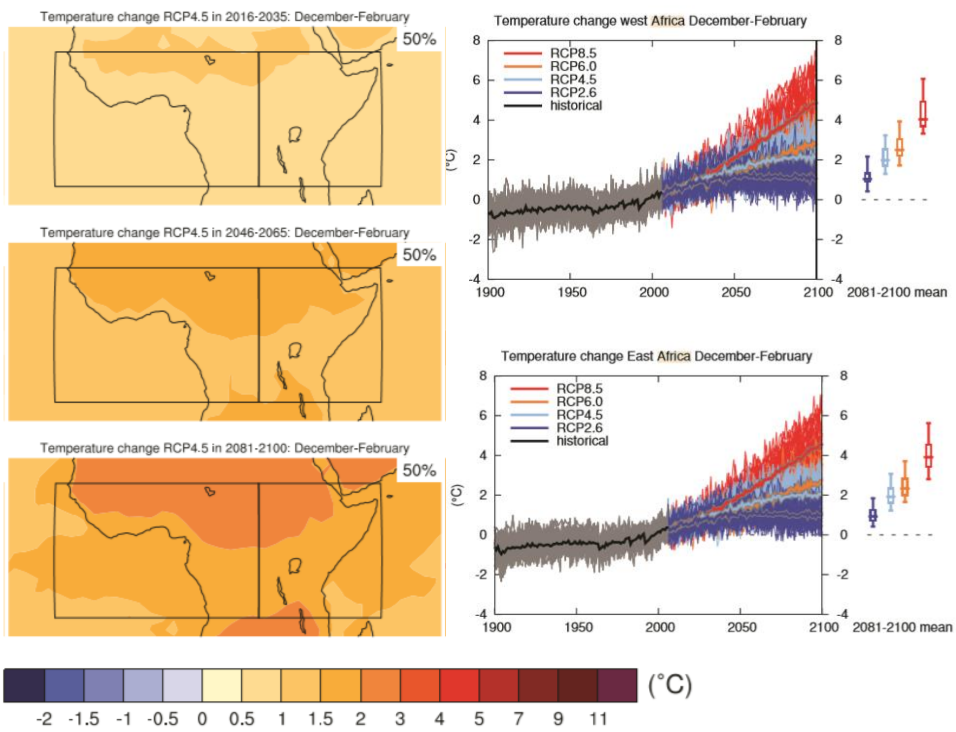


Figure 2: IPCC projections for the study area between December and February, the Dry Season for East and West Africa at the 50th percentile (IPCC, 2013a).Reproduced from the IPCC (2013a).

3. Background Literature

3.1 DGVM-crop

Dynamic global vegetation models (DGVMs) are used to project past, present, and future vegetation patterns, which both influence climate and are themselves manipulated by it (Bonan *et al.*, 2003; Scheiter, Langan and Higgins, 2013). Such models are especially complex as terrestrial ecosystems impact climate (and vice versa) through a multiplicity of fluxes including momentum, CO_2, trace gases, energy, water etc. (Bonan *et al.*, 2003). Early vegetation models did not include biogeochemical cycles; however, the inclusion of such cycles is vital as CO_2-vegetation dynamics have a significant impact on climate warming and cooling (Bonan *et al.*, 2003). DGVMs are a platform though which scientists can expand their understanding of plant and ecosystem function and were developed to primarily understand ecosystem response under rapid climate change (Cramer *et al.*, 2001; Prentice and Cowling, 2013).

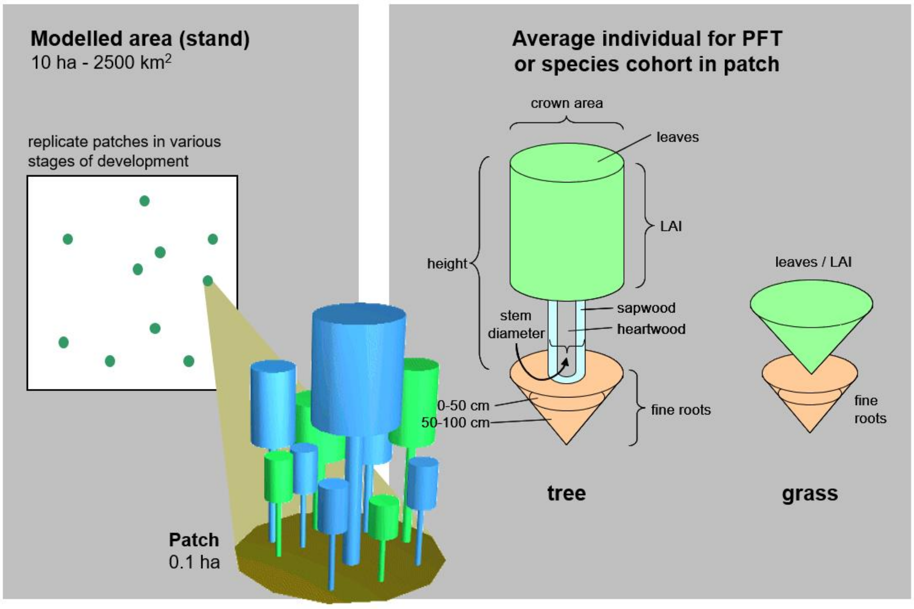


Figure 3: A visual representation of vegetation in LPJ-GUESS for each stand and plant functional type (PFT): the simulated plants are classified into one of a number of plant PFTs separated by phenology, photosynthetic pathway (C_3 or C_4), growth form, bioclimatic limits for establishment and survival. Reproduced from LPJ-GUESS open source documents – required no reference or permissions.

Chapter Nine of the IPCC report *Climate change 2013: the physical science basis*, gave an evaluation of climate models within which it was stated that DGVMs did not yet include managed forests or agriculture (Flato *et al.*, 2014). More recent models such as the Lunds-Potsdam-Jena General Ecosystem Simulator i.e. LPJ-GUESS, now include these land uses (Smith *et al.*, 2014; Olin *et al.*, 2015). LPJ-GUESS is a global dynamic vegetation model, developed collaboratively by Lund University and IMK-IFU PAI group, which combines biogeochemical cycles with patch-based and individual characterisations of vegetation dynamics to predict future scenarios under differing climate conditions (Smith *et al.,* 2014). Vegetation in this model is represented using plant functional types (PFTs), where each PFT is modelled in three ways; as an individual plant carrying the average properties of its population (crown area, height etc.); the number of individuals in that population; and the fractional cover of the grid-cell, Fig. 3. (Bonan *et al.*, 2003). Specifically, crops in this model are represented by using crop PFTs, Fig. 3., where modelled crop growth depends upon several variables: temperature limits, carbon allocation schemes, heat requirements, and carbon to nitrogen ratios (and limits) (Olin, 2015). Inputs to LPJ-GUESS span over two different time scales (days and years) although outputs are generally produced as yearly values and individual processes are scaled explicitly at a grid-level, 0.5arc-degree longitude and latitude (Bonan *et al.,* 2003; Cramer *et al.,* 2001). Changes in land-use and land-cover, for example, are modelled yearly, following such change; carbon, nitrogen and water are subsequently transferred to a new stand (Olin, 2015). Sowing dates have a significant impact on the growth and yield of crops, which has been shown extensively within the literature, and are therefore highly important in the modelling process (Ghosh et al., 2020; Midmore, Cartwright, and Fischer, 1984). Within LPJ-GUESS, sowing and harvesting dates are dynamically set i.e. they are based on climatic conditions at each grid-cell with planting determined by precipitation and harvesting based on the crop heat sum requirements (Olin, 2015). Furthermore, to reflect varieties grown in various climatic zones, the model allows crop adaptation to local conditions by adjusting the heat requirements of the crop to the historic climate (Olin, 2015). LPJ-GUESS enables nitrogen fixation and the allocation of carbon and nitrogen, which is modelled daily, based on the plant development stage, which is subsequently based on radiation and temperature (Olin, 2015). A flexible carbon to nitrogen ratio enables a variation in nitrogen uptake depending upon different plant structure, such as stems, roots and grains – the nitrogen content of the canopy in turn decides the leaf area sustained by the crop (Olin, 2015). LPJ-GUESS facilitates the modelling of several management strategies including irrigation, nitrogen fertilisation and changing the growing season (start/end of season).

3.2 DGVMs for predicting future crop yields

DGVMs and climate models are becoming increasingly important in the face of future climate variability. The FAO identifies food security as every person having sufficient and timely access (through social, physical and economic means) to secure, and nutritious food necessary to lead an active and healthy life (FAO, 2006; World Food Summit, 1996). Small-holder farmers are considered to be the 'backbone' of Africa's food production (Kalungu and Harris, 2013). Within the sub-humid and semi-arid regions, many farmers are dependent on seasonal rainfall for their crops and livelihoods to thrive (Tsowa and Abdulkadir, 2019). With an increasing population, producing more food is essential and hence, agricultural intensification becomes an attractive possibility to farmers in Africa (Kalungu and Harris, 2013).

Agricultural intensification is currently considered a viable method of ensuring food security and eradicating poverty and hunger in the sub-humid and semi-arid zones of Africa, it would also promote sustainable and socio-economic wellbeing (Tsowa and Abdulkadir, 2019). However, climate variability is making it more difficult to intensify with increasingly harsh and extreme conditions (Kalungu and Harris, 2013). Sorghum is drought resistant and is therefore an appropriate alternative to crops predicted to fail under new climate conditions (Chipanshi, Chanda and Totolo, 2003; Kalungu and Harris, 2013). For this reason, it is important to study future crop yields using DGVMs, such as LPJ-GUESS, in order to adapt farming strategies to these changes. It enables scientists to establish which crops will thrive best in Africa and where they should be planted, which can contribute to achieving food security by 'Monitoring food security and vulnerability', 'Diversifying Agriculture' and 'Enhancing food supply to the most vulnerable' which are factors outlined by the FAO for ascertaining resilient food systems (FAO, 2006). Food security is also an important route to achieving the sustainable development goal of Zero Hunger (United Nations, 2015). It is now becoming pertinent in scientific research to predict and model new management strategies in an effort to secure the future of food production in vulnerable regions (Guan *et al.*, 2017).

In this report, management strategies refer to the way in which crop production methods are managed i.e. the amount of fertilisation, whether they are irrigated or rainfed, when crop seeds are planted and the length of the season. Irrigation is defined as additional water being supplied to crops by diverting water from an external source e.g. river water or pumping groundwater - ~40% of current agricultural production uses this management practice (Zhuo and Hoekstra, 2017). However, in semi-arid areas there is limited access to water and different sectors compete for its use and therefore more refined methods of irrigation which reduce the amount of water wasted, such as to evaporation, are sought after (Zhuo and Hoekstra, 2017). Hand-in-hand with irrigation comes the need to fertilise soils in order to maintain the essential nutrients required for healthy plant growth. Within the literature, it has been repeatedly shown that conventional tillage methods degrade the soil quality but that if crop residue is retained on the soil surface than an increase in soil carbon and nitrogen can be seen (Beukes and Swanepoel, 2017). Other methods used to retain nitrogen in the soil include using cover crops: a method by which nitrogen fixing crops, such as legumes, are grown over the cropped area between seasons (Olin, 2015). Grasses can also be used to achieve the same effect (Olin, 2015). There has been significant effort focussed on predicting the future of crop yields themselves, and whilst many adaptation strategies to counter the expected decline in yield can be found in the literature, very few of these have been modelled for Africa (Guan *et al.*, 2017). Currently, one of the biggest issues with modelling crop yields is uncertainty, and the large disparity between different climate models which are then fed into crop models (Corbeels *et al.*, 2018). Furthermore, the model's capability to simulate more refined management strategies (such as micro-dosing nitrogen or limiting water evaporation from irrigation) is limited (Olin, 2015).

3.3 Climate data and projections

Emissions Scenarios

As well as climate data, many studies have used climate scenarios to study the future of vegetation growth and crop yields, especially because it is widely considered that the worst climate effects will take place if global warming exceeds 1.5^{o}C (Betts *et al.*, 2018). Food security is no exception, with the continent of Africa being regarded as the most vulnerable (Betts *et al.*, 2018). Some such scenarios available are the Special Report on Emissions Scenarios (SRES), produced by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2000; Schmidhuber and Tubiello, 2007). Research suggests that very low changes in agricultural Gross Domestic Product (GDP) globally, in the range of -1.5% and +2.6%, would be associated with these scenarios (Schmidhuber and Tubiello, 2007). However, at regional levels these changes are more severe, in particular sub-Saharan Africa where GDP is predicted to decline by ~2-8% (Schmidhuber and Tubiello, 2007). Such research was crucial in highlighting the risks climate change poses to food security and the need for further research and action in this area (Schmidhuber and Tubiello, 2007). The SRES emissions scenarios and their associated research have now been replaced with more recent data, such as the newer IPCC Representative Concentration Pathway (RCP) scenarios which describe four 21st century pathways for various GHGs, atmospheric pollutants and land-use scenarios (IPCC, 2013b; Pachauri *et al.*, 2014). These are consistent with ~300 baseline scenarios and ~900 mitigation scenarios reviewed by the IPCC and therefore are considered to be the standard emissions pathways for current climate models (Pachauri *et al.,* 2014). The RCP 2.6 scenario represents a low emissions pathway achieved by assuming the introduction of policies which bring about negative net carbon emissions before 2100, whose aim is to keep global warming to below 2^{o}C as is outlined in the Paris agreement (Melillo, Richmond and Yohe, 2017; Pachauri *et al.,* 2014). In this scenario, CO_2 is stabilised at 442 parts per million (ppm) by 2050 (Defrance *et al*., 2020*).* The two intermediate pathway scenarios are considered to be the RCP 4.5 and RCP 6.0 where CO_2 atmospheric concentrations will reach 487 and 478 ppm respectively; however the latter can also be considered the lower bound of emissions scenarios where no effort to reduce GHGs are made (IPCC, 2013a; Pachauri *et al.,* 2014). RCP8.5 is the business as usual, high emissions scenario reaching an atmospheric CO_2 concentration of 540 ppm by 2050 (Defrance *et al*., 2020; Pachauri *et al.,* 2014). The RCP scenarios are named by the amount of radiative forcing which would take place in each scenario (IPCC, 2013a). Currently, the IPCC suggests that all RCP scenarios except RCP2.5 are *likely* to cause a global warming >1.5^{o}C with a high confidence (Pachauri *et al.,* 2014). Thus, these scenarios are of most interest as not only are they very plausible emissions scenarios, but they are likely to cause devastating impacts on global food security (Deryng *et al.*, 2014).

Climate Models

A climate model is a tool through which the effects of climate dynamics on Earth's systems are evaluated, and they are more imperative now than ever before to increase scientists' understanding of climate change (Flato *et al.*, 2014). Climate models were developed because traditional scientific experimental design, i.e. field and laboratory studies, alone are not capable of representing the entirety of Earth's immense and complex systems (Edwards, 2011). Early climate models originated from conceptual models and were in use by Greek astronomers when connecting Earth's climate to the inclination of the sun (Edwards, 2011). Conceptual models form the basis of all climate models; they include all information pertinent to the model's function, including assumptions for the model and its interactions with the surrounding system (Arnold, 2019). Naturally, mathematical modelling progressed these early techniques to the computer-based climate models used today, such as general circulation models (GCMs), modelling the transfers of energy and large-scale weather and climate dynamics (Edwards, 2011). Climate models can be regional or global, depending on their intended use (Stieglitz *et al.,* 1997). Global climate models are more widely used, however there is an increasing need for high resolution regional models, which can resolve issues left unanswered by global-scale projections (Gutowski *et al.*, 2020). This is especially true as regional models are considered to simulate extreme conditions more accurately, including high temperatures and large storms (Gutowski *et al.*, 2020). The Max-Planck-Institute Earth System Model (MPI-ESM), is a climate model which couples ocean, atmosphere, and land-surface interactions (momentum, water, energy and CO_2) with ECHAM6 [atmospheric general circulation model], Max Planck Institute ocean model (MPIOM) [ocean sea-ice component], JSBACH [land component] and HAMOCC5 [simulates biogeochemical tracers in the oceanic water column and in the sediment] (Fig. 4.) – this enables the inclusion of the carbon cycle to the model system (Giorgetta *et al.*, 2013; MPI, 2020). More details about the model and its components can be found in the summary paper by Giorgetta *et*

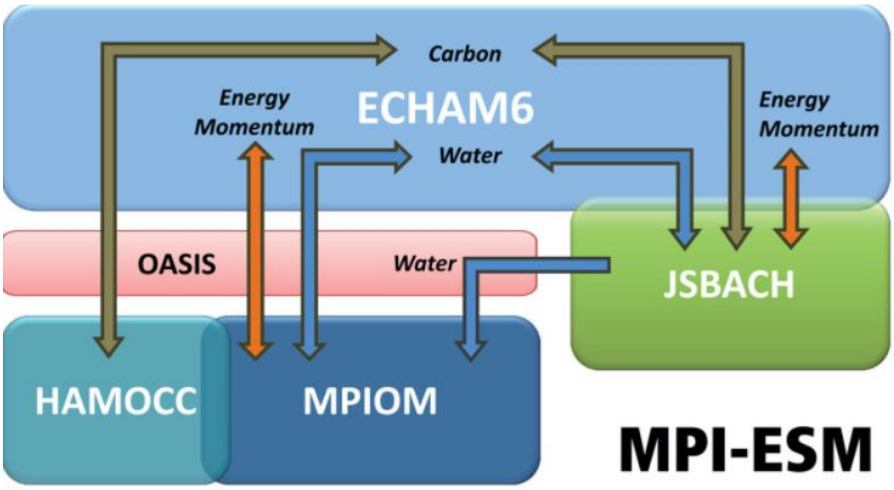


Figure 4: The conceptual schematic of the climate model MPI-ESM, taken from Giorgetta et al. (2013). It illustrates the multiple coupled components of the model; ECHAM6 for the atmospheric component, MPIOM and HAMOCC for the ocean component and JSBACH for the terrestrial biosphere (Giorgetta et al., 2013). The OASIS3 component is used to separate the atmospheric and land coupling processes from the ocean and biogeochemistry processes (Giorgetta et al., 2013). Reproduced from Giorgetta et al. (2013).

al. (2013). It is the output from this model which subsequently forces LPJ-GUESS.

3.4 Aims and Structure of the Report

For this report, LPJ-GUESS, driven by the MPI-ESM climate model, is used to achieve the first objective of this study: to project the future of crop yields in Nigeria under the RCP 4.5 and 8.5 climate scenarios. MPI-ESM was selected as it has been proven to perform highly with the CMIP5 RCP scenarios, it is also widely regarded as a high-performing model even at regional scales (Ayugi *et al.*, 2020a; Ayugi *et al.*, 2020b; Perez *et al.*, 2014). The second objective of this report attempts to begin to fill the aforementioned lack of research into modelled agricultural adaptation strategies, specifically for Nigeria (Guan *et al.*, 2017). Pugh *et al.*, (2016) simulated the future of global crop yields under the future climate scenarios provided by the IPCC (2013), however the focus of that paper was climate analogues and the amount of appropriate land for growing crops. Therefore, this study aims to expand on the work by Pugh *et al.* (2016) and begin to fill this gap in scientific knowledge on a regional basis, studying alterations to management which may improve the stability of crop yields in Nigeria. The chosen management strategies are additional nitrogen, the use of cover crops and, implementing irrigation.

4.Methods

4.1. The Model Requirements

The project uses LPJ-GUESS version 4.1, driven by the MPI-ESM climate model, to simulate crop-growth under different climate scenarios, in cohort mode (Olin *et al.*, 2015; Smith *et al*., 2014). The model uses plant functional types (each of which vary in phenology, nitrogen requirements and development stages etc.) to represent crop growth (Olin *et al.*, 2015; Smith *et al*., 2014). The model was run under two climate scenarios; the RCP 8.5 scenario and the RCP 4.5 scenario, which enabled the construction of adaptation strategies for both a more and less extreme climate future (Roy *et al.*, 2018). These provide the CO_2 data for the study, tables containing these data can be found in Appendix A. Other inputs for the model include radiation, land-use data, a soil map and nitrogen deposition. The sowing dates are decided by the encoded algorithm, previously mentioned, which works on the basis that when variation in water availability for crop growth is high (the precipitation to potential evapotranspiration ratio is above 0.2), the sowing date was modelled on a 30-day period around the date when the rain season began during the previous 20 years (Olin, 2015). However, if the temperature of the grid cell is <10^{o}C, then it is deemed to be temperature dependent and therefore the sowing window is instead based on a temperature constraint and a 20-year memory in mean monthly temperatures (Olin, 2015). When neither of these conditions are met than the grid cell will not be assigned a seasonality, subsequently a fixed date per hemisphere is used (day 15 north of the equator, and south of the equator day 196 will be used) (Olin, 2015). Whilst there are many possible sources for data, crop area and harvesting dates will be taken from the MIRCA2000 database as this is the first instance of such a dataset which has been made at a spatial resolution of five by five arc-minutes (Portmann, Siebert and Döll, 2010). It is a compilation of 26 irrigated and rainfed crops for 402 spatial units, between 1998 and 2002 (Portmann, Siebert and Döll, 2010). Some of these data were already prepared to be fed into LPJ-GUESS, therefore, despite these data being very similar to a compilation by Sacks *et al.* (2010), the MIRCA2000 data were the preferred choice as it has been used in similar studies previously (Minoli *et al.*, 2019).

4.2. Time Frame and Step

The model was run using a 500-year spin-up period and simulated outputs for the time frame from 1850 to 2100, Fig. 5, taking known percentage grid cell cover for each crop from the MIRCA2000 dataset, are from 1901-2006. This time frame was selected as the next 80 years will hold dramatic and rapid changes for the climate - the human population is predicted to reach nine billion by 2050 requiring a doubling in food production (Pugh *et al.*, 2016; Wolf, Ouattara and Supit, 2015). Therefore, it is critical that adaptation strategies focus on a timeframe which encompasses these periods of expected pressure in order to avoid disaster. LPJ-GUESS simulates daily allocations and outputs yearly yield values. Thus, a sufficient length of time has been simulated in order for adaptation strategies produced from these data to be relevant to the scientific community, smallholder farmers and the generally population.

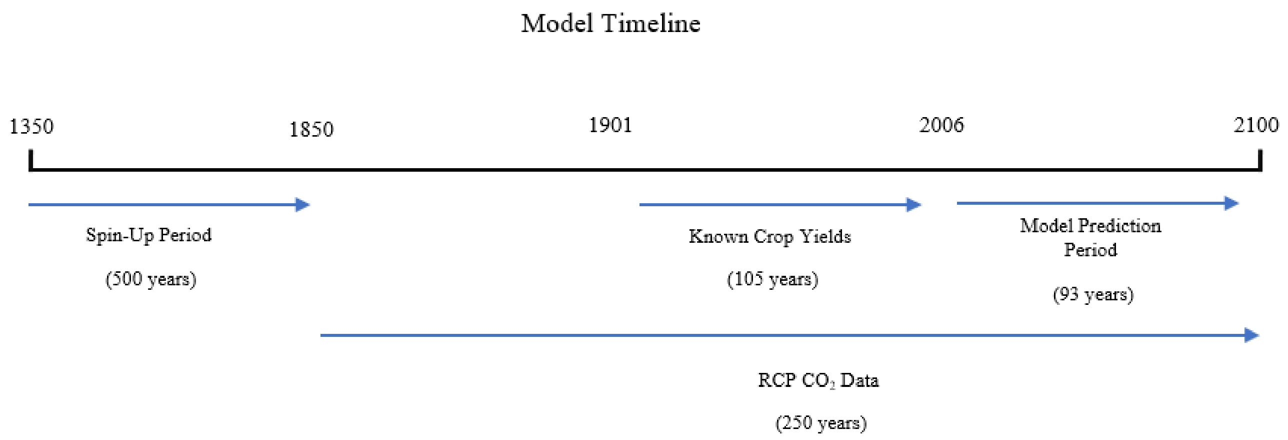


Figure 5: The timeline for the model methodology in this report. The model, LPJ-GUESS, ran with a 500-year spin-up period, followed by 156 years of data input and finishing by projecting 93 years of data into the future. The CO_2 data is known and is an input for this period. The model was forced with time variant climate information from the climate model simulations, which was also bias corrected with CRU-NCEP.

4.3. Crop species

Historically, international focus on increasing crop-yields through agricultural intensification has transpired as an effective strategy for increasing food availability, especially in developing nations (Dixon, Gibbon and Gulliver, 2001). However, it is also stated in the same publication from the FAO for the United Nations that poorer smallholder farmers have not experienced the advantages of increasing cereal crop yields (Dixon, Gibbon and Gulliver, 2001). Shortfalls and reductions in yields of cereal crops across many African countries have been reported by the FAO (2020b), and this has been listed as one of the main causes for chronic food insecurity in Africa (Khan *et al.,* 2014). The model will therefore focus on cereal crops for the climate simulations.

This report simulates crop yields for four main crops:

1. wheat (TeSW)
2. maize (TeCo)
3. sorghum (TrMi)
4. pulses (TeFb)

As has been previously mentioned, maize is the preferred crop by small-holder farmers, however sorghum is relatively drought resistant and considered to be the superlative crop for semi-arid conditions thus, it may be a suitable crop to grow in the face of climate change (Chipanshi, Chanda and Totolo, 2003; Kalungu and Harris, 2013). For these reasons, it is pragmatic to model their success under the IPCC climate scenarios in order to ascertain their productivity over the next 70 years. Pulses formulate a significant proportion of protein in the human diet and further food security, for example the Cowpea is a key pulse-crop in the Sahel and small-holder farmers who have small areas of land are able to produce substantial amounts of protein by growing it (Ali and Dov, 2017; Pradhan, Katiyar and Hemantaranjan, 2019). Predominantly in Nigeria, sorghum is intercropped with pulses, legumes, and in more humid regions, maize - this is the dominant method for maintaining the fertility of the soil (Hoffmann, *et al.,* 2001). Maize accounts for a significant proportion of the total cereal crop production and is typically grown in the more humid, wet regions of Nigeria (Defrance *et al.,* 2020). Wheat, however, is rare for the study area but is traditionally a high yielding crop when irrigated, maize is also traditionally much higher yielding when irrigated (Agriculture Organization of the United Nations. Food and Nutrition Division, 1997; Sánchez, 2010; Tsowa and Abdulkadir, 2019).

4.4. Management Scenarios

Although climate change is projected to alter cereal crop yield in Africa, there are still many possible adaptation strategies in the continent – ranging from adjusting management strategies to planting different crop species or increasing irrigation (Pugh *et al.,* 2016). This theory forms the premise of this report, to explore cropland management alternatives in and demonstrate their potential effectiveness at increasing food production (Olin *et al.,* 2015; Pugh *et al.,* 2016). Within Nigeria itself, there are two prominent factors which restrict crop yields: water limitations and low soil fertility, therefore the methods outlined in the section are based around the premise of solving these two issues (Bado, Savadogo, and Manzo, 2016).

4.4.1. Control Scenario

The initial control simulation was run with no specified management strategies. The water source for this scenario was rainfed as this is the current standard for Nigeria, and no grassy land cover or intercrop cover was included to mimic the intensification of croplands in the area. An input of five kilograms of nitrogen per hectare (5 kg N ha^{-1}) was used to represent minimal fertiliser application, this is because currently, little to no fertiliser is used in a widespread manner in Nigeria, with an average application rate of less than 10 kg N ha^{-1} (Rezaei and Gaiser, 2017; Zaehle, Friedlingstein and Friend, 2010). Nitrogen application within the model occurs when the plants require additional nitrogen input, depending upon the growth stage of the crop and the sewing dates (Olin, 2015). It is applied in segments of the total quantity at the development phases 0, 0.5 and 0.9 (between sowing and flowering) (Olin, 2015). Tillage is included in all scenarios as its effects are not being studied and it is common agricultural practice, given that this will be used across all model simulations it will have negligible bearing on the difference between results.

4.4.2. Irrigation

Strategies which continue to intensify agriculture in the region, but that do not decrease soil fertility are required if farmers are to continue to provide a secure food source to the region, unhindered by the changing climate. Irrigation is identified within the literature as a possible adaptation strategy in Nigeria, but one that would require significant financial input (Guan *et al.*, 2017). The first experimental scenario assumes that more money has been invested into the industry allowing irrigation to occur, this could be from the construction of small dams which trap water or outsourcing water from elsewhere. Water is a scarce and valuable resource and thus, it would require large amounts of money to irrigate within this region. LPJ-GUESS models irrigation by simulating a scenario where each plant receives exactly as much water as it needs and therefore it is an “optimised” irrigation scenario for all crops included (Olin, 2015). A limit to how much water each crop can receive, based on daily evapotranspiration, is set at 5 mm d^{-1} (Olin, 2015). All other parameters are maintained to be the same as the control scenario, including fertiliser use.

4.4.3. Cover Crops

The second experimental scenario modelled the use of cover crops as an intermediate between two seasons as a way to increase the nitrogen stored in the soil and subsequently increase crop yields (Olin, 2015). This report uses grass as a cover crop, which is not harvested and therefore nutrients and carbon are retained within the soil - LPJ-GUESS models this as carbon and nitrogen moving into the soil as litter, promoting better crop growth (Olin, 2015). This scenario is a very common management strategy in Nigeria; however, it is still important that it be compared to other management options in order to find the most efficient method by which crop yields can be increased.

4.4.4. Additional Nitrogen

The final model simulation increased nitrogen inputs for all crops and all years uniformly, from 5 kg N ha^{-1} to 50 kg N ha^{-1}, as nitrogen is often the limiting nutrient for maize and other crop yields (Rezaei and Gaiser, 2017). The method through which fertiliser was applied remained the same as the control scenario. Like the irrigation scenario, this strategy assumes that constraints on access and implementation of fertiliser use have been removed. The use of additional nitrogen as a management strategy has been observed for different regions throughout the literature, with many papers drawing different conclusions about the optimum amount of nitrogen which should be applied. 50 kg N ha^{-1} falls in the middle of several literature values observed and is also ten times the control amount – large enough to see a significant difference between the experimental scenario two and the control. Overall, including all management strategies, there will be eight model runs as each management scenario will be run for both the RCP4.5 and the RCP8.5 climate scenarios.

4.5. Analysis

LPJ-GUESS produces large amounts of output data, but the analysis of this report focussed on only the yield (kg/m^2 of dry mass). This was then used to assess both the temporal and the spatial relationships of the data to identify the highest performing management strategy not only over time but across the different AEZs.

4.5.1. Temporal relationships

The yield data from the eight model runs was aggregated into four time periods for analysis which are based on those used by Pugh *et al.* (2016):

- Reference period = 1986-2006
- Test period 1 = 2020-2040
- Test period 2 = 2050-2070
- Test period 3 = 2080-2100

The mean yield of each crop, for each time period on its own and for each time-period per grid cell, was calculated in R-studio. From these, bar charts illustrating change over time were made. This enabled a direct comparison between different climate scenarios and crops over time. A bar graph illustrating the change in yield was also produced to illustrate which of the crops improved most over time.

Anova

An Anova (Type II) test was conducted in R-Studio. This was to establish if there is a significant difference between the means of the yield in test period three, between all management strategies for each crop, therefore, highlighting which strategy is most effective for each crop. The data must be approximately normal in distribution, and the residuals should be unbiased and homoscedastic, furthermore a Type II test assumes no significant interaction between means (Townend, 2013). It focusses on the sum of squares for the A main effect after the B main effect and ignoring interaction (SS(A | B)) and the sum of squares for the B main effect after the A main effect and ignoring interaction (SS(B | A)), where A and B refer to two factors i.e. the management strategies being compared (Townend, 2013). This tests each main effect after the other main effects (Townend, 2013). Type II has been frequently suggested that in most cases it is more powerful than Type I or Type III, however because the yield data were all balanced i.e. each management strategy was conducted for the same number of grid-cells and number of years within each crop, then there is no difference between Type I, II or III (Langsrud, 2003). Overall, for each individual crop, if the management strategies are significantly different from each other the resultant p-value must be <0.05, as the limit is set to a 95% confidence (Townend, 2013).

Tukey Test

A post-hoc comparison test was then conducted: The Tukey multiple pairwise comparison, $\alpha = 0.05$ (Tukey's Honestly Significant Difference Test) (Abdi, and Williams, 2010). This is undertaken without any prior assumptions in mind, to establish precisely which management strategies were significantly different from which, it also has a low false positive rate (Gill, 1973).

4.5.2. Spatial relationships

The average values per grid cell for each defined time period were used to calculate the difference between test period three and the reference period, which was then displayed visually using ArcGIS Pro. The yield difference data were imported, displayed as a point file, and then converted to a raster shapefile: zero yield values were set to no data values. This highlighted any spatial patterns in the data. The spatial relationships were assessed statistically using the Spatial Autocorrelation (Global Moran's I) tool with the settings of inverse distance squared and Euclidean. Inverse distance squared tells the tool to apply a weighting of one to any two points which occur close together and Euclidean tells the tool to use the straight-line distance between two points (ESRI, 2020b). This tool ascertains whether the data are random, dispersed (negative Global Moran's value) or clustered (positive Global Moran's value) and whether this spatial distribution is significant, using a 99% confidence interval (ESRI, 2020b). The null hypothesis states that the data are randomly distributed: to reject this the relationship must have a p-value <0.01 and a critical z-score >2.58. This tool was run individually for each crop, and for each model run. Finally, to confirm where these clusters lay, a cluster and outlier analysis (Anselin Local Moran's I) was conducted with the same conditions as the spatial autocorrelation. This highlights only statistically significant clusters to a 95% confidence interval (p-value < 0.05) and then assigns them one of four categories; high-high (HH), a high value surrounded by other high values; high-low (HL), a high value comparative to the data in the cells around it; low-high (LH), a low value comparative to other values in the cells around it; and low-low (LL), a low value surrounded by other low values (ESRI, 2020a).

4.5.3. Model validation

Mathematical models simulating real world processes should be compared to known data where possible to assess the capability of that model to reproduce real world processes accurately and its ability to perform the task required of it (Tedeschi, 2006). Accuracy refers to how close a model's output data is to the observed value (Tedeschi, 2006). Data of known crop yields (dry grain only) in Nigeria from 1961 to 2018 were downloaded from the FAO website (FAO, nd; FAO, 2019a). These data were converted from hectograms per hectare (hp/ha) to kilograms per square metre so that a direct comparison could be made with the data produced by LPJ-GUESS: both the FAO data and the LPJ-GUESS yield data are reported as dry weight. The FAO data is treated as the objective truth so that conclusions about the robustness of management strategies drawn from LPJ-GUESS can be assessed. The FAO has collated these data by computing it from detailed area and production data. It is based on data reported by Nigeria for the total harvest for that calendar year, via questionnaires, however because of how different countries report some data it is possible that some harvest data is not included until the following year (FAO, nd). The time series of FAO data is long and therefore, whilst methods for gathering data are monitored by the FAO, it may not be consistent from 1961 to 2018, and may affect time-series comparisons (FAO, 2019a). However, old statistical methods were revised and updated by the FAO to ensure high data quality (FAO, 2016). The comparison was done for each crop (wheat, maize, sorghum, and pulses) for the RCP 8.5 and RCP 4.5 control run to determine if the model is suitable for its purpose in this study of modelling crop yields. These data were plotted over time so that comparisons between observed and modelled yields could be made.No further model validation was undertaken as assessing the suitability of the model is not the main purpose of this report, it is however important to understand how well the model performs in this context when considering management strategies for agricultural optimisation.

5.Results

5.1. Model Validation (against FAO statistics)

Finally, to have a complete understanding of the usefulness of the model in aiding climate change adaptation strategies, it is important to compare the modelled data to known data. The data for both the RCP 8.5 and RCP 4.5 control run was compared to known crop yield data for Nigeria, converted from hp/ha to kg/m^2, Fig. 13. (FAO, 2019a). The model does not begin to alter climate until 2006 and therefore, the LPJ-GUESS time series data only begins to vary between each RCP scenario after this point. Overall, maize and sorghum are over-estimated by the model and wheat and pulse yields are underestimated but none of these differences exceed 1 kg/m^2, where the smallest difference is shown for pulses: 0.022 kg/m^2 in 1961 and 0.005 kg/m^2 by 2018. Wheat also only demonstrates a small yield difference of 0.04 kg/m^2 by 2018.

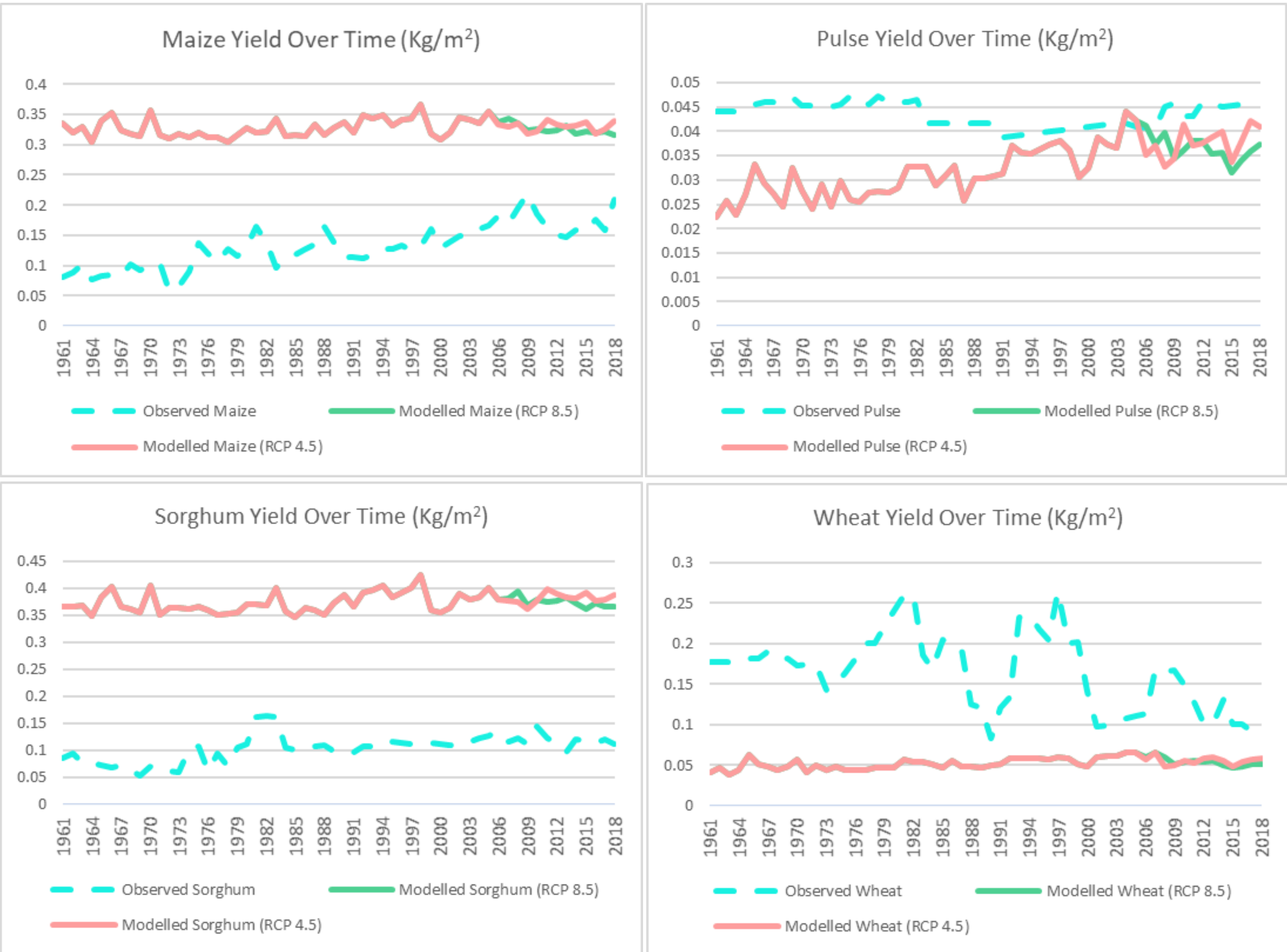


Figure 13: Model validation: The observed crop yield (dashed) compared to the modelled crop yield. The y-axis is the dry mass yield in kilograms per meter squared and the x-axis is the year. These data are for Nigeria between 1961 and 2018.

5.2. Key findings

The overall trend in the results illustrates an increase in crop yields over time, Fig. 6., this rise is consistently smaller in the RCP4.5 scenario than in the RCP8.5 scenario. Of all the crops reviewed, maize and sorghum produce the highest yields and the maximum average yield of a grid-cell by test period three, across all model runs, was 0.85 kg/m^2 of maize (RCP 8.5 irrigated scenario) which could be found at 13.75°E and 12.25°N.

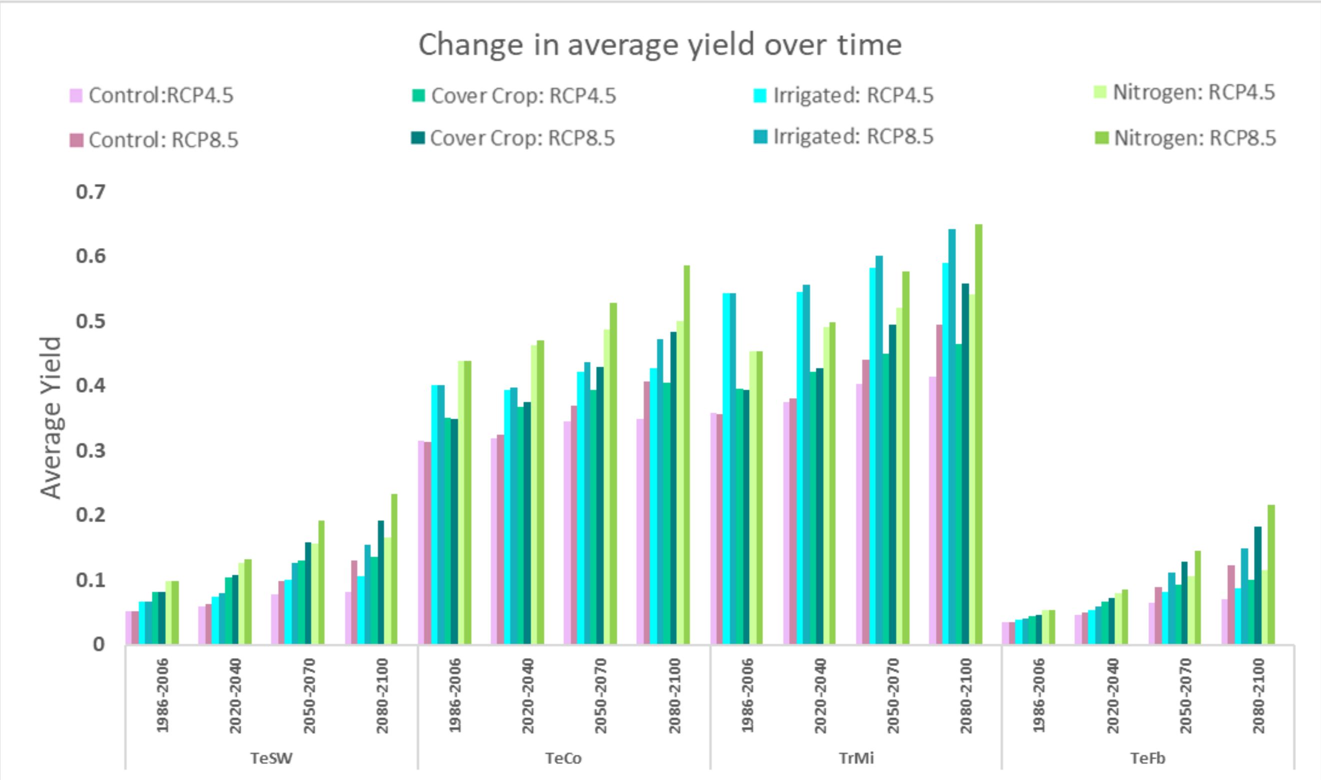


Figure 6: A bar chart illustrating the change in crop yield over time, this is divided first by crop species, then by time period and finally by management strategy (see legend for colour association). Each management strategy shows data per RCP scenario (lighter = RCP 4.5 and darker = RCP 8.5). The average yield was calculated from the average yield per grid cell and its units are kg/m^2 (dry mass weight). The crop species are labelled as follows: TeSW = Wheat, TeCo = Maize, TrMi = Sorghum and TeFb = Pulses.

5.3. How do yields vary over time?

Across all crop species, the additional nitrogen strategy consistently produces the highest crop yield, with sorghum and maize producing the greatest amounts of dry mass. However, despite the fact that sorghum may give the highest yield, pulses demonstrate a significant improvement in yield over time, more so than maize, and it especially thrives under the RCP 8.5 scenario, Fig. 7. During the control run, wheat tended to exhibit the lowest increase in yield over time, but when irrigated, this exceeds the increase found in maize yield. Nevertheless, sorghum overall is still much higher yielding than wheat. In Nigeria wheat is very fragile because it has an optimal growth temperature of 12-25 °C, but the maximum temperature in Nigeria ranges between 22–43°C; which is often too high for wheat to survive (Curtis, Rajaram, and Gómez, 2002; Okoh *et al.*, 2015). Nevertheless, wheat responds well to fertiliser use, in fact, additional fertiliser increases crop yields the most for wheat and maize. The use of cover crops to increase nitrogen retained in the soil generated greater crop yields than irrigation for both wheat and pulses. It is easy to determine from figures 6 and 7 that crop yields are increasing over time, but that this increase can be furthered through the use of management strategies, however it is unclear explicitly which management strategies are the most advantageous, due to the large variation in response.

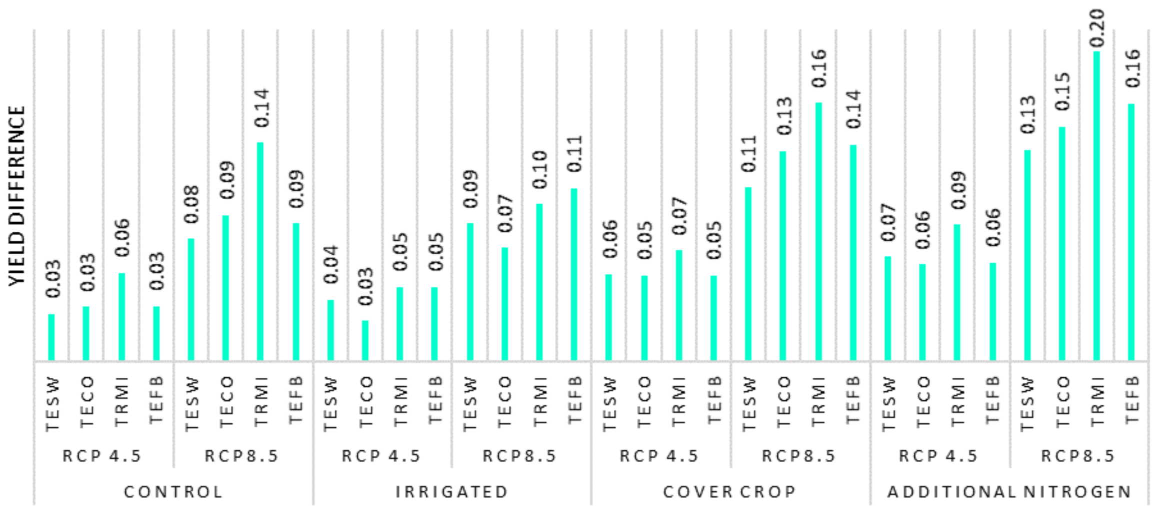


Figure 7: A bar chart illustrating the change in average crop yield, over all grid cells, between the reference time period (1991 to 2006) and the final test period (2080 to 2100). This is divided first by management strategy, then by RCP scenario, and finally by crop species. The units are measured in kg/m^2 (dry mass weight). The crop species are labelled as follows: TeSW = Wheat, TeCo = Maize, TrMi = Sorghum and TeFb = Pulses.

5.4 Statistical Relationships

An Anova (Type II) test was conducted to test for a significant difference in means between management strategies for each crop type, over the RCP 4.5 and RCP 8.5 climate scenarios, Appendix B. All four tests held p-values < 0.05 and therefore, the null hypothesis can be rejected i.e. there was a significant difference. Whilst the p-value indicates that there is a significant difference between means, it does not indicate which management strategies were significantly different from eachother. An HSD Tukey test was therefore conducted in R-Studio, the output from which can be found in Appendix C, means labelled with the same letter are not significantly different from eachother. A box plot of the means for each scenario was also produced, Fig.8.

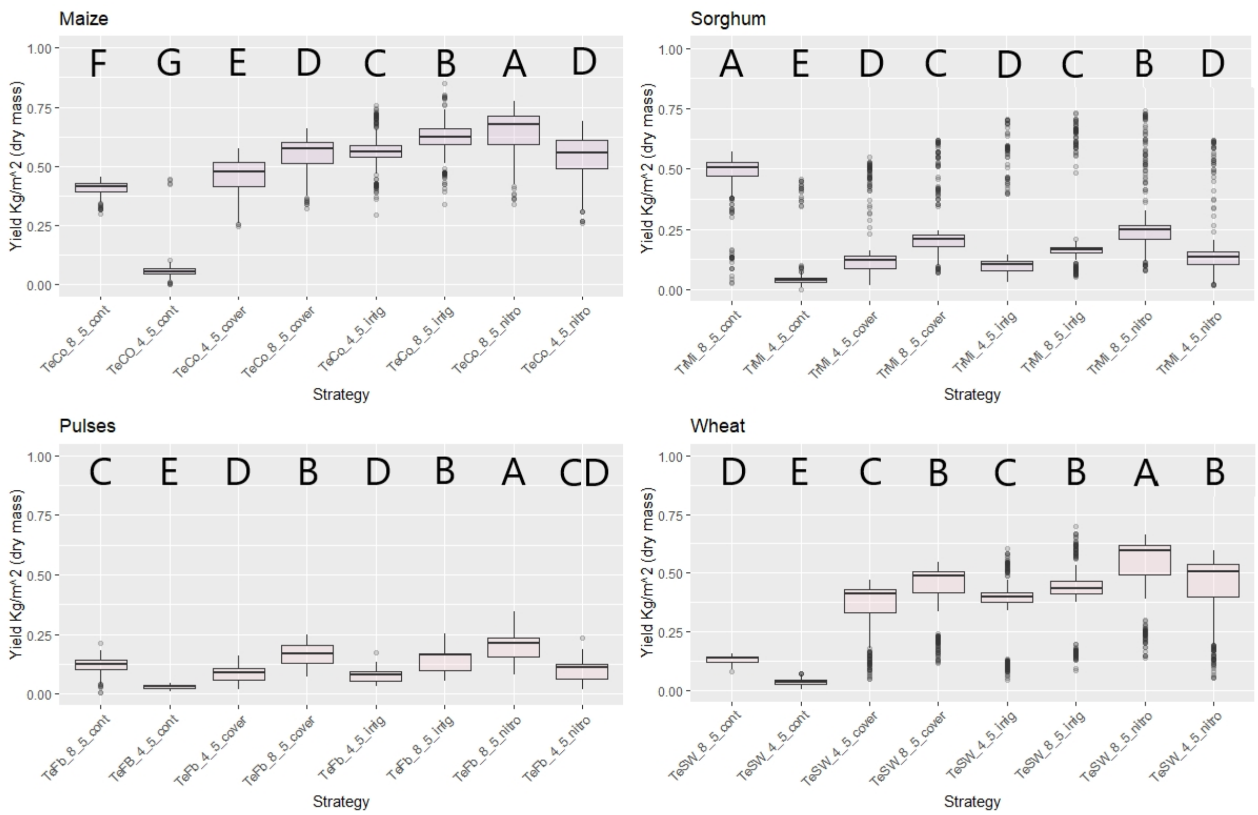


Figure 8: These box plots illustrate the spread of values for crop yields obtained over each management strategy per individual crop assessed. The strategy labels use the following structure: crop species_RCP_scenario_management strategy where 8_5 is used to represent the RCP 8.5 and 4_5 represents the RCP 4.5. The management strategies are abbreviated as follows: "cont" = control strategy, "cover" = cover crop strategy, "irrig" = irrigations strategy and "nitro" = additional nitrogen strategy. Strategies are labelled alphabetically where A represents the highest mean value and each subsequent letter represents a mean value lower than the last. Those strategies with the same letter are ***not*** *significantly different from eachother.*

The Tukey test revealed that the RCP 4.5 control scenario consistently produced the lowest mean yield for all crops (0.03 kg/m^2 for pulses and wheat, 0.06kg/m^2 for sorghum and maize), Fig. 8., and that this was significantly different from all other mean values. The RCP 8.5 additional nitrogen strategy yielded the highest average value for each crop (the highest being 0.64kg/m^2 of maize), except sorghum, where the RCP 8.5 control scenario produced the highest yield. For all crops, the Anova test suggested that there is a significant difference between the means of many of the management strategies, within each RCP scenario and the Tukey test implies that overall, the control scenario was the least effective, followed by the use of cover crops, then irrigation and finally, nitrogen was the most effective, see Appendix C, however there is a slight variation between individual crop species. Finally, something which should be observed from the box plots is the temporal variation in yields and large range of values within each management strategy, this suggests that the average values are not showing the full picture of how crop yields vary with each management type.

5.5. How does this vary spatially?

It is important to understand how management strategies affect crop yields over time, yet the spatial distribution of these changes is also integral to food security on a regional basis. The spatial distribution of crop yields will likely explain the large difference in values seen in Fig. 8. Point data, for both the RCP 4.5 and the RCP 8.5 scenarios, all management strategies and all crops were spatially autocorrelated (Global Moran's I) in ArcGIS Pro. The z-scores obtained from the spatial autocorrelation all exceed 2.58 and all p-values are less than 0.01. This suggests that the difference in yield from the reference period to time period three is significantly clustered for all scenarios and that there is <1% likelihood that the clustering shown is the product of random chance. Therefore, not only is there a change over time in yield but that some other spatial characteristic is affecting the results, such as the AEZs, or socio-economic factors.

Control

The results from the control scenario illustrate lower yields, and even a yield decline in the eastern, cool sub-humid AEZ for both RCP climate scenarios, Fig.9. This is true for wheat, maize, and sorghum and is shown firstly by the orange colour of the grid cells and then by the overlaid cluster analysis, which highlights significant Low-Low clusters even where the grid cells are green. Pulses display lower yields in the northern arid and semi-arid region of Nigeria, and higher yields in the southern warm humid region. The opposite is true for all other crops. The differences between both RCP scenarios remain the same, although yields in the RCP 4.5 are smaller.

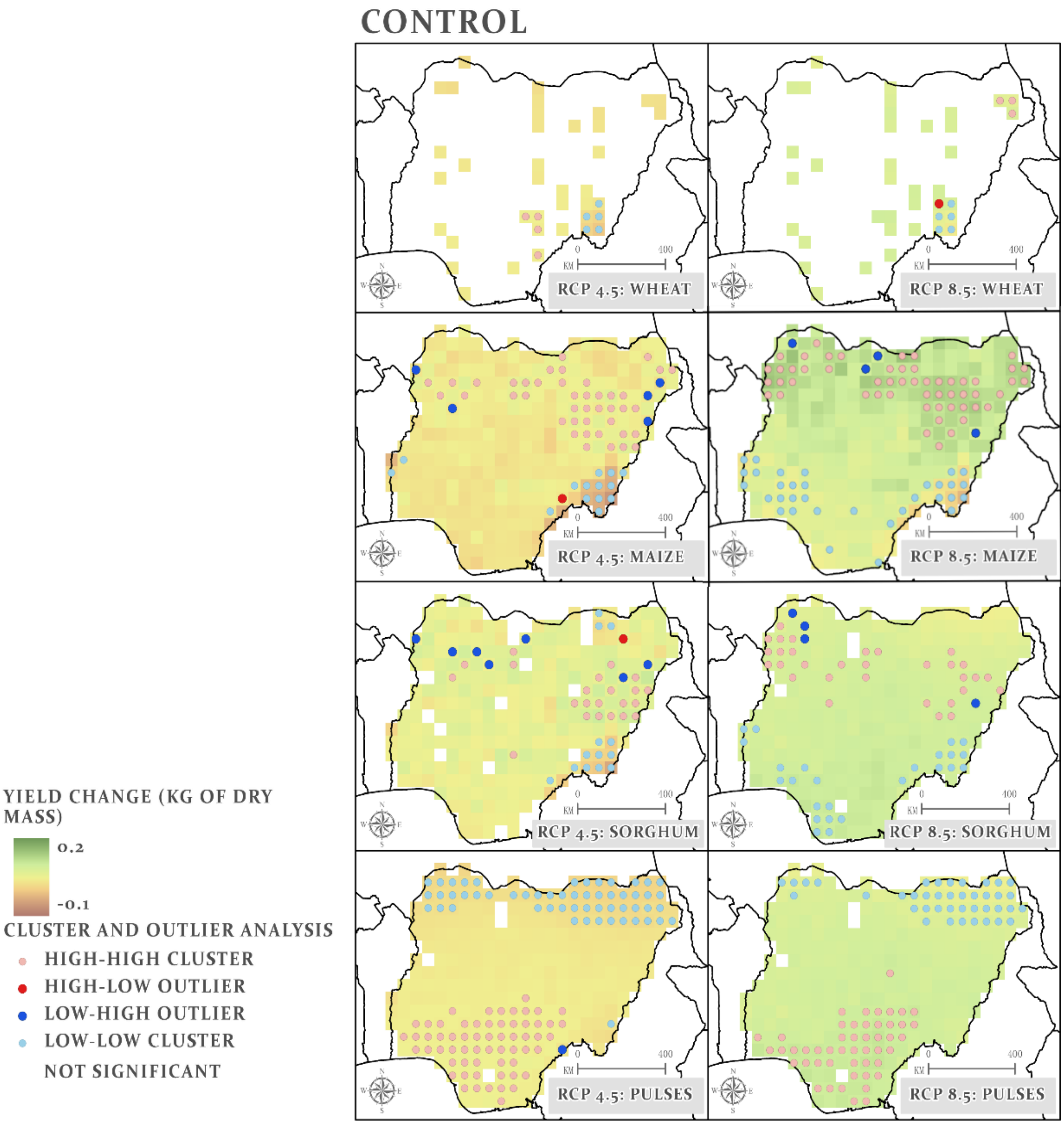


Figure 9: A map representing the crop yield difference (kg/m^2) per each 0.5° LPJ-GUESS grid cell in Nigeria during the Control Run management strategy for the RCP 4.5 (left) and RCP 8.5 (right) climate scenarios. The difference is between the reference period (1991-2006) and time period three (2080-2100). The white grid cells illustrate areas where that crop is not grown, and therefore there is no data. The scale bar shows 400km and the map spatial reference is GCS WGS 1984. Mention the clusters in the caption for all figures

Irrigation

The distribution of crop yield changes within the irrigated scenario when compared to the control, however the main change observed is the large increase in yields on the eastern cool sub-humid zone, highlighted by darker red grid-cells. Although for the RCP 4.5 scenario the patterns of crop yield difference appear to be much the same between strategies, overall the crops perform less well when irrigated than when not asmore grid cells showing a lower or a declining increase in yield can be seen, Fig. 9. And Fig. 10. To confirm this, histograms of the data were created and viewed in ArcGIS Pro, which illustrated a shift of the data to the left when irrigated. This occurred even for wheat. There is a strong band of irrigated grid cells in the north, which is clearly visible in Fig. 10. This band of darker green for maize and sorghum was not present in the control scenario. Finally, the data for the RCP 8.5 scenario shows the movement of HH clusters of pulse yields toward the east of Nigeria.

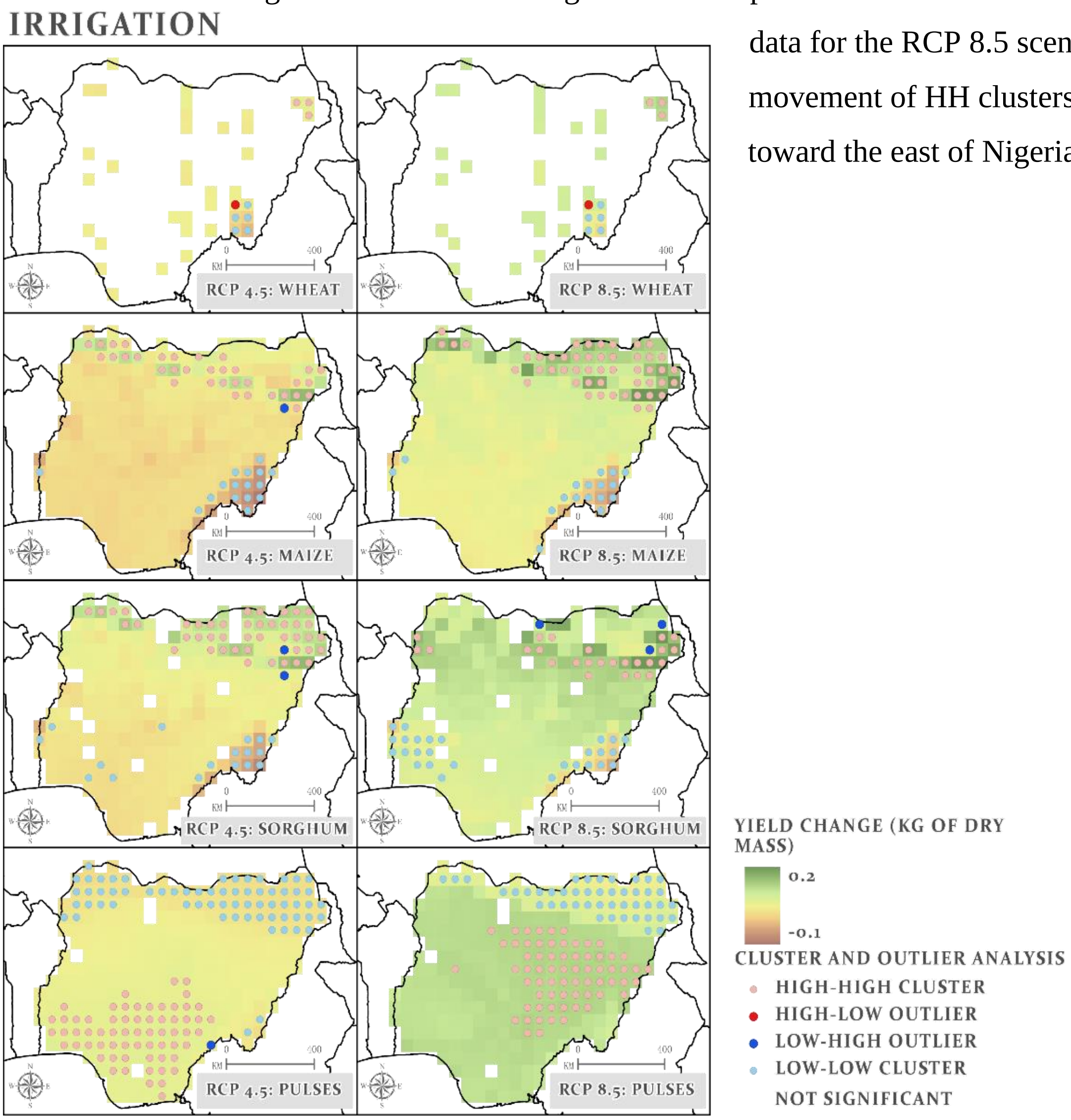
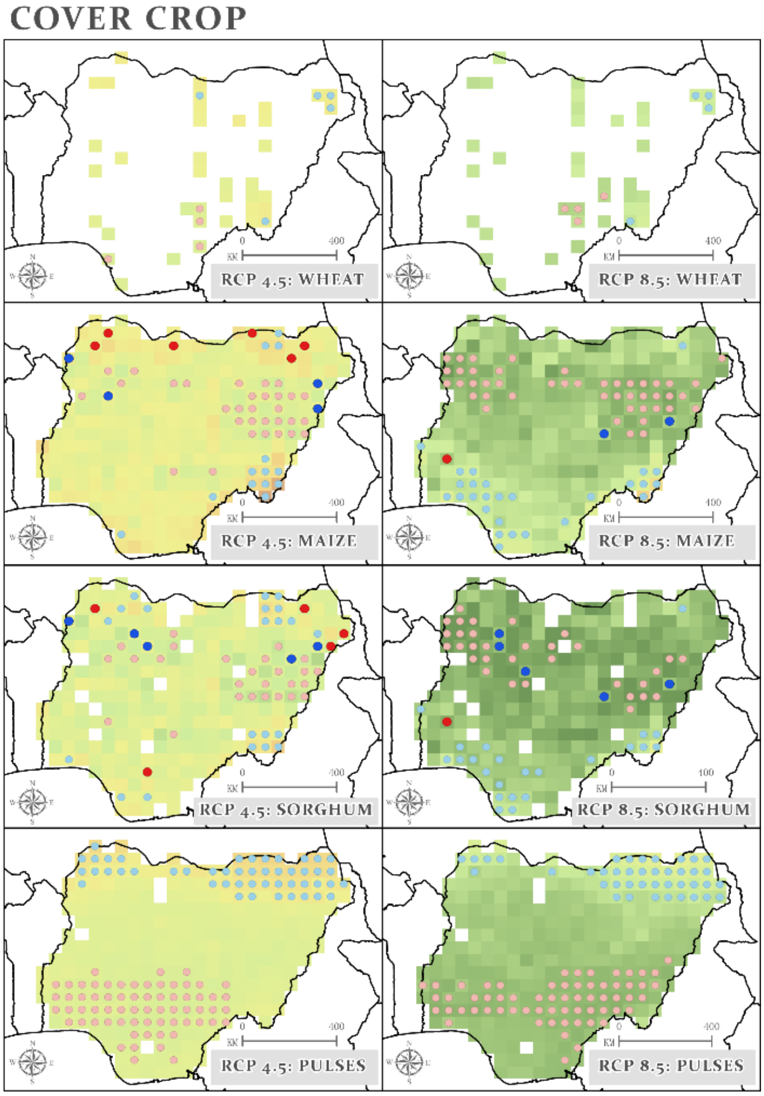


Figure 10: A map representing the crop yield difference (kg/m^2) data per each 0.5° LPJ-GUESS grid cell in Nigeria for the Irrigated strategy for the RCP 4.5 (left) and RCP 8.5 (right) climate scenarios. The difference is between the reference period (1991-2006) and time period three (2080-2100). The white grid cells illustrate areas where that crop is not grown, and therefore there is no data. The scale bar shows 400km and the map spatial reference is GCS WGS 1984.

Cover Crop

When applying the cover crop strategy, out of all the crops, maize demonstrates the highest increase in yield per grid cell . Spatially, when compared to the control scenario there is little difference in patterns – there are still some lower yields in the south for maize, and sorghum illustrates the same opposite trend of lower yields in the north and higher yields in the south and there is a shift of HH clusters to the east, Fig. 11. However, cover crops do little to increase the yield of pulses in the northern low yield areas. Compared to the control scenario, grid-cells in the maize and sorghum maps are much greener and therefore show higher yields, there are also greater numbers of HL cells. The LL clusters found for wheat in the control disappear when cover crops are used.



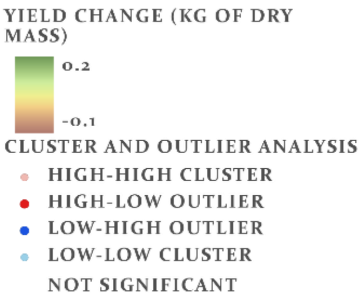


Figure 11: A map representing the crop yield difference (kg/m^2) data per each 0.5O LPJ-GUESS grid cell in Nigeria during the Cover Crop management strategy for the RCP 4.5 (left) and RCP 8.5 (right) climate scenarios. The difference is between the reference period (1991-2006) and time period three (2080-2100). The white grid cells illustrate areas where that crop is not grown, and therefore there is no data. The scale bar shows 400km and the map spatial reference is GCS WGS 1984.

Additional Nitrogen

Finally, when the use of nitrogen fertilizer is increased as a management strategy, grid cells are noticeably greener, yield much higher values and the decline in yields seen in the eastern corner of Nigeria is eradicated, although LL clusters are still present in this region, Fig. 12. This scenario was most successful at increasing the yields of pulses, further increasing the number of HH grid cells. During this scenario, crop yields of sorghum are increased most in the centre of Nigeria, in the warm sub-humid AEZ band and this is where most HH grid-cells can be seen. The distribution of high and low yields of maize and wheat is relatively unchanged, even though overall the yield has increased.

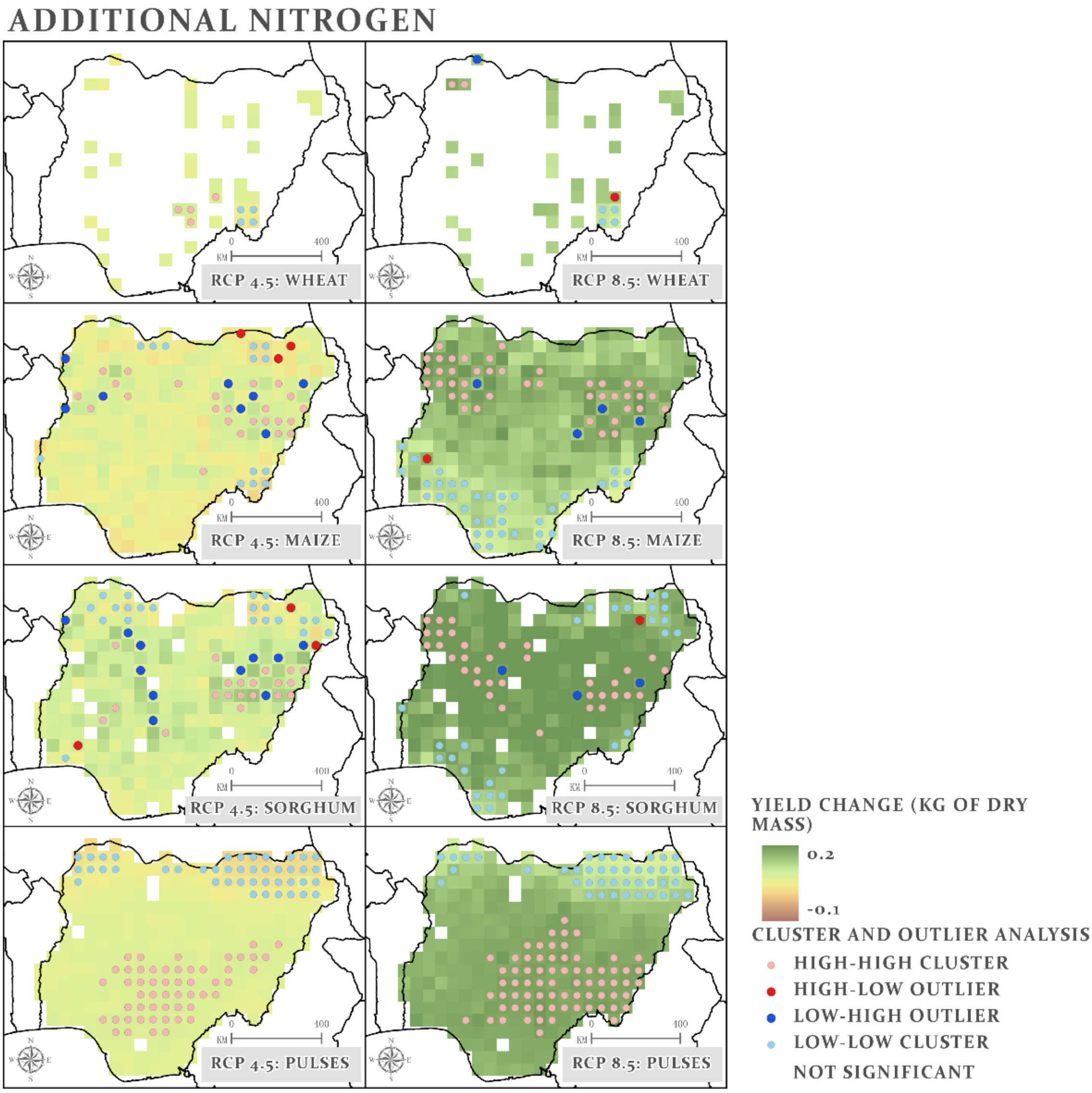


Figure 12: A map representing the crop yield difference (kg/m^2) data per each 0.5O LPJ-GUESS grid cell in Nigeria during the Additional Nitrogen management strategy for the RCP 4.5 (left) and RCP 8.5 (right) climate scenarios. The difference is between the reference period (1991-2006) and time period three (2080-2100). The white grid cells illustrate areas where that crop is not grown, and therefore there is no data. The scale bar shows 400km and the map spatial reference is GCS WGS 1984.

Overall, the number of grid cells showing a decline in yield over time is smaller when cover crops or additional nitrogen are used. Pulses illustrate a clear north to south gradient of yield difference, with the lowest being in Northern Nigeria, the Tropic, warm semi-arid region. Also, compared to other crops when irrigated, pulses show a very low yield, the highest being 0.07 kg/m^2 in the RCP 4.5 scenario and 0.13 kg/m^2 under the RCP 8.5 scenario. This is much higher than the average values shown in Fig. 9 and therefore demonstrates the importance of not just assessing the average values over time, as yields vary dramatically across space.

5.6. Summary

Currently in Nigeria, crop yields are not predicted to decline with either a lower emissions scenario or a higher emissions scenario. This is a positive outcome for the country; however, based on the above analysis, it is clear that the use of certain management strategies could improve crop yields. These experiments indicate that the highest increase in crop yield over time resulted from the addition of nitrogen fertiliser to the soil. The crops producing the highest average yield are maize and sorghum. The most susceptible region of Nigeria to crop yield declines is the east, where a small area of cool sub-humid climate can be found; this is because although pulses do not decline in this climate, maize and sorghum are the main food crops. Therefore, a decline in their yield puts food security at risk. There are differences in both the pattern and crop yield between observed FAO statistics and the modelled crop values, which should be considered when viewing the results. These differences are slight but do demonstrate the inability of models to exactly replicate real life scenarios and therefore, the results from the model should only be used in conjunction with other supporting evidence.

6. Discussion

6.1. Change over time and the RCP scenarios

It is immediately obvious from the results that, in Nigeria, crop yields are projected to increase. It is important to note that this conclusion is drawn only from the projections produced by LPJ-GUESS and it should be compared to the output from other such models. This could be because Nigeria falls just below the Sahel, and therefore is not experiencing the absolute worst effects of climate change. Nevertheless, in a region shrouded with uncertainty around the future of its food security this is a positive result. There are other factors which will influence crop yields, i.e. temperature and precipitation, but these have been controlled for by maintaining the same parameters for each model run. The main difference which will affect such parameters comes from the difference between the RCP 4.5 and the RCP 8.5 climate scenarios, in particular the levels of CO_2. The effect of CO_2 on plant growth, i.e. CO_2 fertilisation, is well documented and therefore it is likely that this explains the higher yields seen in the RCP 8.5 scenario and explains some of the increase in yields over time seen due to elevated CO_2 levels (Holden *et al.*, 2013). However, it has also been widely suggested that an increase in temperature of 4˚C above pre-industrial levels would be detrimental to Africa's food security and systems; Fig. 4. shows that in an RCP 8.5 emissions scenario 4˚C of warming is a possibility (New *et al.*, 2011). These are two conflicting statements. It is possible that LPJ-GUESS is overestimating the effect of CO_2 fertilisation on crop growth, therefore assuming that continuing on a course towards an emissions scenario such as the RCP 8.5 would not be problematic for crop yields in Nigeria is not recommended. For this reason, a comparison of the same study run with other DGVMs is advisable. A very similar study has been conducted by Defrance *et al.* (2020) which removed the CO_2 effect for one of its experimental scenarios during the RCP 8.5 and compared it to a model run which included the CO_2. This illustrated that, for the RCP 8.5 when CO_2 was removed from the model, yields were equivalent to or lower than those found in the RCP 2.6 emissions scenario (Defrance *et al.*, 2020).

Despite the effect of CO_2 fertilisation, the yields shown in the control run are still lower than their potential – with food security on the rest of the continent at risk, it may fall to areas such as this to provide food for greater numbers of the population and therefore more efforts should be placed on increasing the yield in already thriving areas. The increase in maize yield shown is consistent with findings from other models in the literature, for example Yang *et al.* (2020). Understanding how even less vulnerable countries will have to respond to climate change is important because, in reality, providing a secure food source by 2100 will provide cross country collaboration. Countries which are able to produce high yields may be able to support those which cannot, and therefore understanding the response of maize, sorghum, pulses, and wheat in Nigeria still has an important place amongst scientific research.

6.1.1. Irrigation

Fig. 6 illustrates the importance of irrigation in increasing yield for some crops when compared to the control scenarios and compliments the suggestion in the literature that water is a limiting factor. It would be pragmatic to increase irrigation to some extent for all crops, except pulses, to increase the yield (Moris, 2019). This fits into the range of literature suggesting that irrigation is positive for food security and crop growth; very few reports detail irrigation as having a negative effect (Oti, Enete, and Nweze, 2019). Although, it is known that irrigation is required and would benefit countries in Africa, but present infrastructure and access to water supplies does not allow for large-scale irrigation. Thus, practical considerations and investment need to be considered with the results of this report (Moris, 2019). In terms of sourcing irrigation for other crops, some papers have looked into the effect of using grey water from laundry to combat water scarcity and prevent competition between the agricultural sector and cities in Nigeria (Ikhajiagbe *et al.,* 2020). Laundry grey water does not need to be treated before it is used for irrigation and it contains nutrients essential for plant growth such as nitrogen, organic matter from broken skin cells and phosphorous (Ikhajiagbe *et al.,* 2020). However, there is research suggesting that the chemical present in this water could result in water propellant soil and inhibit plant growth – a less than desirable impact for healthy crop growth (Ikhajiagbe *et al.,* 2020).

Whilst irrigation is successful at increasing crop yields, it is not the most effective management strategy studied, the report from the spatial autocorrelation still implies that yields are still significantly clustered, even after irrigation is applied and therefore yield increase in not uniform throughout Nigeria. This trend, along with the still obvious differences between the RCP4.5 and RCP8.5 irrigation scenarios suggests that, whilst irrigation increases crop yields, it is not the most effective management strategy and considering the costs involved in its implementation, may not be the most effective use of resources, especially when considering that irrigation is a privilege and often too expensive to implement. Furthermore, when irrigation use is expanded alongside the increased use of fertiliser, it has been known to result in large-scale water pollution in the area (Zhuo and Hoekstra, 2017). It is therefore vital that when new methods are being considered, a much wider analysis of the area and ecosystems takes place to avoid further negative impacts on the environment than those deemed necessary to feed the population, which is the priority. It is known that Africa has continued low-level investment in irrigation and in some cases investment in irrigation has even shown a decline, this report adds to the multitude of evidence supporting the need for increased funding for irrigation (FAO, 2005).

6.1.2. Cover Crops

Cover crops are a management strategy used in the off-season to prevent the leaching of nitrogen from the soil and is a method frequently operated in Nigeria (78% of rural farming households) (Oti, Enete, and Nweze, 2019; Shelton, Jacobsen, and McCulley, 2018). Therefore, assessing the effectiveness of this strategy at mitigating the impact of climate change on crops is central to the functioning of many smallholder farms (Oti, Enete, and Nweze, 2019). Cover crops help prevent erosion, maintain soil fertility, increase soil quality and manage soil water (Oti, Enete, and Nweze, 2019). Thus, it is a valuable adaptation method which covers a wide range of limiting factors for crop growth. However, because of this large spread, it is less effective, and retains less nitrogen than directly fertilising the soil and less water than irrigation. This was reflected in the results. Whilst the cover crop scenario certainly increased crop yields above that of the control scenario, it was often less effective than irrigation or additional nitrogen. Despite this, it is likely to be the most practical approach as it does not incur additional costs to the farmers and is therefore significantly cheaper (Oti, Enete, and Nweze, 2019). The moderately effective result of cover crops seen in this report is reflected in the literature in studies such as that by Oti, Enete, and Nweze (2019).

6.1.3. Additional Nitrogen

Fertiliser application is less common than cover crops but more common than irrigation in Nigeria (Oti, Enete, and Nweze, 2019). Like the other management strategies, the effective impact of additional nitrogen on crop growth in this report can also be seen in other studies such as that by Oti, Enete, and Nweze (2019). However, a key difference was that within this report it was highlighted as the most effective strategy, but Oti, Enete and Nweze (2019) listed it as only a moderately effective method. Maize requires high amounts of soil fertility, which is likely why it responded so well to additional nitrogen compared to other crops, and yet over all scenarios the increase in maize over time was very poor. One study has suggested, that whilst it is easy to increase maize yields with fertiliser application, this is not profitable for the farmer (Liverpool-Tasie *et al.*, 2017). Therefore, although within this study additional nitrogen is treated as the most effective at increasing yield, further consideration into the economic value of undertaking this management strategy should be considered. Maize yields are unprofitable in this manner because the yield of maize per kg of nitrogen is much lower in reality than its potential shown when modelled (Liverpool-Tasie *et al*., 2017). Within this study, during the RCP 8.5 yields of maize were increased by 0.15 kg/m^2 over time when additional nitrogen was used. However, the transport costs of bringing in additional fertiliser reduce the profitability further. If this could be reduced by creating a source of fertiliser locally, profitability would increase (Liverpool-Tasie *et al*., 2017). This may even outweigh the low yield of maize produced per kg of nitrogen, making it an effective strategy despite this (Liverpool-Tasie *et al*., 2017). Despite its apparent inability to turn profit, fertilisers are still used in Nigeria (albeit not that commonly) because profit is not the main concern of smallholder farmers – rather food security is (Liverpool-Tasie *et al*., 2017). This is also the main concern of this report; thus, it is still reasonable to suggest nitrogen as an effective management strategy to increase food security in the face of climate change. Furthermore, fertiliser subsidies would be a very beneficial method of making fertilisers more economically viable for farmers and would help achieve the UN's Sustainable Development Goal Two – Zero Hunger. (Liverpool-Tasie *et al*., 2017). Further research into the amount of additional nitrogen used should also be established. This study used ten times the amount in the control scenario (50 kg) to establish a clear difference between the two scenarios, however other studies suggest that 60 kg is the optimum amount (Bloem, Trytsman, Smith, 2009) and another suggests that the optimum yield of cereal crops is reached by 40 kg per hectare (Tesfahunegn, 2019). Naturally, this varies between crops and a better understanding of individual crops reactions to different amounts of nitrogen would be greatly beneficial.

6.1.4. Agroecological Zones

Spatially, the aforementioned increase in crop yield over time is reflected over most grid cells when compared to the control scenario. However, this does vary, particularly with latitude and longitude. The most obvious difference takes place in an area of Nigeria where the AEZ is the tropic cool sub-humid zone, the smallest AEZ in Nigeria by the number of grid cells and yet it has a large impact on crop yield. This is particularly present for maize and sorghum, which is surprising when these have been the two most robust crops when looking at the data over time. This disparity worsens when irrigated. Alongside the warm semi-arid AEZ, the cool sub-humid has the highest percentage of poor households (Note, 2014). However, much more livestock is owned in the cool sub-humid AEZ than any other in Nigeria, and therefore the declining crop yields, whilst still an issue, may not be the predominant livelihood for households in that region (Note, 2014). The area also holds the fewest amounts of farms (Note, 2014). However, of these farms, despite holding more livestock, a greater proportion of their income comes from crops (Note, 2014). In contrast to irrigation, when additional nitrogen is used, there is virtually no crop yield decrease in this region, and it is reduced significantly by cover crops. Furthermore, maize is the predominant crop grown in that area, which also responded best to additional nitrogen (Note, 2014). Hence, additional nitrogen is the most effective management strategy to improve yields in this particularly vulnerable section of Nigeria. This is echoed in a study by Tesfahunegn (2019) which highlights the cool sub-humid AEZ as being particularly responsive to additional nitrogen.

When irrigated, the decline in yields north to south flips, with the exception of pulses. This could be because in these northernmost Sahel areas, water is the limiting factor whereas at lower latitudes, nitrogen is the limiting factor. In regard to pulses, they require little water and this research suggest they actively thrive on drier conditions (Loke *et al.,* 2016). This trend is very clear and is likely the cause of the significant clustering revealed by the spatial autocorrelation analysis. Furthermore, when pulses are irrigated, they exhibit very low yield values across the entire country. Within the literature, it has been suggested that nitrogen addition is the most useful form of management for pulse crops and Majumdar (2011) suggests that within Nigeria typically, pulses are not irrigated at all (Asaduzzaman *et al.,* 2008). Some studies suggest that pulses fix more nitrogen under dryland conditions than when irrigated (Lal, 2017). This combined with the knowledge that irrigation can cause soil leaching, removing essential nutrients from the soil, suggests that irrigation is an ineffective management strategy for pulse crops.

Ultimately, there are much more complex biophysical and socio-economic factors which can affect yield growth and drawing simplistic conclusions about crop yields from models using only a few management strategies should be cautioned against. Whilst reviewing such factors can be vitally important, they form part of a more complex pattern of factors which will affect crop yields across Africa. Thus, crop yields can vary between each smallholder farm without simple explanation, and therefore the variation of yields across grid cells, and the aforementioned clustering shown in the spatial autocorrelation analysis can have many other explanations outside of the four management strategies assessed here.

6.2. Methodological considerations

6.2.1. Considering crop yields in the wider context of food security

It is important to consider peoples food preferences as well as food needs when discussing food security and therefore sorghum alone is not the sole most appropriate crop for food security (FAO, 2003). Sorghum, being a drought resistant crop, is a viable and secure crop to grow in the face of climate change and it consistently produced high yields across all management strategies. According to some research however, smallholder farmers prefer to plant maize as their children prefer maize-based meals to those with sorghum (Kalungu and Harris, 2013). Another point to consider is that, whilst crop-yields are a major component of food security, livestock contributes a significant percentage of agricultural GDP (Zampaligré *et al.,* 2019). Therefore, it is important to note that the suggestions outlined in this report should not be considered as a complete solution to improving food security in the face of climate change, rather a small part of the answer. Further to this, genetically improved species, fertilisers, herbicides, and agrochemicals are also relied upon for crop yield success and agricultural intensification (Tsowa and Abdulkadir, 2019). This report is also very country-specific and does not assess the entire continent of Africa, nor does it assess an entire agroecological zone, however it has the potential to be highly useful in the context of Nigeria. This is beneficial because it enables crop yields for this area to be assessed specifically and therefore, more effective adaptation strategies to be formulated. However, because of the variability of climate within Africa, and in fact the globe, the results of this study are not necessarily relevant outside of the study zone. Wheat is very rare and does not grow well in this region of Africa, thus the relatively few grid cells this was modelled for in comparison to the other crops. Despite this, wheat consumption in Nigeria is rising, and if the demand for it increases then likely so will the amount of grid cells growing wheat (Bruinsma, ed., 2003). Adding to the wider discussion on food security, if a higher percentage of the population is consuming wheat then its yield in the face of climate change is especially important as it is currently difficult to grow and will only become more so. This is furthered by the lack of consideration for the political environment. Wars and conflict can dramatically alter the ability of a region to be food secure as food production is often reduced (Teodosijevic, 2003). These kinds of issues are difficult to model and therefore the model will never truly be representative of real life

6.2.2. Country Reported Yields and Data Uncertainties

Assumptions were made in relation to the validation of the model and the true values against which model outputs are compared. It was also assumed that the model is calibrated, optimised and that the mathematical formulae within the model are correct i.e. the internal workings of the model were not explicitly assessed. For this study, these assumptions are not entirely detrimental to the method, however, future research should confirm these assumptions if the results are considered to be robust. It is very difficult to make field data representative of the study area as it is not possible to sample all places ubiquitously (Illian *et al.,* 2008). Computation modelling allows data to be produced at very high resolutions, in much less time and over much larger scales than field data (Mihailović, Balaž, and Kapor, 2017). The data considered to be truth data in this study is taken from figures reported to the FAO via questionnaires distributed annually (FAO, 2019a), whereas LPJ-GUESS is modelling yield per each 0.5° grid-cell that makes up Nigeria. It is therefore highly likely that whilst LPJ-GUESS over-estimates crop yields that are abundant and under-estimates those that are rare, the data from the FAO are not as precise or holistic in nature; it is unlikely that questionnaire data accounts for every kilogram of each individual crop to the same precision as a mathematical model. Thus, despite the discrepancies in the model's apparent ability to model crop yields, it is still highly valuable and would greatly benefit the development of agricultural adaptation to climate change, especially if supplemented with field studies. Furthermore, for most crops the graphs show that the truth data is much closer to the modelled data by 2018 than in 1961, this could be because methods of data recording were less precise and not standardised historically (Tingley and Beissinger, 2009). This can affect how accurate the FAO data is and it also affects how well models can reproduce historical data as the model inputs are also less well recorded. However, it could also be the result of FAO questionnaires capturing trends caused by an increase in the efficiency of farming crops, such as maize whose observed yield increases toward modelled values, which the model is not designed to capture. Another explanation for this is that it could reflect increasing climatic strain reducing the capability of farmers to grow wheat, where observed values are declining towards the modelled, as a result of too high temperatures and the number of dry days increasing. Thus, it is important to be cautious when using mathematical models to draw conclusions about agricultural crop yields as they are not designed to capture changes in policy and knowledge related to farming. Other such studies with similar conditions also found a disparity between the observed yield and modelled yield. This was as much as 30%, therefore it is pertinent to consider this when viewing the results (Akumaga, Tarhule, and Yusuf, 2017).

Model parameterization is defined as the process by which an algorithm or statistical approach relates actual observed processes to those recreated by the model to make the output more accurate (Beven, 2009; Stensrud *et al.,* 2015). In this report, it relates to the yield values and it is often suggested that model parameterisation increases the explanatory power of that model (Schmaltz *et* *al.*, 2019; Stensrud *et al.*, 2015). If parameterisation of the model were to be conducted to match these yields, this would have altered the results, and consequently the conclusions which have been drawn from them. Ultimately, parameterisation does not change the probabilities of a model, simply the magnitude and shape of the data. However, parameterisation is also reductionist in the sense that the model output post-parameterisation become situation and location specific (Beven, 2009). This would prevent generalisations about AEZs and management practices in the broader context of Africa being made, but it would improve the prediction power of the model for Nigeria – if the data it is parametrized against is accurate (Beven, 2009). The yield values in this report are produced using fundamental principles included within the model, parameterisation would change these principles and thus, whilst parameterisation may give more 'accurate' results when compared to the FAO observed values, it would be at the cost of altering these principles and therefore may reduce the accuracy of the projected yield values for the future. Therefore, no parameterisation process was undertaken in this report as it was decided that the underlying principles of the model were more important than matching the data to observed values.

6.3. Future Research

Further to the research presented here, there are many areas of uncertainty and several gaps in the research not covered in this report. Should this study be repeated or expanded upon, there are several areas of development which would greatly improve it. Firstly, it would be pertinent to develop the management strategies explored here so that they include a combination of strategies because it is unlikely that one strategy will ever be used in isolation of the others. For example, cover crops may be used but alongside the use of irrigation. Although the research presented here is useful for isolating the most effective management strategy, it would be of scientific interest to understand how such combinations would benefit crop yields. Additionally, if possible, including methods by which more complex management strategies would benefit this research. This could include specific tillage and soil practices to retain water within the soil or testing different types of fertiliser such as phosphorus or potassium inputs to the soil (Jones *et al.*, 2017). Such detailed strategies are not currently encoded within the model and thus work to develop this would improve the usefulness of computer modelling for adaptation strategies (Jones *et al.*, 2017). Furthermore, should there be the available time and resources, combining mathematical modelling with practical field trials would greatly improve its usefulness of this report and also act as a valid comparison for observed yields. Agricultural field trials are implemented by many larger companies who aim to improve and optimise their crop yields, thus, if this same enthusiasm shown by large companies was applied to small holder farms it would greatly improve both the validity of the research and solidify the conclusions drawn here. Finally, the model itself required large amounts of preparation and adjustments before it could be used in this report, it then also took significant amounts of time to run the number of grid cells required to cover Nigeria, and sort and analyse the output data. However, expanding the study area to include countries such as Burkina Faso and Niger, which contain larger stretches of more vulnerable land i.e. that classified as tropical warm semi-arid and arid AEZ, would further enhance the usefulness of this research (HarvestChoice, 2010). These AEZs are even more vulnerable to climate change than those in Nigeria, and including a larger study are containing a greater number of grid cells for each AEZ classification would reaffirm conclusions drawn from this initial study.

7.Conclusion

The results of this study clearly answer the research questions set out at the beginning of the study. The results present a clear trend of increasing crop yields over time, up to the year 2100, with sorghum projected to increase the most over time. Furthermore, they show overarching improvements that additional management strategies can make to the yields produced in Nigeria. In particular, the results show the effectiveness of the additional nitrogen strategy, implying that nitrogen is currently a limiting factor within the region. The impact that these strategies had on the crops was mirrored within the literature and is therefore likely to be an accurate representation of reality. Uncertainty in the modelling process when predicting the future of crop yields is already high, as has been demonstrated in the literature. This report has been able to give good suggestions for smallholder farmers in Nigeria to consider using, however, these should only be taken as suggestions and not the objective truth. Furthermore, additional detailed management strategies which could be significantly more effective cannot be included presently in the model. Pests are also not included within LPJ-GUESS and therefore it fails to represent certain yield losses (Jones *et al.*, 2017). In summary, crop yields in Nigeria are clearly increasing between the years 1986 and 2100 and the promotion and utilisation of management strategies in Nigeria can improve crop yields and promote better food security in the face of climate change, however more detailed research should be undertaken in order to maximise the effectiveness of such strategies.

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Appendix A.

Table S1: CO_2 predictions for the RCP 4.5 and RCP 8.5 climate scenarios (in parts per million) from the year 2000 until 2100, taken from the IPCC (2013a) Annex I: Atlas of Global and Regional Climate Projections. These CO_2 data are those which were fed into LPJ-GUESS for this report. These data in the model were put into the model annually, however this table gives an idea of the difference between the two scenarios.

Year	RCP4.5 CO_2 (PPM)	RCP8.5 CO_2 (PPM)
2000	368.9	368.9
2005	378.8	378.8
2010	389.1	389.1
2020	411.1	409.4
2030	435	428.9
2040	460	450.7
2050	486.5	477.7
2060	508.9	510.6
2070	524.3	549.8
2080	531.1	594.3
2090	533.7	635.6
2100	538.4	669.7

Appendix B.

Table S2: A table illustrating the results from a One-Way Anova (Type II) statistical test for each crop species assessed in this report. For each crop, four management strategies were assessed (control, irrigation, cover crops and additional nitrogen), as well as two emissions scenarios (RCP 4.5 and RCP 8.5). The P-values shown are < 0.05, and therefore the differences between the yield produced by 2080-2100 for these strategies and climate scenarios are all significantly different.

Anova				
Maize	Sum Sq	Df	F-Value	P-Value
Key	69.464	7	1825.2	< 2.2e-16 ***
Residuals	12.385	2278		
Wheat	Sum Sq	Df	F-Value	P-Value
Key	45.358	7	425.04	< 2.2e-16 ***
Residuals	32.273	2117		
Pulses	Sum Sq	Df	F-Value	P-Value
Key	0.78305	7	72.318	< 2.2e-16 ***
Residuals	0.86005	566		
Sorghum	Sum Sq	Df	F-Value	P-Value
Key	29.559	7	187.11	< 2.2e-16 ***
Residuals	53.306	2362		
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				

Appendix C.

Table S3: The statistical results from a Tukey test performed on all maize yields in the report. Strategies with the same letter classification are not significantly different from eachother.

Maize		
Strategy	Mean value	Classification
Additional Nitrogen (RCP 8.5)	0.64	A
Irrigation (RCP 8.5)	0.62	B
Irrigation (RCP 4.5)	0.57	C
Cover Crops (RCP 8.5)	0.55	D
Additional Nitrogen (RCP 4.5)	0.54	D
Cover Crops (RCP 4.5)	0.46	E
Control (RCP 8.5)	0.41	F
Control (RCP 4.5)	0.06	G

Table S4: The statistical results from a Tukey test performed on all wheat yields in the report. Strategies with the same letter classification are not significantly different from eachother.

Wheat		
Strategy	Mean value	Classification
Additional Nitrogen (RCP 8.5)	0.52	A
Additional Nitrogen (RCP 4.5)	0.44	B
Cover Crops (RCP 8.5)	0.43	B
Irrigation (RCP 8.5)	0.41	B
Irrigation (RCP 4.5)	0.36	C
Cover Crops (RCP 4.5)	0.35	C
Control (RCP 8.5)	0.13	D
Control (RCP 4.5)	0.03	E

Table S5: The statistical results from a Tukey test performed on all pulse yields in the report. Strategies with the same letter classification are not significantly different from eachother.

Pulses		
Strategy	Mean value	Classification
Additional Nitrogen (RCP 8.5)	0.20	A
Cover Crops (RCP 8.5)	0.17	B
Irrigation (RCP 8.5)	0.14	B
Control (RCP 8.5)	0.12	C
Additional Nitrogen (RCP 4.5)	0.10	CD
Cover Crops (RCP 4.5)	0.09	D
Irrigation (RCP 4.5)	0.08	D

Control (RCP 4.5)	0.03	E

Table S6: The statistical results from a Tukey test performed on all sorghum yields in the report. Strategies with the same letter classification are not significantly different from eachother.

Sorghum		
Strategy	Mean value	Classification
Control (RCP 8.5)	0.47	A
Additional Nitrogen (RCP 8.5)	0.29	B
Cover Crops (RCP 8.5)	0.24	C
Irrigation (RCP 8.5)	0.24	C
Irrigation (RCP 4.5)	0.18	D
Additional Nitrogen (RCP 4.5)	0.17	D
Cover Crops (RCP 4.5)	0.17	D
Control (RCP 4.5)	0.06	E