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# *Three essays on climate change, agriculture and adaptation*

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# Abstract

This thesis consists of three chapters, each dealing with a different aspect of the impact of climate change on agriculture: the analysis of past evidence, the possible new solutions and the anticipation of future problems. The topics chosen are different but complementary and reflect the complex and multifaceted impact of this phenomenon on agriculture. This work uses global spatial data and information from the literature, combines weather forecast with a crop model, and uses an economic model coupled with robust econometric estimation approaches. The findings indicate that major crop yields in tropical and subtropical regions will likely suffer adverse effects, while temperate and continental areas, historically less favourable for agriculture, may experience mainly positive impacts. Under a medium development scenario, global crop production is projected to remain largely unaffected, masking a compensatory mechanism between tropical and temperate regions. Adaptation covers a significant positive role, and short- and medium-range weather forecasting can be an important and affordable tool for farmers to adapt their agricultural practices, if they know how to use it. The adoption of such meteorological information can enable rural households in developing countries to increase yields of staple crops, although the potential contribution of it may be hampered by social and economic barriers. However, adaptation in agriculture can have negative externalities, potentially creating a vicious circle, and the livestock sector is particularly vulnerable. Indeed, changing climate conditions may induce farmers to adjust the distribution of grazing livestock per unit of land in order to maximise profits. Temperate and continental countries may increase the number of grazing livestock per unit of land as climatic conditions improve for agricultural purposes, thereby increasing carbon dioxide emissions. On the other hand, tropical areas, mainly populated by developing countries, will see a deterioration of agricultural conditions and less livestock can be raised on rangelands and pasturelands. Once again, countries with pressing agricultural productivity needs bear a disproportionate burden of climate change effects, exacerbating already precarious living conditions. Conversely, northern countries, primarily developed, are likely to experience more beneficial effects.

**Keywords:** Climate Change, Impacts, Agriculture, Meta-analysis, Econometric Modelling, Crop Model, Weather Forecast, Developing Countries, Livestock, Land Use, Spatial Data.

**JEL classification:** C13, C21, C24, C50, O13, O30, Q00, Q10, Q50, Q15.

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# Introduction

In recent decades, climate change has emerged as the greatest challenge facing humanity. It is now clear that anthropogenic emissions are the main cause of it (IPCC, 2023) and there is great confidence among climatologists that we can never return to pre-industrial climate, as UN Secretary-General António Guterres recently told the Security Council (UN, 2021). Even if we were to immediately stop all human-induced greenhouse gas (GHG) emissions, it would take thousands of years for the planet to return to its pre-industrial state (Zickfeld et al., 2013). However, we continue to emit GHGs into the atmosphere.

From 2011 to 2020, the global surface temperature increased by 1.09 °C compared to 1850-1900, with a larger increase on land (1.59 °C) than in the ocean (0.88 °C). Even in the best sustainable future development scenario we will still face a temperature increase (IPCC, 2023). Temperature increase is just one of the many consequences of climate change and there is growing evidence in the literature of an increase in the intensity and frequency of extremes such as heat waves, heavy precipitations, droughts and cyclones, which can be even more damaging to human activities than changing climatic variables (IPCC, 2023). Among all affected economic sectors, agriculture is undoubtedly the most vulnerable, as it heavily depends on climatic (and weather) conditions. It is therefore necessary to be prepared for these changes and understand when, where, how and to what extent they will impact our lives.

Approximately 3.3-3.6 billion people currently live in areas that are highly vulnerable to climate change and heavily rely on agriculture for their livelihoods, and this number is expected to increase. By 2050, the world's population is likely to increase by about 33% leading to a corresponding 70% increase in food demand due to rising living standards (FAO, 2009; UN, 2013). Despite this, the total area under cultivation worldwide has remained relatively unchanged since the 1990s, placing increasing pressure on the agricultural sector (O'Mara, 2012). While agricultural productivity has grown substantially since the 1960s, it has significantly been impacted by climate change (Lobell, Schlenker and Costa-Roberts, 2011; Ortiz-Bobea et al., 2021), and future efforts to sustain productivity will need to be much greater than observed so far (IPCC, 2023).

Agriculture is therefore called upon to satisfy the increasing demand for food while coping with worsening weather conditions. The aim of this thesis is threefold: to analyse past literature and draw conclusions on the impact of climate change on major crop yields, to shed light on new technologies to adapt agriculture to a changing climate, and to anticipate the potential environmental externalities of adaptation in the agricultural sector. This thesis consists of three chapters, each dealing with a different aspect of the impact of climate change on agriculture: the past, potential new solutions, and the anticipation of future problems. The chosen topics are different but complementary, reflecting the complex and multifaceted nature of climate change on a vital sector such as agriculture. The following sections introduce each chapter, highlighting the main motivations and the conceptual framework.

## 1st chapter

One of the clearest consequences of climate change on agriculture is its impact on crop yields. Numerous studies have employed statistical or process-based methods to quantify the effects of temperature, precipitation, and carbon dioxide ($CO_2$) on crop yields, and have projected their future implications. Since the pioneering studies of 80s (e.g., Santer, 1985; Warrick, 1988; Adams et al., 1990), the body of literature in this field has significantly expanded. This growth is mainly attributable to the increased availability of observed crop yield data for model calibration, finer climate and weather observations, and advancements in impact modelling techniques.

The existing literature includes a large number of studies on the impact of climate change on crop yields, and new research is constantly being added. This extensive body of research provides the opportunity to draw strong conclusions about the overall impact of climate change on crop production. Evidence suggests that agricultural activity and crop yields in the northern hemisphere have historically been limited by lower temperatures, shorter growing seasons, and higher precipitation, indicating that climate change may have a beneficial impact in these cases. By contrast, agricultural conditions are likely to deteriorate in warmer regions, particularly in the tropics and subtropics, where environmental conditions are already critical for agriculture. Despite the numerous individual works[1] aimed at policymakers and stakeholders assessing the impact of climate change on crop yields, there are only few global assessments (e.g., Parry et al., 2004; Rosenzweig et al., 2014; Asseng et al., 2015; Liu et al., 2016; Wing et al., 2021). However, only a small number of these studies

[1] In this thesis, we employ the terms “articles”, “works”, and “papers” interchangeably when referring to scientific publications. The decision to use a particular term in a given context is driven by the aim of enhancing the overall fluidity of the text.

utilize meta-analysis and meta-regression analysis to synthesize the vast amount of information available in the literature to draw conclusions about this phenomenon.

The most recent global meta-analyses on multiple crops conducted by Easterling et al. (2007) and Challinor et al. (2014) are now considered outdated due to the evolving nature of climate change. Therefore, the research questions in Chapter 1 are: "What does the overall literature indicate about this phenomenon? What is the most reliable and substantiated answer that the literature can provide?" The information available in the literature is subsequently synthesized through a meta-analysis and conclusions are derived based on the collective body of research.

In contrast to the statistical approach that utilizes observed crop yield data to estimate causal relationships with climate or weather conditions, our methodology relies on the final results reported in published works as primary data. This approach is commonly employed in fields such as medicine, where meta-analysis and meta-regression analysis combine results from multiple studies to investigate the effects of drugs or treatments. However, these techniques are not widely used in research fields such as environmental science and economics (e.g. Haidich, 2010), partly due to the great heterogeneity in the methodological approach used in the original works. This study conducts a systematic literature review, collecting 212 original works and more than 5,700 observations. Subsequently, a weighted linear regression is used to estimate the impact of climate change on the three main global staple food crops: rice, wheat, and maize (FAO, 2020). The data generating function is then estimated and the benefit transfer approach is utilized to project the expected future impacts of climate change on agriculture, even in regions where primary information (i.e., original studies) is lacking. This methodology allows us to accurately predict the potential impact of climate change on cultivated areas worldwide. By complementing process-based and statistical methods, this result fills a significant gap in the current research landscape.

Our findings indicate that a slight increase in temperature has a positive impact on crop yields in countries with lower average yearly temperatures, but a negative impact in countries with higher temperature baselines[2]. Additionally, it was found that countries with higher levels of precipitation are more resilient to climate change, and an increase in precipitation can benefit crop yields, although its impact is limited. The

[2] We refer to average annual temperature and average total amount of precipitation as for temperature and precipitation baselines.

fertilizing impact of $CO_2$ is significant, but only few adaptation strategies have been shown to significantly increase crop yields. Without adaptation measures, our projections suggest modest global aggregate impacts for maize (-1.2%), rice (-5.8%), and wheat (-0.003%) under a medium sustainable scenario for 2041-2060. However, these results hide a significant global compensating effect, as many tropical countries are expected to experience consistent negative impacts, while colder countries in the northern regions are expected to benefit from rising temperatures.

## 2nd chapter

The meta-analysis reveals strong negative impacts of climate change on agriculture in countries with higher average temperatures, especially in tropical and sub-tropical regions. However, adaptation strategies can play a significantly positive role in mitigating these negative effects. The need to adapt is driving farmers to seek economically feasible and effective solutions. However, the literature has primarily focused on assessing the long-term impacts of climate change and adaptation strategies, neglecting the effect of year-to-year weather variability and the ability of these strategies to counteract short-term variability. Weather variability challenges the effectiveness of common adaptation strategies as each year presents specific weather conditions that require tailored responses. Consequently, adaptation strategies must also be flexible in order to manage short-term weather fluctuations.

In addition to well-known and commonly used agronomic adaptation strategies such as adjusting sowing dates, cultivar change, and modifying fertilization and irrigation practices, advancements in technology offer new opportunities for farmers that can complement traditional methods. Weather forecasts, both short and long-term, play a crucial role in helping farmers make important decisions each year by predicting future weather conditions (Vaughan et al., 2019; Agyekum et al., 2022). This information can influence farmers' choices regarding agronomic decisions such as crop selection, timing of sowing, and agricultural practices. Surprisingly, the literature has often overlooked the potential of weather information as an adaptation strategy despite its growing adoption by farmers and its increasing availability and accuracy in recent years, particularly over short time horizons (Bauer, Thorpe, and Brunet, 2015; Kusunose & Mahmood, 2016). Weather forecasts are often provided free of charge in both developed and developing countries, and advancements in artificial intelligence and increased computing power hold promising prospects for the future of this technology, not only in the agricultural sector, but also in many other industries (Roberts, Shinn and Riley, 2018; Alley et al., 2019; Schultz et al., 2021).

The aim of the second chapter is to examine the potential contribution of short-term (10-day) and long-term (3-month; seasonal) weather forecasts in helping farmers adapt agriculture to weather variability and climate change. We conduct a simulation in Tanzania, a developing country with environmental and agronomic characteristics that are representative of many sub-Saharan countries. To assess the potential benefit of weather forecasts, we employ the Decision Support System for Agrotechnology Transfer (DSSAT) crop model. This widely used and validated model is utilized to estimate the effects of different sowing dates on the yields of three commonly grown maize cultivars, and considers adjustments based on weather forecasts.

We quantify the value of "short term only", "long term only" and a combination of both methods by comparing the yields obtained with these approaches to those obtained by means of traditional sowing practices that do not consider weather information, i.e., a traditional farmer. Our findings show that farmers who use weather information can not only increase average crop yields in the long term (+14%) but also reduce variability over time, partially neutralizing the negative impact of year-to-year weather variability. Given the increase in weather variability due to climate change, these findings are not only useful for developing countries; they can also inform investments in weather forecasting aimed at meeting farmers' needs and optimizing the allocation of resources.

## 3rd chapter

The first and second chapters show the necessity and feasibility of adapting to climate change. However, it is important to recognize that adaptation may inadvertently conceal undesirable consequences, as human activities are primary drivers of environmental degradation (e.g., Fezzi et al., 2015). In the third chapter, we examine the potential negative environmental impacts of adaptation in the agricultural sector, specifically focusing on the often-neglected livestock industry.

The existing literature has primarily focused on assessing the expected impacts of climate change on crop yields, whereas comparatively less attention has been paid to understanding the impacts on livestock, despite their significant contribution to the overall agricultural industry (Porter et al., 2014). The livestock sector constitutes nearly 40% of the global agricultural gross domestic product (GDP), and is susceptible to the impacts of climate change, which depend on local climatic and environmental conditions (Thronton et al., 2010). These impacts primarily arise from elevated temperatures, increased $CO_2$ concentrations, and altered precipitation patterns, which directly and indirectly affect livestock production. For example, elevated temperatures can decrease livestock size and contribute to higher mortality rates among grazing animals. At the same time, they can foster the growth of C4[3] plant species, thereby increasing forage availability. On the other hand, increased atmospheric $CO_2$ levels can enhance the growth rates of C3[3] grass species but diminish their nutritional quality. The livestock sector accounts for 8% of global water consumption (Schlink et al., 2010), and changes in precipitation patterns may intensify water demand and competition for its use. Consequently, adaptation measures are essential for the livestock sector. It is important to note that this sector also contributes significantly to greenhouse gas (GHG) emissions, accounting for more than 14% of total emissions (Gerber et al., 2013).

The aim of Chapter 3 is to observe the long-term impact of livestock sector adaptation on externalities, specifically GHG emissions. This study utilizes an agricultural model to observe how farmers make decisions regarding the intensity of livestock grazing based on climate conditions in order to maximise profits (Fezzi and Bateman, 2011). We also use emission factors provided by the IPCC (2006) from enteric fermentation and manure management to calculate current and future GHG emissions. By using the parameters estimated by our model, we can predict the potential effects on GHG emissions if there is an increase or decrease in livestock intensity due to climate change. The findings show that countries in cooler regions of the northern hemisphere may experience improved farming conditions, enabling them to sustain higher rates of livestock grazing. Conversely, tropical and subtropical countries may face a decline in livestock grazing intensity. As a result, northern countries, which are largely developed, could increase GHG emissions due to improved grazing conditions, while low latitude countries are likely to experience a decline in livestock production

[3] C4 and C3 are different plant species in using water and $CO_2$ process. C4 plants are more efficient than C3 plants under high temperatures and low $CO_2$ conditions and exhibit higher water use efficiency compared to C3 plants.

conditions, leading to a reduction in grazing intensity. Overall, the GHG emissions from livestock sector are projected to increase by 0.14%. However, as it is the case in Chapter 1, this result conceals a global offsetting process between tropical and temperate/continental countries.

Given the projected increase in demand for dairy and cattle products in the future, which could potentially double in some developing countries mainly concentrated in tropical areas (Alexandratos and Bruinsma, 2012), these results suggest that livestock activities will become even more financially burdensome for countries with the greatest needs. This situation may give rise to various scenarios, including the expansion of landless or intensive livestock systems[4], which not only have negative environmental impacts (Steinfeld et al., 2006) but also require substantial investments (McDermott et al., 2010).

Once again, countries with the least responsibility for climate change but the greatest need to increase their agricultural productivity will inevitably witness further deterioration in their environmental conditions. By contrast, developed countries in the northern regions are likely to experience improved agricultural production and an increase in GHG emissions from livestock, which will undermine efforts to reduce emissions and enhance environmental quality.

[4] Landless livestock systems are defined as a subset of the solely livestock systems, in which less than 10% of the dry matter fed to animals is farm produced, and in which annual average stocking rates are above 10 livestock units per hectare of agricultural land (FAO, 1996).

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# A global meta-analysis of the impact of climate change on agriculture

## Abstract

Climate change poses a concrete risk to global food production through its effects on agriculture. However, the projected impacts on crop yields are not uniform across the globe, and a synthesis of the information provided by the literature is needed to formulate appropriate policies. In this study, we conduct a meta-analysis of climate change impacts on rice, wheat and maize yields using 212 works and more than 5,700 observations. By controlling for historical climate conditions (1970-2000), we find that temperature increases have different effects on crop yields depending on the climate region, with cooler areas likely to benefit. Precipitation has a positive and statistically significant effect on yields, as do carbon dioxide ($CO_2$) and some adaptation strategies. Using the estimated parameters from the meta-regression analysis we project the expected global impacts on crop yields, following the benefit transfer procedure. Under a medium development scenario with no adaptation, there are likely to be modest aggregate global impacts on maize (-1.2%) and rice (-5.8%) yields in 2041-2060, while wheat is essentially unaffected (-0.003%). Although the expected aggregate impacts are modest, they reveal winners and losers among countries, with developing countries, mainly in the tropics, being more negatively affected.

Keywords: Climate change, Agriculture, Global, Meta-regression analysis, Meta-analysis, Projections, Benefit transfer, Adaptation.

# Introduction

Climate change poses a significant threat to global food security, impacting the production of food crops worldwide. Agricultural productivity has already been negatively affected (Lobell, Schlenker and Costa-Roberts, 2011), and even in more optimistic future scenarios, climate conditions are expected to worsen, further exacerbating the difficulties faced by the agricultural sector in food production (IPCC, 2023). Furthermore, the increasing demand for food driven by population growth, particularly in developing countries, adds pressure on the agricultural sector, which is already dealing with the effects of climate change (Molotoks et al., 2021; Van Dijk et al., 2021). However, research suggests that the future effects on yields could vary considerably across different climate regions. It is likely that low-latitude regions will experience adverse consequences while northern regions may benefit from rising temperatures (Adams et al., 1999; Müller et al., 2010; Rosenzweig et al., 2014; Challinor et al., 2014; IPCC, 2021).

Through its impact on agriculture, climate change can profoundly alter the social and economic dynamics of countries. Rising temperatures, changing precipitation patterns, and more frequent droughts and floods have led to increased emigration flows from poorer communities (Falco, Galeotti, and Olper, 2019; Kaczan and Orgill-Meyer, 2020). Extreme weather events have a significant impact on food inflation, especially for communities that heavily rely on the agricultural sector as a source of income. This can lead to economic crises that affect entire countries (Heinen et al., 2015; Parker, 2018; Odongo et al., 2022). Reduced crop yields encourage the expansion and/or the intensification of agricultural land, resulting in biodiversity loss, soil erosion, and degradation. These factors, in turn, lead to water pollution and an increase in greenhouse gases (GHGs) emissions (e,g., Olesen and Bindi, 2002; Nearing et al., 2004; Flynn et al., 2009; Whitehead et al., 2009). Therefore, it is essential to have a comprehensive understanding of the scale and geographic spread of future global impacts to make informed and effective decisions.

Given the critical role of agriculture in shaping both the economy and society, researchers have been increasingly studying the effects of climate change on this sector, adding to the existing literature (Aleixandre-Benavent et al., 2017). While some global assessments of climate change's impact on crop yields have been conducted (e.g. Parry et al., 2004; Rosenzweig et al., 2014; Asseng et al., 2015; Wing et al., 2021), only few studies have drawn conclusions based on the findings of these assessments. This is likely due to the challenges posed by the high degree of methodological heterogeneity characterizing this field of research. Statistical techniques, such as meta-analysis, have proven effective in synthesising evidence (Stanley and Jarrell, 2005; Egger et al., 2008). Meta-analysis has also been used in related disciplines such as agronomy and ecology (e.g. Philibert et al., 2012; Koricheva et al., 2013; Mengist et al., 2020).

To date, only a limited number of meta-analyses have been conducted on the impact of climate change on crop yields. However, these studies often have limitations in their scope, such as focusing on a narrow geographical area, including a small number of original studies, or concentrating on a single crop. For example, Muller et al. (2011) and Roudier et al. (2011) used only 20 and 16 articles, respectively, to examine the impact of climate change on agriculture in Africa and West Africa. Similarly, Knox et al. (2012) and Knox et al. (2016) utilized 52 and 41 articles, respectively, to conduct comprehensive studies on the impact of climate change on crop yields in Africa, South Asia and Europe. Few crop-specific studies have also been conducted, such as Wilkox and Makwoski (2011) on the global impact on wheat and Li et al. (2021) on the global impact on cotton. The most recent global multi-crop assessment by Challinor et al. (2014) is somewhat outdated due to the evolving nature of the phenomenon, although it considers 91 works published up to 2012.

As the number of these publications continues to grow (Aleixandre-Benavent et al., 2017), we take the opportunity to better understand the expected global impacts of climate change on crop yields through a global assessment. We thus present a meta-analysis that examines the impact of climate change on crop yields using 212 published works and more than 5,700 observations. After conducting a systematic literature review, we use the estimated parameters from the meta-regression analysis to project the effects of climate change on a global scale in a spatially explicit manner, using an ensemble of General Circulation Models (GCMs) and the "middle road" scenario SSP245 (Shared Socioeconomic Pathways) for 2041-2060.

We focus on three of the most widely produced crops globally: wheat, maize and rice. This choice is based on the significant global importance of these crops and the fact that they are the focus of the majority of publications, including the most recent global meta-analysis. This strategic choice allows us to directly compare our findings with previous research and provide up-to-date evidence. Using the dataset compiled by Challinor et al. (2014) as a baseline reference, we include the most recent publications available up to 2020.

The results show that a marginal increase in temperature (+1 °C) has a positive effect on crop yields in countries with a low temperature baseline but a negative effect in countries with higher baselines. On the other hand, precipitation levels and variations play a limited, yet positive role, suggesting that countries with higher precipitation levels are more resilient to climate change. The expected aggregate global impacts without adaptation show that under an intermediate development scenario from 2000 to 2041-2060, we may experience a modest aggregate impact for maize (-1.2%), rice (-5.8%), and wheat (-0.003%). However, these results fail to consider a wide range of differences between countries. While many developing countries in the tropics are expected to experience consistent negative impacts on yields, colder countries in the north are likely to benefit from rising temperatures.

This study fills a significant research gap in the literature by significantly increasing the number of complete observations for the meta-regression analysis. Compared to the previous global multi-crop assessment, the number of observations has increased by over 500%, from 882 to 5,705. Consequently, this work stands as the most comprehensive and up-to-date collection of original articles available in the literature. By controlling for historical baseline climatic conditions in the meta-regression, we are able to estimate the relevance of the climatic starting point in assessing the effect of climate change. We are the first in the literature to provide a measure of how warmer and/or drier areas are affected differently by climate change compared to colder and/or wetter ones, while keeping all other variables constant. We estimate the effect of the main adaptation strategies such as cultivar, sowing date changes, irrigation, fertilizer, and the critical distinction between rainfed[5] and irrigated crop system. We offer a novel approach to use estimates from econometric analysis to obtain future impacts of climate change, in adherence to the principles of the benefit transfer approach, thus complementing previous process-based and statistical results[6]. Therefore, we can not only provide an estimate of the main variables affecting crop yields, but also offer a novel method for obtaining estimates of future impacts on a global scale.

[5] Rainfed agriculture is heavily dependent on precipitation as the only source of water for growing crops. In contrast, irrigated fields can cope with periods of water scarcity by pumping water.
[6] Our approach belongs to the family of statistical methods, but we use the final results of other studies as primary data, whereas traditional work uses observed field data to estimate the "data generating function".

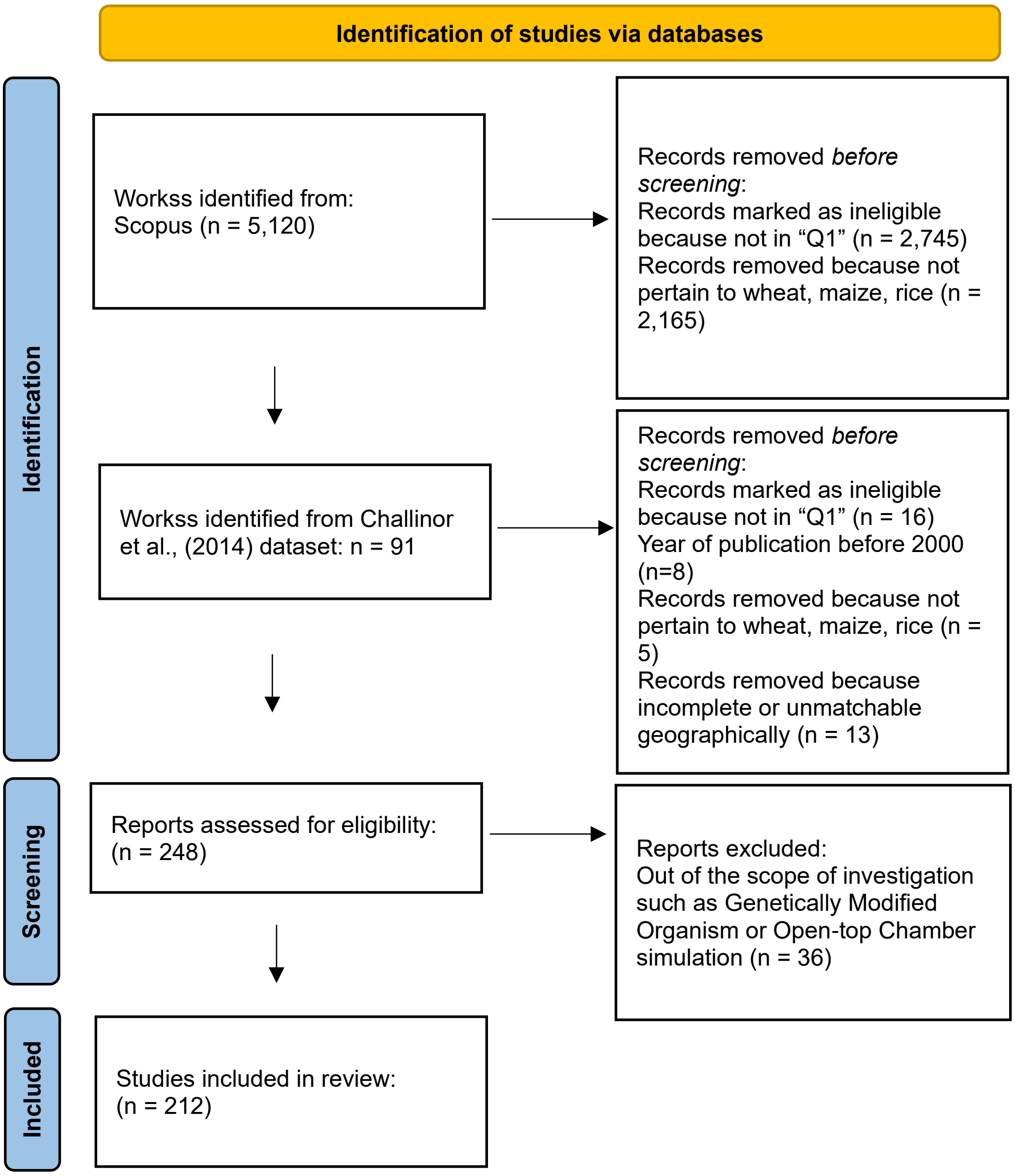
# Data

## Data collection

As a starting point, we use the freely available dataset from Challinor et al. (2014), which compiles studies up to 2012 and can be accessed at http://ag-impacts.org. We augment this dataset by conducting a systematic literature review from 2013 to 2020. The results of this review are presented in Figure 1, according to the PRISMA standards (Page et al., 2021). However, our data collection process introduces few novelties. We exclude all grey literature and consider an article eligible if the publishing journal has an impact factor that falls within the first quantile of the distribution for at least one of the related fields, according to the Scimago Journal Rank indicator (SJR, 2019; see full list of research fields in the Appendix). These preliminary quality filters ensure that all articles in the dataset have undergone a rigorous peer-review process. As a result, 474 journals meet the criteria for inclusion in our dataset (with a minimum SJR indicator of 0.583), ensuring that no relevant studies have been excluded from the review. This initial screening process does not introduce any bias, as works are not excluded based on their results, whether negative or positive[7]. We apply the same criteria to filter the studies provided by Challinor et al. (2014) to maintain consistency.

[7] Publication bias is defined as the failure to publish the results of a study because of the direction or strength of the findings (Stanley, 2005).

Figure 1 PRISMA flow diagram of the literature review.




The number of works found from 2013 to 2020 is considerably high: 163. We added these works to the 49 articles from the previous dataset achieving a total of 212 articles. This implies that in 2013-2020, we found more than three times the number of works collected in 2000-2012, confirming the exponential trend seen in recent literature (Aleixandre-Benavent et al., 2017; Appendix, Figure 4).

In the review, we consider all works that address the impact of climate change on crop yield. However, for the final regression analysis, we can only consider the original works that provide a comparable measure of climate change, such as differences in average temperature and precipitation. Studies that only provide a measure such as "growing degree days" are not included in the final dataset.

Crop type, area/region/country, climatic scenario, management practices combination and the relative percent yield change from the baseline are collected for each original study. However, some studies present their results and climatic scenarios using graphical representations such as histograms and plots, with the main findings discussed in the text. In these instances, we utilize the GetData Graph Digitizer (version 2.26.0.20) software to extract data directly from these graphical figures. This method has already been used in scientific publications to collect data (Barron et al., 2010; Zou et al., 2017), but it has never been employed in this field of research. It allows for more comprehensive observations and increases the number of studies included in the meta-regression analysis compared to traditional review methods that would have excluded studies based on incomplete reporting of information in the text.

This study employs a novel data collection process, the "double-check" process, which has not been previously used in the literature. After collecting the initial data, we ask each author to verify the accuracy of our observations based on their results. We also them to highlight any inaccuracy/make any necessary corrections to reduce any errors or misunderstanding that we may have made[8]. This also allows authors to provide additional data, thereby increasing the number of complete observations for the meta-regression analysis. Out of 212 articles, 37 authors (17.5%)[9] checked our observations, while 154 authors did not respond and 22 could not be reached due to e-mail address issues. 35 per cent of the authors suggested corrections, with the majority expressing concern about the inclusion of $CO_2$ in the simulations and whether the crop was irrigated or rainfed.

## Other data

To ensure consistency in the dataset we match each area, region, or country mentioned in the original articles with climate data (temperature and precipitation) obtained from WorldClim (Fick and Hijmans, 2017).

[8] Although this may seem a minor issue, the heterogeneous nature of the methods and models used in this area of research makes this work rather challenging. The likelihood of errors in data collection is therefore high, and this would reduce the accuracy of our estimates.

[9] The response rate would certainly be higher if one did not consider works published in the early 2000s. Some authors have retired, and others have deactivated their e-mail addresses.

This is necessary as some articles provide baseline data for the growing season[10], while others provide annual averages. The data is available at a 5-minute global spatial resolution (approximately 10km at the equator) and covers the period from 1970 to 2000. Since many of these areas are quite large, such as entire countries, we only extract baseline climatic conditions from the cropland areas used in each specific country in 2000, according to EARTHSTAT (Ramankutty et al., 2008). EARTHSTAT also provides a measure of cropland intensity for each georeferenced tile[11]. We also took advantage of the different intensity of cultivated land for each georeferenced tile by calculating a weighted average rather a simple mean, as a simple average would be incorrect. This implies that areas that are cultivated more intensively have a significant impact on determining baseline climatic variables[12]. From WorldClim data warehouse we also retrieve future climatic projections at the same global resolution by using an ensemble of 12 GCMs (see full list in Appendix), for the period from 2041 to 2060, and the SSP245 scenario. This choice is based on the fact that this scenario is considered the "middle road scenario," as it falls between the more sustainable but less probable SSP119 scenario and the worst-case SSP585 scenario.

To incorporate the effect of rainfed and irrigated cropland into our future projections, we rely on the Global Map of Irrigated Areas v5.0 (Siebert et al., 2013). This map provides data on the percentage of irrigated land compared to the total area, with a global spatial resolution of 5-min for the beginning of the century[13]. Additionally, we utilize the spatial data provided by GAEZ v4 Data (FAO and IIASA) to determine the extent of each crop at the global level in 2000, specifically focusing on the areas where maize, rice, or wheat were cultivated.

To calculate the aggregate impact at the global level, we use the 2000 FAO production estimates for the three crops under consideration. The source and flowchart of data used in this study are presented in Table 1 and Figure 2.

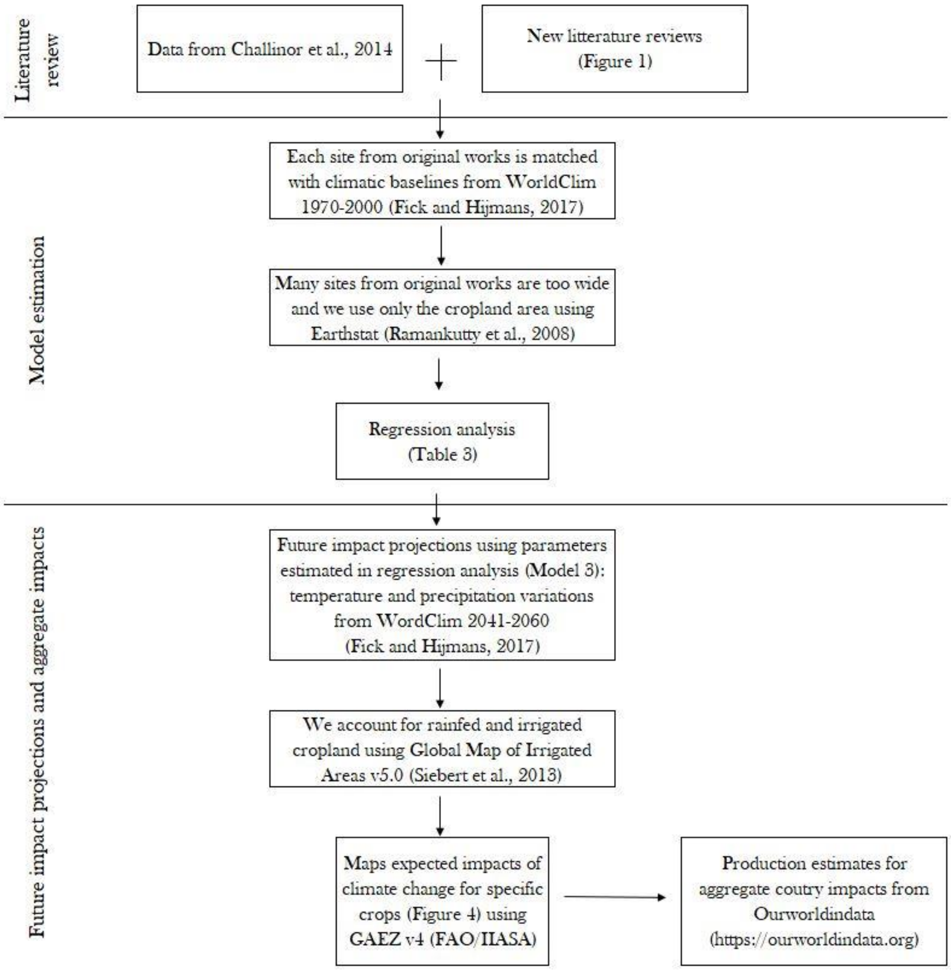
[10] Growing season is the part of the year where principal crops are grown. Then, growing season baselines are largely different from annual ones.
[11] "Tile" means the georeferenced pixel of raster layer.
[12] For example, when we look at a whole country like Algeria to calculate climate baselines, we exclude all the desert areas because there is no agriculture there. After excluding the desert areas, we only calculate baselines for cropland, and more intense cropland areas will have a greater impact on determining the climate baselines for the whole country.
[13] This data is the closest in time to the others, although it refers to 2005. However, we do not believe that there is a significant difference between the irrigated area in 2000 and 2005.

Table 1 Data source, description and use.

| Name | Description | Use | Reference |
|---|---|---|---|
| Challinor et al. (2014) dataset | Collection of works from 2000 to 2012 used in the previous global meta-analysis by Challinor et al. (2014) * | This dataset is used as starting point for our literature review filling the gap from 2013 to 2020. | Challinor et al., 2014 |
| WorldClim | Historical climatic values for temperature and precipitation (1970-2000) at 5-min of global resolution. | We match each site from original works with the climatic baselines. | Fick and Hijmans, 2017 |
| WorldClim | Future climatic values for temperature and precipitation (2041-2060) at 5-min of global resolution. | We use these projections for the expected climate change impacts. | Fick and Hijmans, 2017 |
| Earthstat | Cropland area in 2000 at 5-min of global resolution. | We extract the climatic baselines only for cropland areas. | Ramankutty et al., 2008 |
| Global map of irrigated areas v5.0 | Percentage of irrigated land within each tile at 5-min of global resolution. | We use this information for future climate change projections. | Siebert et al., 2015 |
| Gaez v4 | Spatial extent for each crop considered at 5-min of global resolution. | We use this data to determine the extent of each crop and make our projections. | FAO and IIASA |
| Ourworldindata | Crop production for each crop and each country. | We multiply the expected impact for the relevance of each country. | https://ourworldindata.org |

* Challinor et al. (2014) dataset includes pre-2000 works, but we discard it.

Figure 2 Flow chart of data used.




# Method

To evaluate the effect of climate change on crop yields, we use a weighted multiple linear regression model as follow:

$$\Delta Yield\ (\%) = \beta_0 + \beta_1 * \Delta T + \beta_2 * \Delta T * dummy\ (6 > T.base \leq 14) + \beta_3 * \Delta T * dummy\ (14 > T.base \leq 26) + \beta_4 * \Delta T * dummy\ (26 > T.base) + \sum \beta_d * dummy\ (T.base) + \beta_5 * P.base + \beta_6 * \Delta P + \beta_7 * CO_2 + \beta_8 * CO_2 * maize + \beta_9 * CO_2 * wheat + \beta_{10} * maize + \beta_{11} * wheat + \beta_{12} * rainfed + \beta_{13} * maize * rainfed + \beta_{14} * wheat * rainfed + \sum \beta_i * Adaptation_i + e$$

Where *"ΔYield"* is the dependent variable expressed as a percentage difference from the baseline yield, we use the interaction terms to capture the effect of a temperature increase in different climatic regions. The coefficient of the "*ΔT*" variable captures the effect of a temperature increase for regions with a baseline temperature below 6 °C. Conversely, for regions with baseline temperatures between 6-14 °C, 14-26 °C, and above 26 °C, the effect is captured by the coefficients of the interaction terms with their respective dummy variables[14]. The temperature baseline thresholds were chosen using a threshold regression model (Appendix, Table 7). "*P.base"* is the precipitation baseline *and "ΔP"* is the change in precipitation from local baseline (*Δrain* %). $CO_2$ is the dummy variable for the carbon dioxide effect, with its parameter indicating the effect on rice, which is the omitted crop reference category, which serves as the reference crop category. The parameters of the interaction terms "*$CO_2$*maize"* and "*$CO_2$*wheat"* present the effect of $CO_2$ on wheat and maize, respectively. The variables "*wheat* "and "*maize*" capture the effect of being maize or wheat in comparison to rice. Similarly, we also interact each crop variable with the "*rainfed"* dummy variable to separate the effect of rainfed production for each crop. "$\sum \beta_i$" are the adaptation strategies considered individually i.e., sowing date change, cultivar change, fertilizer, and irrigation, whereas we aggregate the poorly considered adaptation strategies into the residual category "*other adaptation*". Finally, "*e"* is the error component.

In meta-regression analyses, it is common practice to weight each observation according to the statistical significance of the estimate. This means that observations with higher statistical significance (e.g. lower p-value) have a greater impact within the meta-regression (Stanley and Jarrell, 2005; Egger et al., 2008). In this study, we use the SJR indicator of the publishing journal to assign weights to our observations. This is another novelty of our approach that sets it apart from other meta-analyses in the field. We give more weight to observations coming from influential journals in the regression analysis. Journals with a higher SJR indicator, which have more rigorous peer review processes, have a greater impact on our meta-regression results. To prevent studies with more observations from overly influencing the results, we calculate the specific weight of each observation by dividing the impact factor of the publishing journal by the number of observations used in the regression:

$$W_j = SJR_j \,/\, n° \, obs_k.$$

[14] We also include climate dummy variables, which are represented in the formula as "$\sum \beta_d$ * *dummy(T.base)" for brevity.*

Where $SJR_j$ is the impact factor of the journal $j$ that publish the assessment $k$, and "n° $obs_k$" is the number of observations used in the regression for study $k$. Additionally, we use clustered standard errors at the study level due to the possibility of correlated errors among observations from the same study.

We also estimate a model using the same econometric approach as Challinor et al., (2014), i.e. un-weighted regression with the same variable specification. However, we use the new dataset to make direct comparisons. The only difference between the two models is the specification of the $CO_2$ variable, which we consider as dummy, whereas they consider continuous (part per million, ppm). Our variable specification allows us to increase the number of complete observations used in the meta-regression, as many assessments do not report the ppm level but only whether $CO_2$ is included or not. Additionally, our specification helps us reduce the correlation between regressors, as higher $CO_2$ levels are strongly correlated with higher temperature increases.

Future projections are made using the benefit transfer approach. Benefit transfer is defined by Johnston et al. (2015) as the use of research findings from pre-existing primary studies in one or more sites or policy contexts to predict welfare estimates for other, typically unstudied, sites or policy contexts. Benefit transfers are commonly used when time, funding, data availability or other constraints prevent original research, requiring the use of pre-existing estimates instead (Johnston et al., 2015). Differently from the unit value transfer[15], we use the function transfers to obtain information using the estimated parametric function from the meta-regression. This approach enables us to predict the expected global average impact of climate change on every cultivated area on the planet between 2041 and 2060, considering the SSP245 scenario in a spatially explicit manner. In our future projections, we assume that the proportion of irrigated land, the extent of each crop, and all other variables will remain constant at reference levels except for temperature and precipitation.

[15] Unit value transfers involve the transfer of a single numerical value, or a specific set of values derived from pre-existing primary studies. These unit values may be transferred unchanged, or adjusted, such as taking into account variations in income or incorporating expert opinion into the adjustment process.

## Descriptive statistics

Table 2 summarizes the principal variables collected during the literature review process and used in this work. We performed a first quality control on outliers and removed any observations that exceeded the following thresholds: yield change ±70%, temperature 0-8 °C, precipitation ±100%. This is similar with the approach used in Challinor et al. (2014) as well. From 5,977 observations we delete 272 (~4.5%), obtaining a final dataset of 5,705 complete observations. Out of these 1,466 came from a previous dataset while 4,239 were added through the new literature review.

Table 2 Summary statistics of principal variables used in meta-regression.

| | Mean | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|
| Δ yield change (Δ%) | 1.5 | -70.0 | -8.6 | 11.6 | 70.0 |
| Δ temperature (Δ°C) | 2.5 | 0.0 | 1.4 | 3.3 | 8.0 |
| Δ precipitation (Δ%) | 4.6 | -58.0 | -0.7 | 8.9 | 88.0 |
| Temperature baseline (average/year 1970-2000 °C) | 16.4 | -1.2 | 10.8 | 23.4 | 29.3 |
| Precipitation baseline (average/year 1970-2000 mm) | 937.4 | 49.4 | 603.9 | 1'143.5 | 2'880.9 |
| $CO_2$ (1=yes; 0=no) | 81 % | | | | |
| Rainfed (1=yes; 0=no) | 45 % | | | | |
| Rice | 32 % | | | | |
| Maize | 33 % | | | | |
| Wheat | 35 % | | | | |
| Adaptation (1=yes; 0=no) | 38 % | | | | |
| Sowing date change | 19 % | | | | |
| Cultivar change | 14 % | | | | |
| Fertilizer | 8 % | | | | |
| Irrigation | 6 % | | | | |

Notes: n° articles=212; n° observations =5,705

The majority of yield variation, regardless of the crop type (maize, rice, or wheat) and management practice (adapted or not), falls within a relatively limited range (+/- 10%). Around 75% of the studies included in this work project the impact of climate change by simulating a temperature increase of less than 4 °C above the local baseline.

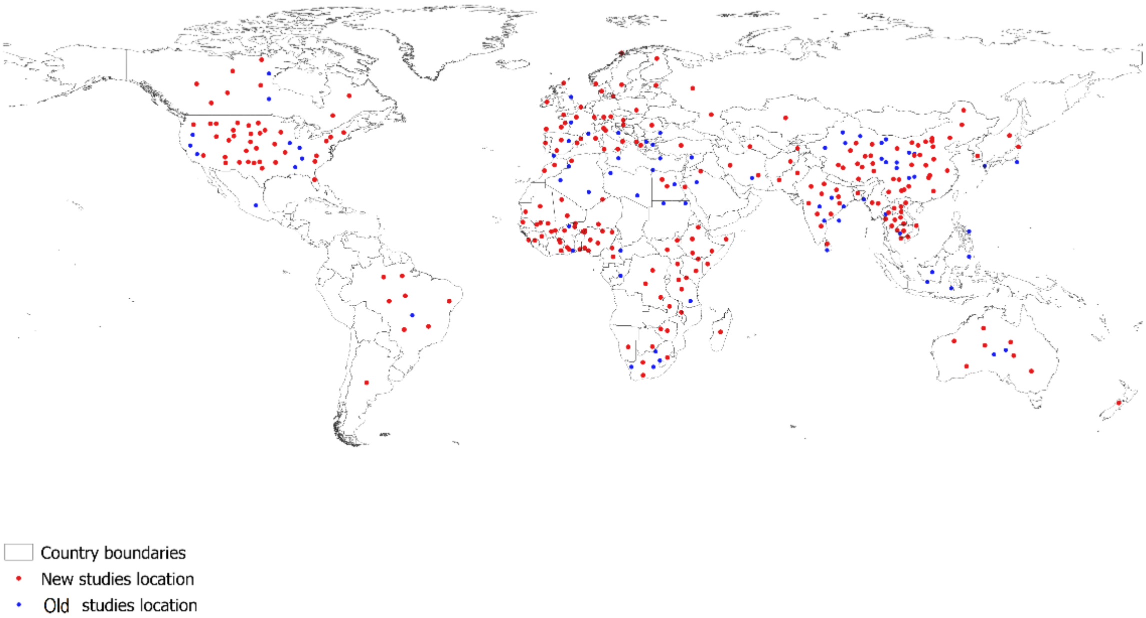
The variability of climatic baselines within our dataset, including temperature and precipitation, shows that our dataset accurately represents all cultivated areas of the globe. The average baseline temperature is 16 °C, with a difference of over 30 °C between the minimum and maximum values. Similarly, the average annual precipitation fluctuates around 900 mm, with minimum values below 50 mm and maximum values exceeding 2,800 mm/year.

More than 80% of the observations include the fertilising effect of $CO_2$. This suggests that the fertilizing effect of carbon dioxide is increasingly being considered when assessing the impact of climate change on agriculture, even though its actual contribution to plant growth is still considered uncertain (e.g., Challinor and Wheeler, 2008; and Asseng et al., 2013; Deryng et al., 2016).

Forty-five per cent of studies simulate the effects of climate change under rainfed conditions, with the three crops being well balanced within the dataset, accounting for approximately 33% each. Approximately 40% of the observations simulate adaptation strategies, with the change in sowing date extensively studied while irrigation is the least. This finding is intuitive, as changing the sowing date is one of the simplest and most cost-effective adaptation strategies for farmers (Lobell et al., 2008).

Figure 3 illustrates the geographical distribution of the original studies used in this work. Our literature review has increased the number of original studies in most cultivated countries as indicated by the red dots. It is therefore possible to accurately represent almost all cultivated global croplands, especially in Africa and Asia. This is further supported by the range of temperature and precipitation variability shown in Table 2. It should be noted that South and Central America are still slightly underrepresented.

Figure 3 Geographical distribution of original works.




Our dataset contains 3,013 observations (53%) for the Asian continent, and the three crops are well represented for this continent, with wheat at 40%, maize at 19% and rice at 41%. The Americas account for 11% of the dataset (n=650) and Africa represents 25% (n=1,440). Maize is the most studied crop in both continents, with 62%. Europe has 323 observations (12%), with a focus on wheat (42%) and maize (54%). Oceania is the least represented continent, with 279 observations, and almost all of them are related to wheat (99%), with only 1% for maize. These percentages are in line with the FAO production estimates for these continents (FAO, 2020).

## Results

Table 3 presents the main results of the meta-regression analysis. Model 1 is the original regression result from Challinor et al. (2014), while Model 2 is our replication using the new dataset; Model 3 is our primary model[16].

[16] We also estimate the Model 2 and Model 3 using the full dataset of 5,977 observations (with outliers) and we found no differences in the magnitude and sign of the main variables, but rather an overall decrease in all goodness-of-fit measures, such as adjusted R-squared and residual standard errors (Appendix, Model 4 and Model 5 in Table 3).

Table 3 Meta-regression model estimates.

| | *Challinor et al. (2014) original* (1) | *Challinor et al. (2014) replicate* (2) | *Our model* (3) |
|---|---|---|---|
| Temperature | -4.90*** | -2.548*** | 3.941** |
| | (1.25) | (0.831) | (1.870) |
| Temperature * dummy (6>Temp. Bas<=14) | | | -6.132*** |
| | | | (2.067) |
| Temperature * dummy (14>Temp. Base<=26) | | | -8.118*** |
| | | | (2.207) |
| Temperature * dummy (26>Temp. Base) | | | -12.773*** |
| | | | (2.617) |
| Precipitation | 0.53** | 0.349*** | 0.162** |
| | (0.18) | (0.055) | (0.066) |
| Prec. base | | | 0.003* |
| | | | (0.002) |
| $CO_2$ | 0.06** | 10.548*** | 3.951* |
| | (0.02) | (2.351) | (2.270) |
| $CO_2$ * Maize | | | 9.590** |
| | | | (4.024) |
| $CO_2$ * Wheat | | | 15.199** |
| | | | (7.066) |
| Maize | | | -10.573*** |
| | | | (3.727) |
| Wheat | | | -12.828** |
| | | | (6.537) |
| Rainfed | | | -10.380*** |
| | | | (3.542) |
| Rainfed * Maize | | | 9.076** |
| | | | (4.502) |
| Rainfed * Wheat | | | 6.032 |
| | | | (5.735) |
| Sowing date change | | | -0.109 |
| | | | (6.636) |
| Cultivar change | | | 6.017* |
| | | | (3.521) |
| Fertilizer | | | 2.419 |
| | | | (3.701) |
| Irrigation | | | 13.508** |
| | | | (6.122) |
| Other adaptation | | | 11.450** |
| | | | (5.362) |
| Tropical (1=yes; 0=no) | -2.83 | -2.99 | |
| | (3.89) | (3.176) | |
| Adaptation | 7.16* | 6.439*** | |
| | (3.11) | (2.475) | |
| M=$C_3$=0; $C_4$=1 | -0.003 | -3.402 | |
| | (3.04) | (2.792) | |
| dummy (6>Temp. Bas<=14) | | | 4.259 |
| | | | (6.815) |
| dummy (14>Temp. Base<=26) | | | 5.484 |
| | | | (7.201) |
| dummy (26>Temp. Base) | | | 13.394 |
| | | | (9.031) |
| Constant | -5.40 | -2.274 | -5.266* |
| | (6.78) | (2.658) | (6.956) |
| Observations | 882 | 5’705 | 5’705 |
| $R^2$ | | 0.165 | 0.277 |
| Adjusted $R^2$ | | 0.165 | 0.274 |
| Residual Std. Error | | 18.268 (df = 5698) | 3.566 (df = 5682) |
| F Statistic | | 188.280*** (df = 6; 5698) | 98.76*** (df = 22; 5682) |

Notes: Model 1 and Model 2 are the Challinor et al. original and the replicate models, respectively; the goodness-of-fit measures in the case of Challinor et al. original are not available and the estimates are rounded at 2 decimal number. Standard errors in parenthesis.

Model 3 significantly improves the fit of the data compared to the previous econometric approach, and also provides new insights into the role of climatic baselines and adaptation strategies in shaping the impact of climate change on crop yields. An increase in temperature relative to the baseline has a positive effect if the average baseline temperature is low (Temp. base < 6 °C), while it has a negative effect in areas where the average baseline temperature is higher. Specifically, a marginal temperature increase (+1 °C) relative to the baseline raises the yield, on average, by 4% if the baseline temperature is below 6 °C. However, if the temperature baseline is between 6-14 °C, a marginal increase in temperature reduces the yield by -2.2%. The effect is amplified when the baseline temperature is between 14-26 °C (-4.18%) and beyond 26 °C (-8.83%). Total annual precipitation is critical in determining the final impact on yields, meaning that countries with higher baseline precipitations are more resilient to climate change. Specifically, for every mm of additional annual precipitation, yields are 0.003% higher. Precipitation variation has a positive and statistically significant effect on crop yields. This means that a +1% increase in precipitation respect to the baseline will, on average, result in a 0.16% increase crop yield. However, the magnitude of the precipitation coefficient suggests that it has limited ability to counteract the impact of a marginal temperature increase. For example, if the local temperature baseline is above 26 °C, a +1 °C increase in local temperature would be offset by an increase in precipitation of more than +55%. Without the effect of $CO_2$, maize and wheat will experience greater negative impacts compared to rice. However, rice will benefit less from an increase in carbon dioxide levels. The effect of $CO_2$ on rice is statistically significant but smaller (+3.95%) compared to maize and wheat, as their interaction coefficients are statistically significant and positive, at +13.54% and +19.15% respectively. Being a rainfed crop, i.e. without using irrigation systems, has a significant and negative effect, with rice suffering more than maize and wheat, although the parameter of the latter is not statistically significant. The adaptation strategies considered individually have a positive effect on contrasting climate change. However, only few of them are statistically significant. Specifically, cultivar change increases yield by an average of almost 6%, whereas irrigation increases yield by an average of 13.5%. On the other hand, varying fertilizing strategy and sowing date seems to be less effective. The "other adaptation" strategy has a positive and statistically significant effect, although it should be interpreted with caution as it combines the effects of multiple adaptation strategies. We confirm the results of our main model by testing an alternative non-parametric specification (Appendix, Table 4). The sign and magnitude of the main variables are consistent with those presented in Table 3.

We also estimate our main model using the climatic baseline extracted from the original articles (Appendix, Model 7 in Table 5). The number of observations is dramatically reduced (2,623) as only few works provide them, but we still confirm the overall effect of the main variables. This indicates that using globally consistent data, such as the data from WorldClim in our case, accurately replicates the effect of using specific baselines extracted from the original articles.

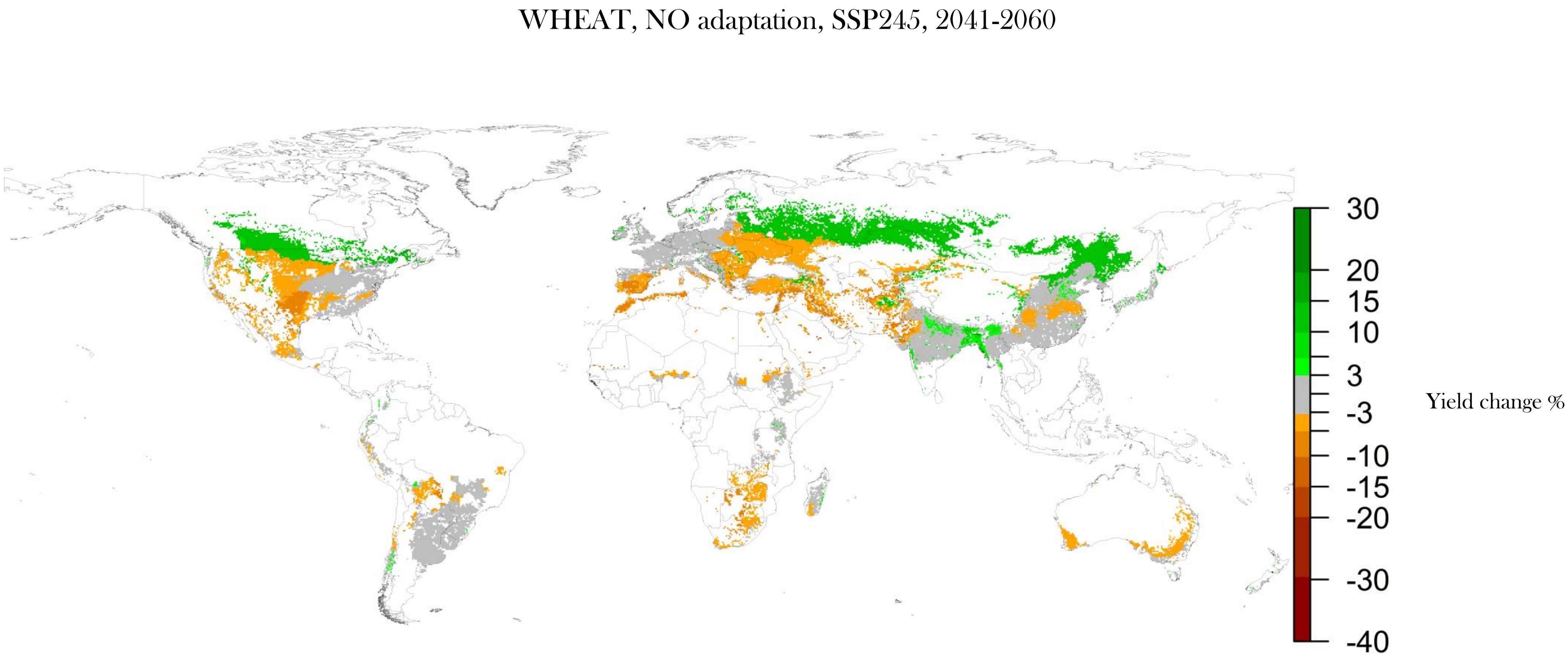
We applied the same econometric approach as in Challinor et al. (2014) to estimate a model using our updated dataset. This allowed us to directly compare the new results with the previous ones. When comparing our new model estimates (Table 3, Model 2) with the previous results (Table 3, Model 1), we observed a significant reduction in the impact of temperature and precipitation variation on yield. However, we also found that the effectiveness of adaptation strategies in mitigating the impacts of climate change, reducing them by about 7%, was broadly consistent with the previous results. Similarly, we observed no statistical significance for either the "*Tropical*" dummy variable or crop type ($C_3$ or $C_4$). Although their sign and magnitude are similar, the effect of $CO_2$ is positive for both but not directly comparable. It is important to note that our model shows the extent to which climate change differently affects countries with higher temperatures and/or lower precipitation baselines, which is not captured by the econometric approach used in Challinor et al. (2014).

The use of "*Tropical*" dummy variable is likely to reduce the accuracy of the estimates. This is because some countries have a wide latitudinal range, with some parts considered tropical, while others may be subtropical or even temperate such as Brazil, Australia and India. Moreover, the simple definition of temperate and tropical countries does not help us to understand the role of precipitation baseline due to the fact that within the same climate definition, countries with high precipitation can coexist with very dry ones. The role of adaptation strategies is also reversed. According to our model estimates, only few adaptation strategies are statistically significant in mitigating the expected impacts of climate change. Finally, the use of specific dummy variables for different crops (wheat, maize and rice) allows us to understand that crops with the same photosynthetic system (C3 or C4) respond differently to the same climatic changes.

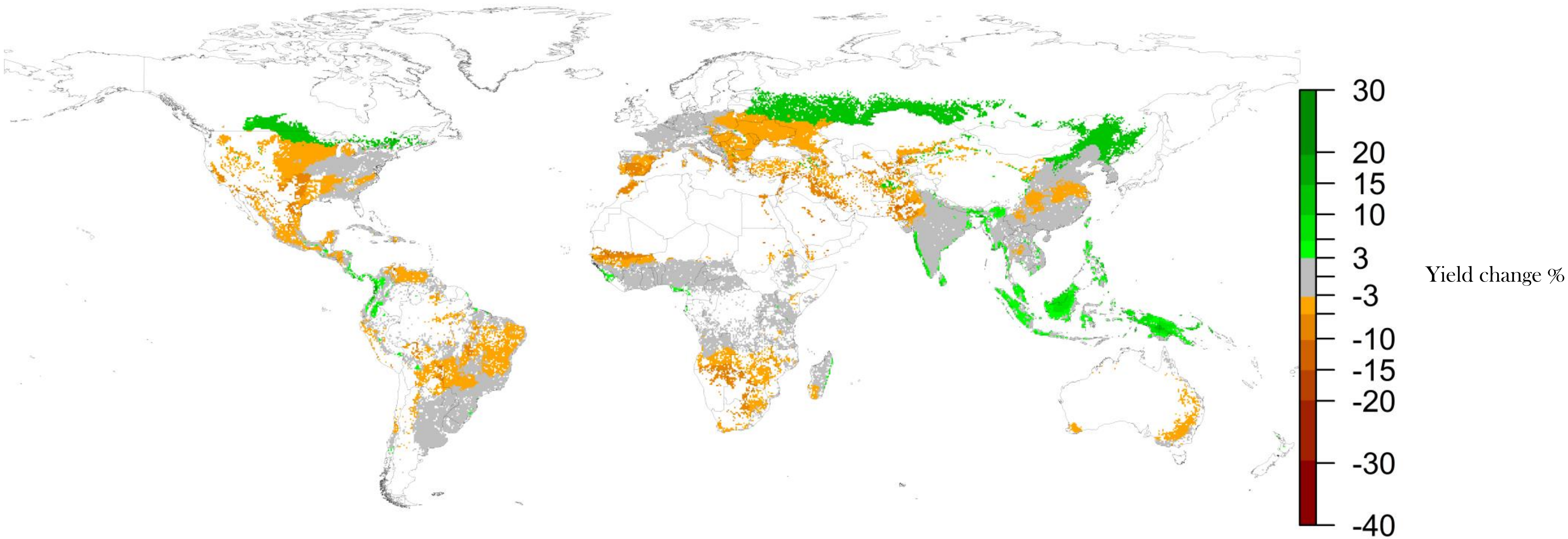
## Future impact projections

Figure 4 shows the expected impacts of climate change without adaptation on wheat, maize and rice between 2041 and 2060 without adaptation. These estimates were derived from Model 3 using the SSP245 scenario. Projections should not be interpreted as the true expected impact of climate change on agriculture, but rather as the average impact on these crops resulting from changes in temperature and precipitation compared to baselines, while keeping all other variables constant.

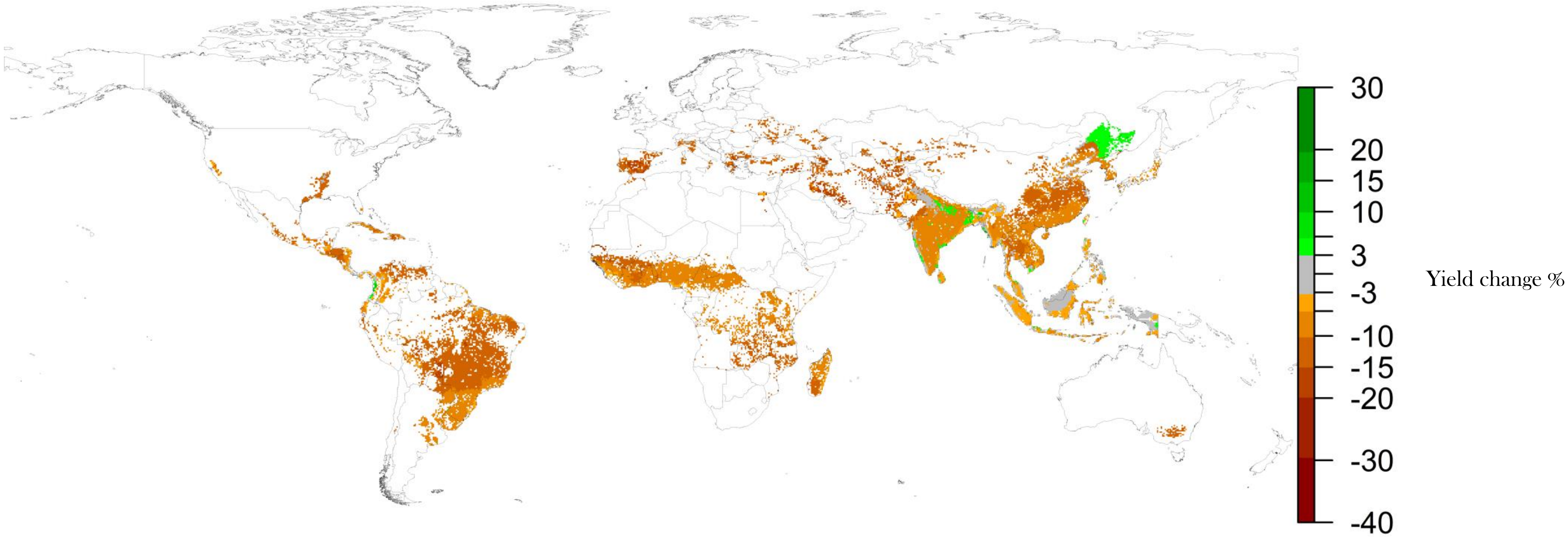
Figure 4 Expected climate change impacts for wheat (top map), maize (middle map) and rice (bottom map) in 2041-2060 for SSP245. Notes: white areas mean that this specific crop is not present or there is no agriculture at all.



MAIZE, NO adaptation, SSP245, 2041-2060



RICE, NO adaptation, SSP245, 2041-2060



The aggregate expected impacts on global yield reduction are quite modest at 1.2% for maize, -0.003% for wheat, and -5.8% for rice. However, they hide a great variability among countries (Appendix, Table 4).

The upper projection in Figure 4 shows that wheat is a widely cultivated crop and it is expected to experience increased yields in countries with cooler climates. These countries include the northern U.S. and Canada (+4.6%), the Scandinavian countries (Norway +2%, Sweden +1.22% and Finland +4.65%), large portions of Russia (+5.2%), northern China (with an estimated +2% increase nationwide), and Japan (+2.13%). Additionally, Northern India and certain areas in South-East Asia may also experience positive impacts in the future. Negative impacts are expected in several cultivated areas around the world, including the central U.S. (U.S. -1.7%), some areas in Latin America (e.g. Bolivia -3.2%), most Mediterranean countries (Spain -3.7%, France -1.3% and Italy -2%), the central parts of the Asian continent (Ukraine -3.4% and Turkey -2.9%) as well as eastern China and all of Australia (-1.8%). Sub-Saharan and southern Africa countries may also see negative results (e.g. South Africa -3.9%), while some central African countries, such as the Democratic Republic of Congo and Ethiopia and Madagascar, may experience a negligible impact at -0.5% and -0.8%, respectively. The rest of the European continent is likely to remain largely unaffected.

Similarly to wheat, maize is grown in all cultivated areas of the planet, even more extensively than wheat. At the aggregate level, production is expected to decline by about 1.2%, compared to the beginning of the twentieth century. The spatial patterns are similar to those for wheat, with the most pronounced differences in Africa and South-East Asia, where the crop is very widespread. On the African continent, most countries in the West and South will be severely affected by climate change. Projections show that Mauritania will experience a -8.2% decrease, Mali a -5.4% decrease, Senegal a -5% decrease, Botswana and Namibia a -4.9% decrease and South Africa a -4% decrease. Maize yields in Brazil may also be negatively affected by more than 2%. On the other hand, positive effects on maize yields are expected in Scandinavian countries (Finland +13%), the Russian Federation (+7%) and Canada (+6.7%). Other Southeast Asian countries are also expected to see an increase in maize yields (Malaysia and Bangladesh +5%, Indonesia +4%, Sri Lanka +3.7% and the Philippines +3%).

Rice is the least widespread of the three crops and is primarily grown in tropical areas, where the impact of climate change will be more severe. Our model also indicates that rice is less sensitive to $CO_2$. Rice yields will be severely affected in Mediterranean countries (Spain -12.9%, Portugal -6% and Italy -7.6%), the Sahel (Mauritania -13.4%, Senegal -10.4% and Gambia -9.8%), much of Central and Latina America (Mexico -9.8%, Honduras and Dominican Republic -9%, Venezuela -11.5%, Bolivia and Paraguay -10.2%) and western India. However, some parts of cooler and/or wetter countries such as China, Japan and South Asia may experience negligible impacts.

The spatial patterns and main findings of this study are consistent with previous assessments, although direct comparisons are not possible. For example, Asseng et al. (2015) found that the marginal effect of an average temperature increase on wheat yields is -6% in areas where the average growing season temperature falls between 15 °C and 32 °C using crop models simulations. Within this temperature range, we also observed yield decreasing ranging from -4 to -8%. However, Asseng et al. provide a less comprehensive of the coldest areas and do not consider precipitation variation when making general predictions for the global predictions, leading to a more severe global impact estimate compared to ours. The time scale and scenario used by Rosenzweig et al. (2014) differ from those used in the present study. Nevertheless, their study, like ours, highlights the importance of considering the effect of $CO_2$ to better understand the predicted impacts, and shows positive results for wheat in colder northern regions. Other studies, such as Wing et al. (2021), have also found a global negative impact on major staple food crops, including wheat, maize and rice ranging from 3-12% by mid-century. Another study by Blanc and Sultan (2015) shows similar spatial patterns, although their results are not directly comparable to ours due to the use of different future scenarios (RCP 8.5) and timescales (2090-2100). However, our aggregate impacts show a less negative picture than the latter study, as we place more emphasis on the influence on cooler areas in the north, which partially compensates for the reductions in yields at lower latitudes.

When making future projections we do not consider the effect of adaptations, as there may be limitations in their adoption in the future. For example, irrigation does not consider future water availability, which could be significantly affected by climate change (Rosenzweig et al., 2004; Elliott et al., 2014). On the other hand, advances in crop development, such as genetically modified organisms (GMOs) and new breeding techniques (NBTs), offer good potential for mitigating the effects of climate change. However, their adoption may be impeded by social and economic issues (Nelson, 2001; Ceccarelli et al., 2010; Oliver, 2014; Zilberman et al., 2018; Qaim, 2020).

We kept the extent and intensity of cropland areas constant in 2000. However, it is likely that some production areas, particularly in the north, will expand to take advantage of the new favourable conditions created by climate change, while most of the negatively affected areas will be converted to other crops or agricultural activities (Zabel et al., 2014; Di Paola et al., 2018). This could potentially have a positive overall impact by offsetting some of the expected losses in the most affected areas. However, it is possible that other environmental issues may arise, such as changes in land use dynamics, which could further exacerbate the effects of climate change (Fezzi et al., 2015).

## Conclusions

Climate change is exerting significant pressure on the agricultural sector, threatening its ability to sustain life and human well-being on our planet. In this study, we summarize the relevant literature and, by explicitly controlling for climatic baselines, we demonstrated that countries with drier and warmer climates are less resilient to climate change than those with cooler temperatures and higher precipitations. A marginal increase in temperature has opposite effects depending on the underlying climate, with colder cropping areas more likely to benefit from climate change compared to warmer regions. In addition, the marginal effect of temperature variation on crop yield increases as the country's climate becomes warmer. Although adaptation measures, such as irrigation and cultivar change, have a significantly positive impact, it is necessary to consider their future availability, as socio-economic and environmental constraints may limit their adoption.

According to our projections, developing countries, which are mainly located in tropical and subtropical regions, could experience further deterioration in the future, leading to a widening gap between them and more developed countries in the northern hemisphere. However, if adaptation measures are not considered, our projections using the SSP245 scenario indicate a global yield decline of -1.2% for maize and -5.8% for rice between 2041 and 2060. Wheat yield, on the other hand, is expected to be relatively unaffected. These results are significantly influenced by the positive effects of $CO_2$, which, in many cases, could potentially reverse the anticipated impacts.

It is important to note that these results may be influenced by systematic gaps in the literature. The original works may not adequately consider pests and diseases, and may underrepresent extreme weather events, resulting in a less severe picture of the phenomenon than what will actually occur (Gregory et al., 2009; Garrett et al., 2013; Cogato et al., 2019). In addition, although beyond the scope of the present work, year-to-year weather variability may further exacerbate the economic sustainability of the agricultural sector by increasing fluctuation in crop yield and challenging the usefulness of adaptation strategies (Kotir, 2011; Thornton et al., 2014).

Finally, this work highlights a gap in the literature that warrants further attention in the future. To enhance the precision of upcoming assessments, it would be crucial to establish a standardized approach for reporting results in this field of research. This will accelerate data collection minimizing the potential for misunderstandings, ultimately improving the accuracy of estimates.

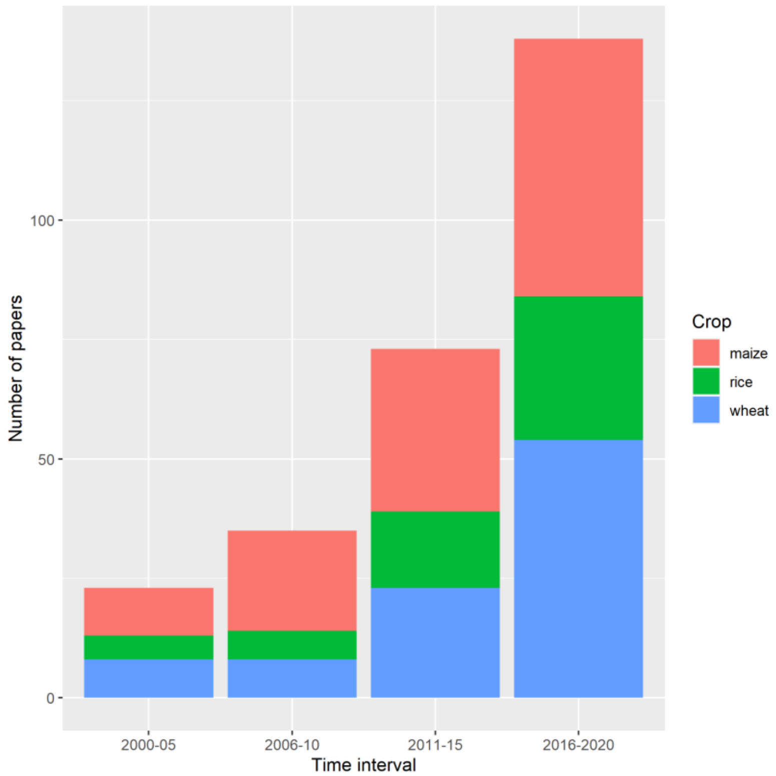
## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the result reported in this work.

## Appendix

List of research categories considered in the literature review: “global and planetary change”, “forestry”, “agronomy and crop science”, “atmospheric science”, “environmental science”, “renewable energy, sustainability and the environment”, “ecology”, “agricultural and biological sciences”, “soil science, environmental chemistry”, “environmental engineering”, “pollution”, “plant science”, “environmental science (miscellaneous)”, “social sciences”. This list has been selected using very broad criteria, which in some cases may be beyond the scope of our review. This allows us to include as potential journals those that deal only marginally with these arguments and ensures that no work estimating the impact of climate change on agriculture is omitted, even by error. As a result, the list of potential eligible journals is huge: 474.

Figure 5 Number of works by 5-year time intervals and crop type.




List of 12 General Circulation Models (GCMs) used in future climate projections: hadgem3-gc31-ll, cmcc-esm2, giss-e2-1-h, miroc6, access-cm2, canesm5, ec-earth3-veg, fio-esm-2-0, mpi-esm1-2-hr, inm-cm4-8, mri-esm2-0, ukesm1-0-ll.

We use a non-parametric model to confirm the main results of Model 3 (Table 3). This procedure is intended to demonstrate that the sign and magnitude of the main variables found and commented in the main text remain consistent across different model specifications. We use the R package "mgcv" (Wood, 2017) for generalised additive mixed model (GAMM) with a Gaussian link function. The crop yield change is modelled as a smooth function of temperature, precipitation and baseline climatic values with five knots (k=5) for each continuous term. In addition, the model includes fixed effects similar to Model 3. The effects of carbon dioxide are positive for all crops and statistically significant. The effect of specific crop is similar for rice and wheat, while maize is not statistically significant. Rainfed is negative but not statistically significant for either crop, while the positive effect of adaptation strategies is confirmed. The plots below Table 4 show the effect of continuous variables. All parameters are statistically significant, but temperature increase is negative and linear and not as intuitive as our main model. Some non-linear effects are found in the case of precipitation variation, mainly positive. Precipitation baseline estimate confirms that wetter countries will experience less harm from the effects of climate change, although its effect is limited. Conversely, countries with higher baseline temperatures will be negatively affected. These results confirm the main effect and magnitude of the variables investigated although their interpretation is not as straightforward as those presented in the main analysis.

Table 4 Non-parametric model estimates.

*Family: gaussian*
*Link function: identity*

| | |
|---|---|
| $CO_2$ | 9.440*** |
| | 1.768 |
| $CO_2$ * Maize | -4.427** |
| | (1.515) |
| $CO_2$ * Wheat | 13.297*** |
| | (1.626) |
| Maize | 1.780 |
| | (1.314) |
| Wheat | -10.078*** |
| | (1.361) |
| Rainfed | -0.226 |
| | (1.964) |
| Rainfed * Maize | -0.013 |
| | (2.177) |
| Rainfed * Wheat | -4.801* |
| | (2.278) |
| Sowing date change | 5.532*** |
| | (0.829) |
| Cultivar change | 11.778*** |
| | (0.972) |
| Fertilizer | 4.743*** |
| | (1.240) |
| Irrigation | 4.562*** |
| | (1.473) |
| Other adaptation | 8.806*** |

| | |
|---|---|
| | (1.277) |
| Constant | -10.818*** |
| | (1.768) |
| | edf |
| s (Temperature) | 1.000*** |
| s (Precipitation) | 3.857*** |
| s (Temp. base) | 2.932*** |
| s (Prec. base) | 1.799* |
| Observations | 5'705 |
| Adjusted $R^2$ | 0.134 |

Notes: signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

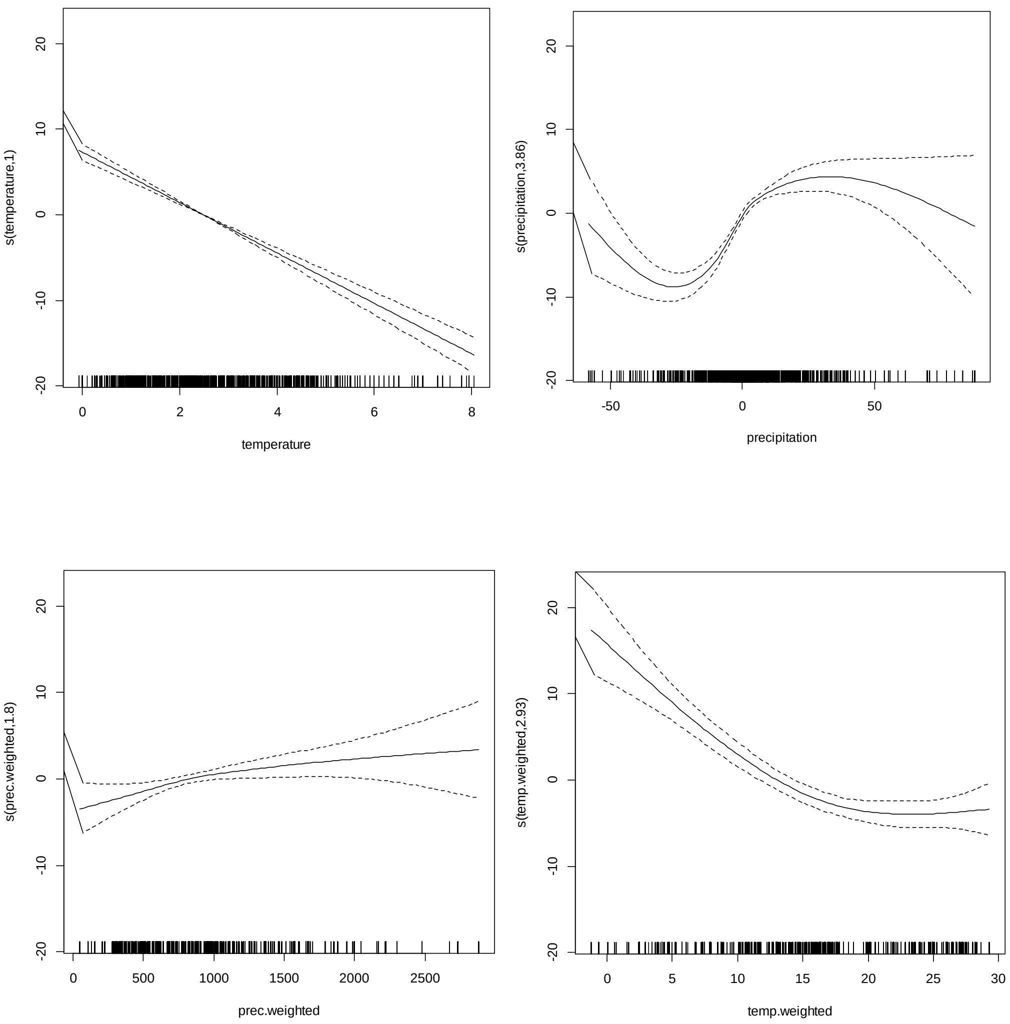



Table 5 Regression models estimated with different datasets.

| | *Challinor et al. (2014) Replicate, full dataset* | *Our model, full dataset* | *Our model, un-checked obs.* | *Our model, precipitation baseline from works* |
|---|---|---|---|---|

| | (4) | (5) | (6) | (7) |
|---|---|---|---|---|
| Temperature | -1.750$^{***}$ | 8.625$^{**}$ | 3.436$^{*}$ | 2.145 |
| | (0.591) | (3.681) | (1.932) | (1.643) |
| Temperature * dummy (6>Temp. Base>14) | | -10.536$^{***}$ | -5.930$^{***}$ | -3.738$^{*}$ |
| | | (3.675) | (2.081) | (1.976) |
| Temperature * dummy (14>Temp. Base>26) | | -11.566$^{***}$ | -7.630$^{***}$ | -4.048$^{**}$ |
| | | (3.916) | (2.258) | (1.838) |
| Temperature * dummy (26>Temp. Base) | | -18.324$^{***}$ | -12.627$^{***}$ | -11.350$^{***}$ |
| | | (4.155) | (2.689) | (3.105) |
| Precipitation | 0.192$^{***}$ | 0.152$^{***}$ | 0.149$^{**}$ | 0.106$^{*}$ |
| | (0.050) | (0.052) | (0.065) | (0.057) |
| Prec. base | | 0.004$^{**}$ | 0.003 | |
| | | (0.002) | (0.002) | |
| Prec. base from works | | | | 0.005 |
| | | | | (0.003) |
| Maize | | -10.157$^{***}$ | -8.601$^{**}$ | -17.877$^{***}$ |
| | | (3.710) | (3.548) | (6.637) |
| CO2 * Maize | | 10.303$^{**}$ | 7.662$^{*}$ | 15.604$^{**}$ |
| | | (4.214) | (4.039) | (6.247) |
| Rainfed * Maize | | 6.654 | 8.655$^{*}$ | 15.760$^{***}$ |
| | | (4.922) | (5.146) | (5.628) |
| Wheat | | -13.749$^{**}$ | -13.269$^{**}$ | -4.700 |
| | | (6.698) | (6.386) | (4.445) |
| $CO_2$ * Wheat | | 14.303$^{*}$ | 14.764$^{**}$ | 6.218 |
| | | (7.717) | (6.515) | (5.590) |
| Rainfed * Wheat | | 4.761 | 7.505 | 4.173 |
| | | (5.936) | (5.546) | (6.126) |
| $CO_2$ | 10.737$^{***}$ | 4.202$^{*}$ | 5.071$^{**}$ | 3.966 |
| | (2.545) | (2.467) | (2.285) | (3.958) |
| Rainfed | | -6.446$^{*}$ | -10.702$^{***}$ | -11.482$^{***}$ |
| | | (3.748) | (4.087) | (4.131) |
| Sowing date change | | -1.221 | 0.004 | -7.314$^{*}$ |
| | | (2.855) | (2.678) | (4.355) |
| Cultivar change | | 6.605$^{*}$ | 4.903 | 12.765$^{***}$ |
| | | (3.574) | (3.692) | (4.067) |
| Fertilizer | | 3.092 | 2.735 | -0.105 |
| | | (4.138) | (3.958) | (4.789) |
| Irrigation | | 19.758$^{**}$ | 6.777 | 20.429$^{***}$ |
| | | (8.687) | (4.597) | (4.126) |
| Other adaptation | | 10.733$^{*}$ | 11.227$^{**}$ | 16.621$^{**}$ |
| | | (5.548) | (5.354) | (7.496) |
| dummy (6>Temp. Base>14) | | 12.508 | 4.658 | -6.573 |
| | | (9.218) | (6.823) | (6.275) |
| dummy (14>Temp. Base>26) | | 11.462 | 5.303 | -11.110$^{*}$ |
| | | (9.800) | (7.270) | (5.839) |
| dummy (26>Temp. Base) | | 21.380$^{*}$ | 14.216 | 1.821 |
| | | (11.369) | (9.249) | (9.653) |
| Tropical (1=yes; 0=no) | -3.504 | | | |
| | (3.704) | | | |

| | | | | |
|---|---|---|---|---|
| Adaptation | 6.870** | | | |
| | (2.746) | | | |
| M: $C_3$=0; $C_4$=1 | -3.948 | | | |
| | (3.329) | | | |
| Constant | -3.085 | -14.933 | -5.557 | 6.987 |
| | (2.910) | (9.585) | (7.126) | (5.046) |
| Observations | 5'977 | 5'977 | 5'670 | 2'623 |
| $R^2$ | 0.126 | 0.276 | 0.263 | 0.367 |
| Adjusted $R^2$ | 0.125 | 0.273 | 0.260 | 0.362 |
| Residual Std. Error | 22.289 (df = 5970) | 3.856 (df = 5954) | 3.603 (df = 5647) | 3.669 (df = 2600) |
| F Statistic | 142.920*** (df = 6; 5970) | 103.045*** (df = 22; 5954) | 91.437*** (df = 22; 5647) | 68.532*** (df = 22; 2600) |

Notes: "*Full dataset*" means a dataset with outliers. "U*n-checked observations*" means observations that are not checked with the double-check process. "P*recipitation baseline from works*" means the dataset with complete information on climatic baselines provided by the original articles.

Table 6 Expected percentage impacts by country for maize, wheat and rice in 2041-2060, according to scenario SSP245.

| Country | Maize | Wheat | Rice |
|---|---|---|---|
| Afghanistan | -2.20 | -1.23 | -9.95 |
| Albania | -2.57 | -1.84 | |
| Algeria | | -2.45 | |
| Angola | -2.91 | -6.48 | -8.47 |
| Antigua And Barbuda | 0.00 | | |
| Argentina | -1.04 | -0.71 | -8.41 |
| Armenia | 0.49 | 2.94 | |
| Arunachal P. | 3.11 | 3.42 | -4.98 |
| Australia | -1.37 | -1.84 | -9.78 |
| Austria | -1.58 | -0.81 | |
| Azerbaijan | -5.86 | -5.07 | -12.88 |
| Bahamas | 0.00 | | |
| Bangladesh | 5.09 | 5.62 | -0.21 |
| Barbados | 0.00 | | |
| Belarus | 2.46 | 2.76 | |
| Belgium | -1.06 | -0.76 | |
| Belize | -0.68 | | -7.58 |
| Benin | -1.35 | | -9.00 |
| Bhutan | 2.32 | 2.79 | -5.13 |
| Bolivia | -3.37 | -3.21 | -10.19 |
| Bosnia And Herzegovina | -2.14 | -1.40 | |
| Botswana | -4.86 | -4.72 | |
| Brazil | -2.24 | -1.15 | -9.02 |
| Brunei | 7.82 | | -0.51 |
| Bulgaria | -3.53 | -3.08 | -12.06 |
| Burkina Faso | -2.91 | -3.03 | -9.70 |
| Burundi | -1.21 | -0.89 | -8.71 |
| Cambodia | -0.20 | | -7.97 |
| Cameroon | 0.21 | | -4.01 |
| Canada | 6.76 | 4.64 | |
| Cape Verde | 0.00 | | |
| Central Africa | -0.07 | | -6.24 |
| Chad | -0.83 | | -7.55 |
| Chile | -1.26 | -0.21 | -6.39 |
| China | 1.35 | 2.11 | -6.86 |
| Colombia | 1.90 | 1.24 | -5.29 |
| Comoros | 0.00 | | 0.00 |
| Congo | 0.12 | | -1.03 |
| Costa Rica | 3.10 | | -3.10 |
| Cote D'ivoire | -1.18 | | -8.57 |
| Croatia | -1.96 | -1.68 | |
| Cuba | -1.22 | | -7.81 |
| Cyprus | | -3.75 | |
| Czechia | -2.60 | -1.92 | |
| D.R. Congo | -0.45 | -0.52 | -3.91 |
| Denmark | -0.84 | -0.67 | |
| Dominica | 0.00 | | |
| Dominican Republic | -2.19 | | -9.03 |
| Ecuador | 1.57 | -0.52 | -6.79 |
| Egypt | -4.91 | -3.39 | -6.32 |
| El Salvador | -1.41 | | -8.58 |
| Eritrea | -3.24 | -2.96 | |
| Estonia | | 8.34 | |
| Ethiopia | -0.89 | -0.48 | |
| Fiji | | | 0.00 |
| Finland | 13.45 | 4.64 | |
| France | -1.53 | -1.17 | |
| French Guiana | | | -3.43 |

| | | | |
|---|---|---|---|
| Gabon | 0.31 | | -1.78 |
| Gambia | -3.70 | | -9.84 |
| Gaza Strip | | -3.47 | |
| Georgia | -1.71 | 0.50 | -12.14 |
| Germany | -1.69 | -1.34 | |
| Ghana | -1.22 | | -8.65 |
| Greece | -3.50 | -3.09 | -9.34 |
| Grenada | 0.00 | | |
| Guatemala | -0.27 | -1.43 | -7.27 |
| Guinea | 0.04 | | -6.81 |
| Guinea-Bissau | -0.65 | | -7.71 |
| Guyana | -1.02 | 0.00 | -6.40 |
| Haiti | -1.55 | | -8.00 |
| Honduras | -2.16 | | -9.20 |
| Hong Kong | 0.17 | | -1.32 |
| Hungary | -3.60 | -3.29 | |
| India | 0.63 | 1.05 | -5.58 |
| Indonesia | 4.28 | | -2.72 |
| Iran | -3.35 | -2.74 | -6.83 |
| Iraq | -7.60 | -6.62 | -12.64 |
| Ireland | | 1.77 | |
| Israel | -4.17 | -3.98 | |
| Italy | -2.73 | -2.07 | -7.60 |
| Jamaica | 0.52 | | |
| Jammu-Kashmi | 0.00 | 0.00 | 0.00 |
| Japan | | 2.13 | -5.34 |
| Jordan | -3.48 | -4.20 | |
| Kazakhstan | -0.95 | 5.45 | -10.00 |
| Kenya | -0.94 | 0.27 | -7.30 |
| Kuwait | -0.78 | -0.75 | |
| Kyrgyzstan | 1.77 | 4.55 | -8.70 |
| Laos | 0.16 | | -7.65 |
| Latvia | | 5.10 | |
| Lebanon | | -4.13 | |
| Lesotho | -2.65 | -2.26 | |
| Liberia | 0.60 | | -1.17 |
| Libya | | -0.57 | |
| Lithuania | 5.14 | -1.96 | |
| Luxembourg | -1.26 | -0.96 | |
| Madagascar | -0.81 | -0.81 | -6.96 |
| Malawi | -2.72 | -2.14 | -8.84 |
| Malaysia | 5.15 | | -2.21 |
| Mali | -5.43 | -1.11 | -10.26 |
| Malta | | 0.00 | |
| Mauritania | -8.20 | -6.38 | -13.45 |
| Mexico | -3.60 | -3.87 | -9.79 |
| Moldova | -4.13 | -3.74 | |
| Mongolia | 10.17 | 9.55 | |
| Montenegro | -1.66 | 0.97 | |
| Morocco | -3.84 | -3.87 | -4.79 |
| Mozambique | -2.46 | -3.02 | -8.52 |
| Myanmar | 1.76 | 1.89 | -5.44 |
| Namibia | -4.85 | -4.57 | |
| Nepal | 1.58 | 1.91 | -6.28 |
| Netherlands | -0.93 | -0.63 | |
| New Caledonia | 0.00 | | |
| New Zealand | 0.38 | 0.55 | |
| Nicaragua | -0.11 | | -7.15 |
| Niger | -3.49 | -2.94 | -9.03 |
| Nigeria | 0.00 | -2.73 | -7.20 |
| North Korea | 2.74 | 4.16 | -5.44 |
| North Macedonia | -3.50 | -2.80 | -11.67 |
| Norway | | 2.16 | |
| Oman | | -0.59 | |
| Pakistan | -5.85 | -4.19 | -9.62 |
| Panama | 3.83 | | -2.78 |
| Papua New Guinea | 5.69 | | -0.67 |
| Paraguay | -2.26 | -1.58 | -10.10 |
| Peru | -0.74 | -1.23 | -8.39 |
| Philippines | 3.15 | | -2.84 |
| Poland | -2.95 | -2.58 | |
| Portugal | -2.59 | -2.31 | -9.58 |
| Puerto Rico | 0.33 | | |
| Qatar | 0.00 | | |
| Rã©Union | 0.00 | | |
| Romania | -3.42 | -2.29 | -12.52 |
| Russian Fed. | 7.10 | 5.17 | -8.21 |
| Rwanda | -1.07 | -0.44 | -8.78 |
| Sao Tome And Principe | 0.00 | | |
| Saudi Arabia | -3.11 | -3.54 | |
| Senegal | -4.96 | | -10.45 |
| Serbia And Montenegro | -3.02 | -2.60 | |
| Sierra Leone | 2.53 | | -2.73 |
| Slovakia | -2.74 | -1.14 | |
| Slovenia | -0.43 | 0.07 | |
| Solomon Islands | | | 0.00 |
| Somalia | -1.24 | -0.53 | -4.62 |
| South Africa | -4.04 | -3.89 | |
| South Korea | 0.56 | | -6.41 |
| South Sudan | -1.06 | -0.88 | -2.92 |
| Spain | -4.19 | -3.73 | -12.86 |
| Sri Lanka | 3.69 | | -3.39 |
| Sudan (Former) | -3.66 | -2.48 | -9.40 |
| Suriname | | | -5.36 |
| Swaziland | -3.09 | | |
| Sweden | | 1.22 | |
| Switzerland | -0.89 | -0.11 | |
| Syria | -5.85 | -4.68 | |

| | | | |
|---|---|---|---|
| Taiwan | 3.07 | | -3.32 |
| Tajikistan | -4.78 | -1.84 | -12.13 |
| Tanzania | -1.26 | -1.17 | -7.68 |
| Thailand | -1.31 | -0.02 | -8.28 |
| Timor-Leste | 0.76 | | -5.54 |
| Togo | -1.24 | | -9.15 |
| Trinidad And Tobago | 1.06 | | -4.66 |
| Tunisia | | -2.37 | |
| Turkey | -4.05 | -2.87 | -12.07 |
| Turkmenistan | -7.06 | -5.96 | -12.07 |
| Uganda | -0.16 | | -6.59 |
| Ukraine | -3.90 | -3.43 | -11.08 |
| United arab emirates | | -4.79 | |
| United Kingdom | | 0.46 | |
| Uruguay | 0.30 | 0.57 | -6.73 |
| Usa | -2.03 | -1.68 | -9.97 |
| Uzbekistan | -6.09 | -4.52 | -10.29 |
| Vanuatu | 0.00 | | |
| Venezuela | -2.86 | 0.35 | -11.53 |
| Viet Nam | 0.57 | 0.00 | -6.35 |
| West Bank | -8.13 | -5.75 | |
| Yemen | -1.69 | -1.46 | |
| Zambia | -3.43 | -3.12 | -10.50 |
| Zimbabwe | -4.50 | -4.18 | 0.00 |

Threshold regression models have traditionally been used in economics and finance literature to address non-linear relationships between dependent and independent variables (Dagenais, 1969; Hansen, 2000). These models estimate the coefficients of the independent variables in both the linear and non-linear parts, as well as the location of the threshold itself. This allows for the identification of the range of independent variable values where a significant change in the effect on the dependent variable occurs. In this work, we used this approach to obtain a rough estimate of the baseline temperature thresholds for our dataset. After obtaining the threshold estimates (last five rows of Table 7), we adjusted them in our main regression model (Model 3, Table 3) to achieve a good balance between the suggestions of the thresholds regression model and what we consider plausible for our purposes.

Table 7 Threshold regression model to identify the structural breaks with 95% of statistical significance in temperature baseline.

| VARIABLES | (1) change | (2) Region1 | (3) Region2 | (4) Region3 | (5) Region4 | (6) Region5 | (7) Region6 |
|---|---|---|---|---|---|---|---|
| Precipitation | 0.246*** | | | | | | |
| | (0.017) | | | | | | |
| $CO_2$ (1=yes; 0=no) | 7.313*** | | | | | | |
| | (0.781) | | | | | | |
| Wheat | -2.802** | | | | | | |
| | (1.156) | | | | | | |
| Maize | -7.947*** | | | | | | |
| | (1.227) | | | | | | |
| $CO_2$* Wheat | 3.330*** | | | | | | |
| | (1.282) | | | | | | |
| $CO_2$* Maize | -0.444 | | | | | | |
| | (1.197) | | | | | | |
| Prec. base | 0.003*** | | | | | | |
| | (0.001) | | | | | | |
| Rainfed | -0.569 | | | | | | |
| | (0.939) | | | | | | |
| Rainfed * wheat | 2.494* | | | | | | |
| | (1.287) | | | | | | |
| Rainfed * maize | 7.399*** | | | | | | |
| | (1.311) | | | | | | |
| Sowing date change | 1.209** | | | | | | |
| | (0.614) | | | | | | |
| Cultivar change | 3.400*** | | | | | | |
| | (0.734) | | | | | | |
| Fertilizer | 2.837*** | | | | | | |
| | (0.830) | | | | | | |
| Irrigation | 7.748*** | | | | | | |
| | (0.868) | | | | | | |
| Other adaptation | 17.675*** | | | | | | |
| | (1.134) | | | | | | |
| Temperature | | 0.897 | -3.009*** | -2.072*** | -2.645*** | -4.691*** | -7.792*** |
| | | (0.560) | (0.310) | (0.718) | (0.303) | (0.757) | (0.621) |
| Constant | | -4.319** | -1.583 | 4.263** | -5.874*** | 14.419*** | -1.305 |
| | | (1.705) | (1.224) | (1.878) | (1.299) | (2.265) | (1.671) |
| Observations | 5,705 | 5,705 | 5,705 | 5,705 | 5,705 | 5,705 | 5,705 |
| Threshold 1 | 6.738 | 6.738 | 6.738 | 6.738 | 6.738 | 6.738 | 6.738 |
| Threshold 2 | 11.68 | 11.68 | 11.68 | 11.68 | 11.68 | 11.68 | 11.68 |
| Threshold 3 | 14.73 | 14.73 | 14.73 | 14.73 | 14.73 | 14.73 | 14.73 |
| Threshold 4 | 26.47 | 26.47 | 26.47 | 26.47 | 26.47 | 26.47 | 26.47 |
| Threshold 5 | 26.95 | 26.95 | 26.95 | 26.95 | 26.95 | 26.95 | 26.95 |

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# The value of weather forecasts in agriculture: a simulation study


## Abstract

The performance of the agricultural sector is highly dependent on weather conditions, which can vary significantly on an inter-annual and intra-seasonal basis, particularly in rainfed regions where agriculture is predominant. As a result, farmers face the challenge of dynamically adapting their production processes to current weather conditions, a task which will become even more challenging due to the expected increase in weather variability caused by climate change. Weather forecasts can provide farmers with information on expected weather conditions, potentially leading to increased yields. However, this topic has received little attention in the existing literature, despite its potential contribution to agriculture. In this study, we assess the value of weather information from short-term (10-day) and seasonal (3-month) forecasts in predicting precipitation for adjusting sowing dates in rainfed maize production in Tanzania. We found that farmers who use weather forecasts achieve better performance and reduced yield fluctuation over time compared to traditional farmers who do not use any weather information. The difference is particularly significant in dry seasons (+31%), while it is reduced in wet seasons (+4%). Seasonal forecasts are more reliable than 10-day forecasts in increasing yields, but the best results are obtained by combining the two (+14%). These findings highlight the need for improved dissemination and use of weather services as a tool for adapting agriculture to weather variability and climate change. However, policymakers should address the social and technological constraints that actually prevent the use of weather services, especially in developing countries.



Keywords: Climate change, Agriculture, Adaptation, Weather variability, Weather forecasts, Seasonal forecasts, Meteorological services, Developing countries, Tanzania, Maize

## Introduction

The first chapter shows that the expected impacts of climate change on crop yields are predominantly negative in countries with higher baseline temperatures and positive in colder countries. This result considers only long-term changes in average temperature and precipitation and does not consider year-to-year weather variability, which is increased by climate change and may exacerbate its impact (Schlenker and Lobell, 2010; IPCC, 2021). Weather variability has rapidly emerged as one of the main concerns for the impact of climate change on agricultural productivity, as crop yields are highly susceptible to both inter-annual and intra-seasonal weather fluctuations[17] (Thornton et al., 2014). However, most studies to date have primarily focused on assessing the impacts of climate change, often neglecting the effects of variability (e.g., Lobell and Burke, 2008; Schlenker and Lobell, 2010; Rosenzweig et al., 2014).

Precipitation variability is crucial in rainfed agriculture, as harsh weather conditions directly impact crop yields. In regions such as sub-Saharan Africa, precipitation patterns show a high degree of erraticism (Eriksen et al. 2008), affecting the onset, duration and offset of the rainy season (Conway et al. 2007; Dore 2005; Haile 2005; Thornton et al., 2009; IPCC, 2021; Suri and Udry, 2022). This uncertainty poses a major obstacle to increasing agricultural production and improving rural livelihoods in most sub-Saharan African countries (Hansen et al., 2009). Understanding precipitation patterns would greatly assist farmers in making yearly agronomic decisions regarding land preparation, seed/crop mobilisation and labour. This understanding could also reduce the risk of sowing too late or too early (Omotosho et al., 2000). In these countries, farmers must therefore contend with highly variable weather conditions and a lack of technology (Hallegatte, 2016), which puts agricultural production at even greater risk from the impact of climate change.

The literature on adaptation has consistently focused on the effectiveness of strategies in reducing long-term impacts, rather than their ability to mitigate short-term impacts caused by weather variability. However, there is uncertainty about their effectiveness at the local level, even though the first chapter demonstrates that some of these strategies are statistically significant in reducing negative impacts globally. For instance, Ahmad et al. (2020) argue that adapting cultivars may lead to a 6% increase in maize yields in semi-arid conditions. Other studies (Thornton et al., 2009; Hellin et al., 2012; Cairns et al., 2014; Gummadi et al., 2020) suggest that

[17] Inter-annual refers to the meteorological variability from one year to the next, while intra-seasonal refers to the variability within the same year.

optimizing sowing dates and densities or enhancing crop cultivars could potentially yield benefits of up to 42%. In contrast, some researchers (Kassie et al., 2015; Volk et al., 2021) caution that these adaptation strategies may have limited, or negligible effects compared to the prevailing findings.

Changing the sowing date is one of the most widely used and affordable strategies among farmers (Lobell et al., 2008). By selecting the appropriate sowing date, farmers can prevent critical stages of crop development from coinciding with periods of high temperature and water scarcity, thereby increasing yield (Tao and Zhang, 2010). In regions with limited precipitation, such as sub-Saharan Africa, farmers typically sow their crops at the beginning of the rainy season (Katinila et al., 1998; Lema and Majule, 2009; Baijukya et al., 2020) to reduce the risk of crop failure due to sowing during heavy rains. However, this approach also increases the risk of waiting too long if the rainy season is delayed within the appropriate sowing window. In such cases, there is a higher likelihood of water stress during the later stages of crop development, which can potentially reduce yield[18]. This conservative approach allows farmers to accurately determine the beginning of the rainy season and avoid false starts that often cause crop failures.[19] An alternative sowing strategy, explored in this study, is known as dry soil sowing. This method involves sowing the crop a few days before the onset of heavy rain, when the soil is still dry. The advantage of this approach is that when the rains do start, the seeds are already in the soil and can immediately begin to germinate.

By providing advance information on future weather conditions, weather forecasts can support farmers' decisions, potentially mitigating the negative effects of weather variability. However, despite their increasing usefulness, weather forecasts are still underutilized in agriculture (Mase and Prokopy, 2014; Kusunose & Mahmood, 2016; Vaughan et al., 2019; FAO, 2021; Agyekum et al., 2022). There is evidence in the literature that farmers can benefit from weather forecasts in various agronomic practices, such as crop and cultivar selection, determining sowing dates, irrigation scheduling, and adjusting fertilization strategies (see reviews by Meza et al., 2008; Tall et al., 2018; Parton et al., 2019; Agyekum et al., 2022). The accuracy of weather forecasts has significantly improved, reaching almost 99% for horizons of less than three days (Bauer et al.,

[18] Although there is no consensus in the literature on how to define the onset of the rainy season, it is common practice to identify the onset of the rainy season when significant cumulative precipitation occurs over several consecutive days (e.g. Fitzpatrick et al., 2015).

[19] Alternatively, the staggered sowing approach consists of separate and sow few plots of land at regular intervals (for example 1 or 2 weeks) to increase the probability that at least one of them will match properly the rainy season onset (Lema and Majule, 2009). Based on similar idea, the dryland sowing aims for sowing on still-dry soil while waiting for heavy rains and leveraging all possible precipitations during the growing season (Lana et al., 2018). However, sowing too early may harm the seeds if no precipitations occur quickly, reducing yields or failing the crop.

2015). Recently, deep learning artificial intelligence has been found to outperform even the most accurate deterministic systems in 90% of tasks, particularly in predicting extreme weather events (Lam et al., 2022). Forecast accuracy is expected to improve further in the future (Alley et al., 2019; Schultz et al., 2021), with tangible benefits not only for the agricultural sector but also for other industries (Roberts et al., 2018).

This study assesses the usefulness of short-term (10-day) and seasonal (3-month) weather forecasts in predicting precipitation for adjusting sowing dates in rainfed maize crops in Tanzania. Weather forecasts can allow for early sowing in dry years, increasing water availability for crop growth, and delayed sowing in wet years to avoid potential water damage. We use the Decision Support System for Agrotechnology Transfer (DSSAT) crop model to simulate the impact of different sowing dates, adjusted on the basis of weather information, on maize yield. We examine the effects of individual adjustment (short-term only and seasonal only) and combined adjustment (short-term + seasonal), while keeping all other variables constant. However, the aim of this study is not to determine the exact amount of predicted precipitation for sowing adjustments, but rather to demonstrate the potential of using weather forecasts to develop a sowing strategy that can increase yields compared to traditional practices.

This study complements the research conducted by Roudier et al. (2016) by incorporating both short-term and seasonal weather forecasts. Additionally, it introduces important novel findings that set it apart from previous research, making it a unique contribution to the existing literature. While Roudier's work focuses on millet, our study highlights the significance of weather forecasts for the cultivation of maize, the most widely grown crop in Africa and one of the most important crops in the world (OECD/FAO, 2020). Roudier's research examines various aspects of the agricultural production process while our study specifically focuses on the sowing date as a weather-dependent decision that offers the simplest and most cost-effective adaptation solution. This strategy is crucial for developing countries and impoverished farming communities that are reluctant to invest in new technology (Wood et al., 2014; Hallegatte, 2016), as weather forecasts are often readily available and widely accessible even to the poorest individuals (Oyekale, 2015; Daly et al., 2016). Our aim, therefore, is to disentangle the effects of different sowing dates on maize yield using weather forecasts, without introducing potential confounding effects.

The results show that using 10-day and seasonal forecasts alone yields positive results compared to traditional sowing without weather forecasts. However, the most effective strategy is using combined forecasts (+14%). Additionally, the use of weather forecasts leads to more stable yields over time, with a reduction in variability ranging from -11% to -14% compared to the traditional method. The significance of weather forecast is higher in dry years and lower in wet years, as above-average precipitation can reduce the effectiveness of the optimal sowing date. When adjusting the sowing date to maximize yield, seasonal forecasts are more valuable than short-term forecasts, although short-term forecasts are more effective in reducing variability.

This study makes a significant contribution to several strands of literature, such as climate change adaptation strategies, the value of information, and the production of weather forecasts[20]. Furthermore, this research provides valuable insights into poverty alleviation literature by showing how even the poorest farmers can improve their yields through simple adaptation strategies[21]. This study expands the literature on precision agriculture by presenting a replicable approach that can be applied in different contexts. It demonstrates how the use of agricultural resources can be optimised through the informed and strategic use of information, further advancing the debate on sustainable and efficient agricultural practices.

## Data and study area

We simulate a farm in the north-east of Tanzania, an area that can be representative of the environmental and agricultural conditions found in much of Sub-Saharan Africa. This area is characterized by poor and erratic precipitation (Figure 1). According to the National Sample Census of Agriculture (NSCA, 2021), this area[22] is particularly critical for Tanzanian smallholder maize growers and is home to over 3 million people (Tanzania census, 2012), with nearly 5,000 households relying on the primary sector as their main source of income (NSCA, 2021). Maize is the most important crop grown in this area, and for the African continent as a whole, in terms of both quantity and economic relevance (OECD/FAO, 2020; NSCA, 2021). Therefore, maize production is critical not only for subsistence agriculture but also for the country's economic

[20] Despite the free distribution of weather forecasts, there are significant costs associated with their production. Identifying the most useful information for farmers could enhance the efficiency of resource allocation.

[21] although access and ability to process information can be a crucial aspect.

[22] For general information on population, households and maize production, we consider the provinces of Arusha and Manyara, as the hypothetical farm is located between these two provinces.

development. Almost all agricultural land is rainfed and cultivated using antiquated methods such as oxen, ox ploughs and hand sprayers, with only 10% using tractors (NSCA, 2021).

Figure 1 Exact point of simulated farm (red cross).

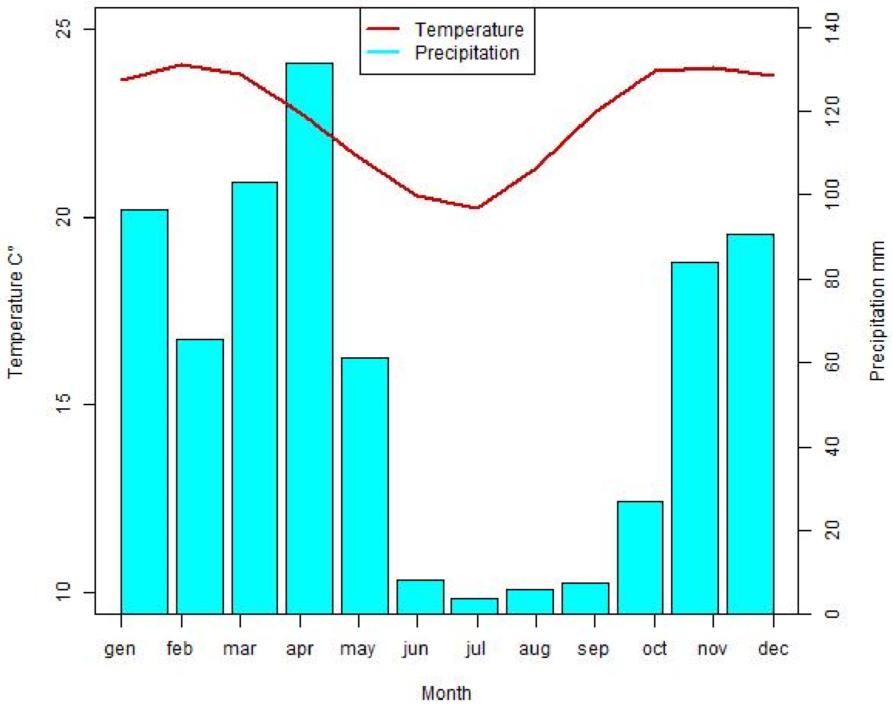

Notes: coordinates: -4.013725; 36.462978. The black lines are the country boundaries. Source: own elaboration from Google maps.

Daily weather data to run the DSSAT crop model are gathered from the NASA POWER project, which includes information on minimum and maximum temperature, precipitation, solar radiation, wind, and relative humidity. In Figure 2, we present the monthly average values for precipitation and temperature in the region investigated in the simulation for the entire period 1984-2020[23]. The average annual historical precipitation is 678 mm, whereas the average annual temperature is about 23 °C. Precipitation is bimodal and there are two growing seasons. This study focuses on the "Masika" growing season, which is the most important for crop production in the area and lasts from March to May. The maize sowing window for the "Masika" season extends from mid-February to the end of March, coinciding with the expected onset of the rainy season. To define the growing season as dry, normal or wet, we adopt the Greater Horn of Africa Climate Outlook Forum (GHACOF) approach (example of GHACOF seasonal bulletins in Appendix, Figure 5), which considers the cumulative precipitation in March, April and May and the available data from 1984 to 2020 using

[23] We use this period because it is the longest available on the NASA POWER project website at the time of data extraction.

the tercile distribution.[24] We exclude the years 2000 and 2001 from the analysis as they were characterized by exceptionally dry conditions. Based on this approach, growing seasons with less than 238 mm cumulative precipitation are classified as dry, seasons with more than 312 mm are classified as wet and seasons falling in between are classified as normal (Appendix, Figure 6).

Figure 2 Average temperature (left axis) and precipitation (right axis) per month, 1984-2020.




## Methods

We assess the value of two weather forecasts in predicting the amount of precipitation amount: the 10-day forecast and the 3-motnh seasonal forecast[25]. The 10-day weather forecast provides information on the cumulative/total amount of precipitation expected over the next 10 days, whereas the seasonal forecast predicts whether the next three months will be dry, wet, or within the normal range based on historical precipitation

[24] This approach to define dry, normal and wet years is consistent with the Roudier's work.

[25] We consider only the amount of precipitation with no distinction made between the intensity or timing of the precipitation over the predicted period. This approach is consistent with other studies in the literature that evaluate simpler information rather than more sophisticated ones (Roudier et al., 2016; Asseng et al., 2016).

records. In our simulation, we assume that both forecasts are 100% accurate, i.e. perfect, and that both are available at the specific farm location at the beginning of sowing window.

We only consider the sowing date as the agronomic practice that can be adjusted based on weather forecasts. We keep all the other variables constant and simulate four farmers: i) the traditional farmer using no forecasts (reference one), ii) the farmer using only 10-day forecasts, iii) the farmer using only seasonal forecasts and iv) the farmer using both 10-day and seasonal forecasts. We then calculate the value of weather forecasts as the difference in crop yields between each sowing strategy and the reference one.

To simulate maize yield for different sowing dates, we use the DSSAT crop model (Jones et al., 2003) and the Crop-Environment-Resource-Synthesis (CERES) module integrated into the software (Jones and Kiniry, 1986). This crop model has been extensively used and validated by scientists worldwide to estimate crop yields, including maize[26] (e.g. Dar, Hoogenboom and Shah, 2023). It uses a variety of equations based on physiological and ecological principles to simulate maize crop growth and yield. These equations include:

i) A phenology model that represents maize development in a thermal time framework including growing degree days.

ii) Growth and development equations that detail biomass accumulation in leaves, stems and roots. These equations govern photosynthesis, respiration, and biomass allocation.

iii) An equation model for leaf area development, which is critical for solar energy use.

iv) Water uptake and soil water balance equations that measure soil moisture dynamics and root water uptake.

v) Nutrient uptake equation that considers nutrient-related growth effects.

vi) Equations to estimate yield components such as the number of ears, kernel quantity per ear and kernel weight. These equations consider plant growth, development and environmental variables.

[26] As reported in the main web page of DSSAT: "*It has been in used by more than 25,000 researchers, educators, consultants, extension agents, growers, and policy and decision makers in over 187 countries worldwide*" (https://dssat.net/about/).

We evaluate the value of weather forecasts using three popular maize cultivars with different yield potentials: TMV1, H612 and STUKA[27] (Katinila et al., 1998; Westengen et al, 2014; Mourice et al., 2014; Tanzania government, 2022). The genetic parameters required by DSSAT to run the simulation for TMV1 and STUKA are retrieved from Mourice et al. (2014), whereas H612 parameters are already included in the software (Gude, 2016; Mfwango et al., 2018)[28].

The four simulated farmers act as follows:

a) The reference farmer (traditional) does not have access to the weather forecast or does not follow it. They sow the maize in an attempt to match the onset of the rainy season, typically after heavy rain. The precipitation threshold that mimics the onset of the rainy season and triggers the sowing is "at least 20mm" of cumulative precipitation in the previous 6 days. Although this threshold can vary in different parts of Tanzania and depends on many factors, such as soil type, it accurately represents the decision-making rule in the area under investigation. This is supported by similar thresholds reported in other related studies (Marteau et al., 2011; Mourice et al., 2014).
b) The first farmer, whose strategy is based on forecasts, has access to the 10-day weather information only. We use a specific threshold of predicted precipitation to determine the beginning of sowing. If the 10-day forecast predicts at least 10 mm of precipitation in the coming 10 days, the farmer immediately sows. This threshold is consistent with the work of Roudier et al. (2016) and is derived from Sivakumar (1992), who suggests that this is the minimum amount of precipitation to be considered for this type of decision making in these areas. This strategy makes it possible to sow as soon as this information is available, giving an advantage over rain and sowing when the soil is still dry.
c) The second farmer's strategy is based on forecasts and is limited to seasonal forecasts. The farmer chooses the sowing date based solely on this information. However, instead of selecting a specific date, the farmer opts for a sowing period. To simulate different sowing periods, we use a fixed interval of 10 days starting from the first day of the sowing window, which is February 16.

[27] The names of the cultivars have no specific meaning. They have been named by the companies that hold the planting rights or are derived from old rural traditions. Hereafter, we simple refer to them as TMV1, H612 and STUKA cultivar.
[28] We do not include irrigation in our model as the greatest part of Tanzania and the simulated area are dominated by rainfed agriculture (NSCA, 2021).

Following the same reasoning as before, the lower the predicted precipitation (dry, normal or wet), the earlier the sowing date and vice versa. For example, if a dry year is forecasted, the farmer will sow on February 16, the first day of the window. If a normal year is predicted, the farmer will sow on February 26, and so on.

d) The last farmer's strategy uses a combination of 10-day and seasonal weather forecasts. The sowing period is determined based on seasonal information, and the specific date within each period is selected according to the 10-day weather forecast. Different precipitation thresholds are chosen for each type of growing season (dry, normal, or wet): 5mm for dry years, 10mm for normal years and 20mm for wet years. We explore specific thresholds for dry and wet years to identify more tailored sowing strategies for different growing seasons. This is because if a dry season is predicted, the amount of precipitation required to trigger sowing would be lower compared to a wetter season, and vice versa. In the case of an insufficient amount of predicted precipitation within the chosen sowing period based on seasonal forecast, the last day of that period is automatically selected.

Table 1 shows the four farmer strategies described above and Figure 3 illustrates a hypothetical dry year's timeline.

Table 1 Maize sowing determination date for each farmer strategy.

| Farmer strategy | Determination of maize sowing date | Sowing date |
|---|---|---|
| Traditional | Immediately if "at least 20mm" of cumulated precipitations occurs in the previous 6 days. | Flexible |
| 10-day | Immediately if a prediction of "at least 10mm in the coming 10 days" of cumulate precipitation comes. | Flexible |
| Seasonal | At fixed dates according to 3 types of growing season (dry, normal, wet) | Fixed: 16 February if "dry" is predicted, 26 February if "normal" or "wet" is predicted* |
| 10-day + Seasonal | Sowing period decided based on seasonal and specific date within each period based on 5, 10, and 20mm of cumulated precipitations predicted by 10-day forecasts for dry, normal, or wet years, respectively. | Flexible: 16-25 February if "dry" is predicted; 26 February - 7 March if "normal" or "wet" is predicted. |

*In the case of "normal" and "wet" years the best results are obtained using the same period.

Figure 3 Timeline of four simulated farmers strategy for a hypothetical dry year.

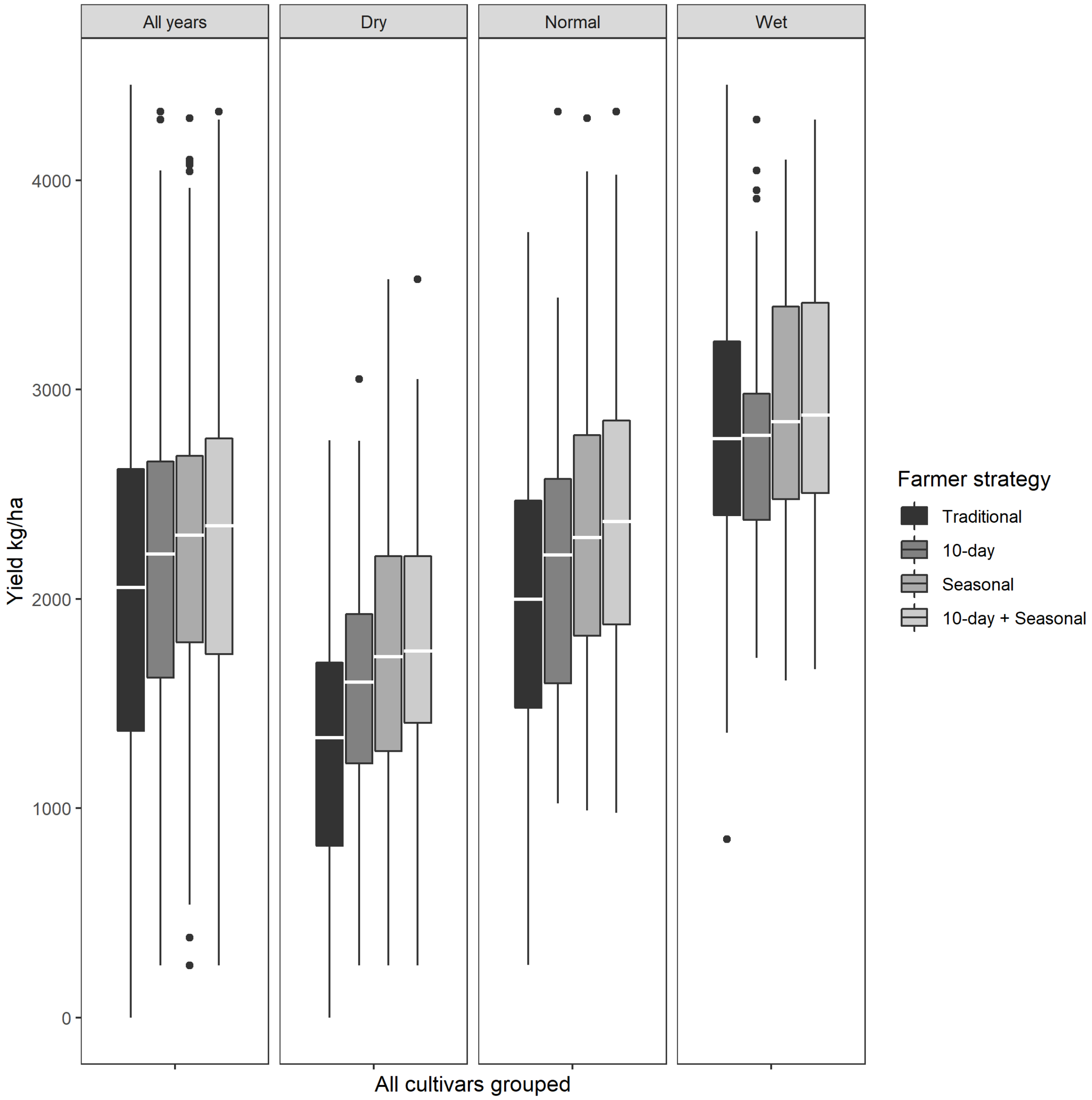
| Month | February | | | | | | | | | | | | | March | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Day of the year | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 1 | 2 | 3 | 4 | ... |
| Precipitation, day/mm | 1 | 1 | | 1 | 1 | | | | | | 2 | 3 | | 4 | 1 | 10 | 8 | ... |
| TRADITIONAL | | | | | | | | | | | | | | | | | SOW | |
| 10-DAY | | | | | SOW | | | | | | | | | | | | | |
| SEASONAL | SOW | | | | | | | | | | | | | | | | | |
| 10-DAY + SEASONAL | | | SOW | | | | | | | | | | | | | | | |

To calculate if the maize yield difference between the sowing strategies is statistically significant, we use the bootstrap method (Efron, 1992). Due to the limited number of observations and the non-normal distribution, we cannot use the parametric t-test. The bootstrap method is able to work in critical conditions, as it doesn't assume normality and it can manage a small number of observations (Adèr, 2008). We create 10,000 resamples with replacement and calculate the effect size of interest (mean of paired differences) on each of these resamples. Thanks to the central limit theorem, the resampling distribution of the effect size will approach normality and we can therefore compute confidence intervals.

## Results

In Figure 4 and Table 2 we present the results for all cultivars grouped together, averaged over the three cultivars, for the entire period from 1984 to 2020. These results are also differentiated by growing season type (dry, normal, and wet). The percentage yield differences from traditional sowing are shown, along with the level of statistical significance. The standard deviation is used as an indicator of variability. Figure 5 in the shows the disaggregated results for each cultivar (the numerical table in Appendix, Table 4).

Figure 4 Boxplots of maize yields sowed with different sowing strategies applied over the whole period (leftmost column) and by growing season type.



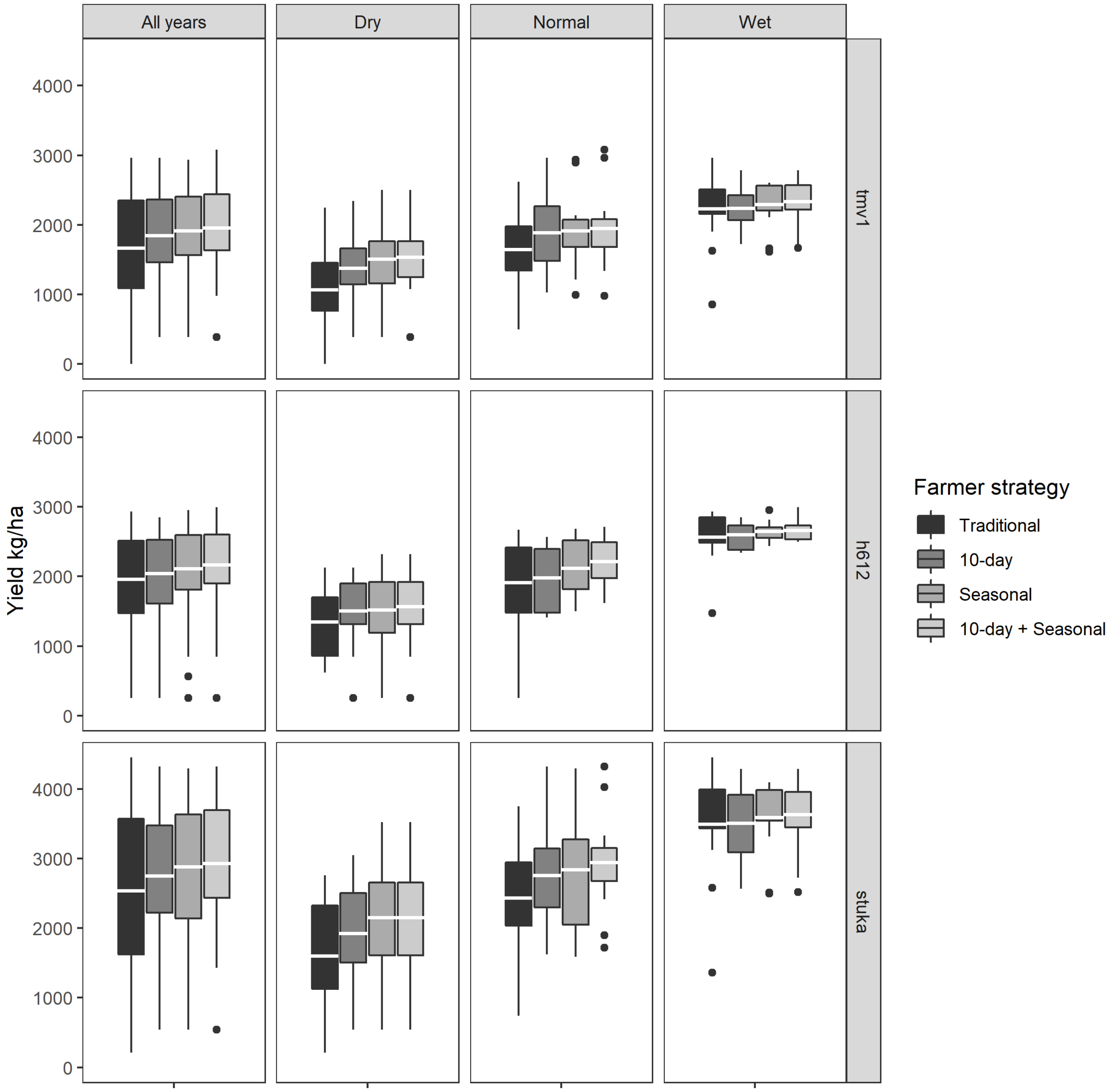

Notes: the horizontal white line represents the mean, the bottom and top of the box represent the first and fourth quartiles, and the whiskers are defined as: upper whisker = min(max(x), Q_3 + 1.5 * IQR) and lower whisker = max(min(x), Q_1 – 1.5 * IQR). All the cultivars are grouped.

Table 2 Absolute and relative maize yield differences from traditional sowing rule and standard deviation.

| | | All cultivars grouped | | | | |
|---|---|---|---|---|---|---|
| | N° | Farmer strategy | Yield (kg/ha) | % diff from TRAD | Standard deviation (kg/ha) | % diff from TRAD |
| All years (1984-2020) | 105 | Traditional | 2'054 | | 953 | |
| | | 10-day | 2'216 | *7.89* *** | 818 | *-14.17* |
| | | Seasonal | 2'305 | *12.22* *** | 848 | *-11.02* |
| | | 10-day + Seasonal | 2'350 | *14.41* *** | 835 | *-12.38* |
| Dry | 33 | Traditional | 1'338 | | 707 | |
| | | 10-day | 1'603 | *19.00* ** | 650 | *-8.06* |
| | | Seasonal | 1'726 | *29.00* *** | 753 | *6.51* |
| | | 10-day + Seasonal | 1'751 | *30.87* *** | 726 | *2.69* |
| Normal | 36 | Traditional | 1'998 | | 760 | |
| | | 10-day | 2'211 | *10.66* ** | 701 | *-7.76* |
| | | Seasonal | 2'293 | *14.76* *** | 741 | *-2.50* |
| | | 10-day + Seasonal | 2'370 | *18.62* *** | 714 | *-6.05* |
| Wet | 36 | Traditional | 2'767 | | 810 | |
| | | 10-day | 2'783 | *0.58* | 654 | *-19.26* |
| | | Seasonal | 2'846 | *2.86* | 673 | *-16.91* |
| | | 10-day + Seasonal | 2'879 | *4.05* * | 672 | *-17.04* |

Notes: stars next to the yield percentage difference are calculated by bootstrapping 10'000 repetitions with replacement: (*) significant at 90% confidence interval, (**) significant at 95% confidence interval, (***) significant at 99% confidence interval. Number (N°) of dry years is lower because 2000 and 2001 are deleted from the analysis.

Figure 5 Boxplots of maize yields sowed with different sowing strategies applied over the whole period (leftmost column), by cultivar and by growing season type.




Notes: the horizontal white line represents the mean, the bottom and top of the box represent the first and fourth quartiles, and the whiskers as: upper whisker = min(max(x), Q_3 + 1.5 * IQR) and lower whisker = max(min(x), Q_1 – 1.5 * IQR).

On average, farmers who receive weather forecasts achieve higher maize yields than traditional ones (first main row of Table 2). It is also evident that the longer the forecast information the higher the yields. For example, the 10-day weather forecast leads to an average yield increase of almost 8%, while using the seasonal forecast results in a +12% increase. However, only the combined use of both forecasts achieves a +14% increase. These results support the hypothesis that having more information about future weather conditions helps farmers make better choices. On the other hand, the greatest reduction in variability is achieved with the 10-day forecast sowing strategy. This suggests that short-term information, unlike the alternative weather-informed strategies, does not lead to an increase in maize yield. However, it is a good option to help the farmer reduce variability over time. Moreover, as shown in the first column of Figure 4, all three farmers who use the weather forecasts reduced the probability of crop failures compared to the traditional farmer; the lower whisker of the box plot reaches 0 with the traditional farmer.

In dry seasons, the absolute yields are significantly lower compared to normal and wet years, resulting in significant differences in percentage terms from traditional sowing. Using combined weather forecasts leads to a +31% increase in average yield, while using forecasts alone results in a slightly lower increase. Similar to the general case, only the strategy based on a 10-day forecast effectively reduces variability, while the other strategies have a standard deviation similar to the traditional sowing strategy. This result may be due to the tendency of the seasonal and combined strategies to obtain very high maize yields, which justifies a slight increase in variability. During such years, crop failure due to insufficient precipitation is significantly more likely to occur only with traditional sowing. This may be due to the late onset of the rainy season, which in turn may cause a delay in traditional sowing. Therefore, the optimal sowing date is narrowed down to just a few days at the beginning of the growing season. However, yields from weather-informed strategies may be quite low in absolute terms, amounting to only a few hundred kilograms per hectare. Although this prevents total crop failure, it could still prompt the farmer to abandon the crop in favour of alternative uses.

In “normal” years, the percentage differences from the traditional farmer are lower compared to the "dry" ones (third column of Figure 4; third main row of Table 2). The differences in average yield are +11%, +15%, and +19% for the 10-day, seasonal and combined weather strategies, respectively. Variability is also reduced compared to the traditional farmer, with values ranging from -2.5% to -7.8%. Traditional sowing is unlikely to fail completely, although there is a higher probability of very low yields. Therefore, weather-informed strategies are still particularly valuable in avoiding poor performances.

In "wet" years, the average differences between the yields obtained by weather-informed farmers and traditional farmers flatten out and the statistical significance disappears. Only the combined forecast strategy, which yields +4%, is statistically significant at a 90% confidence level (fourth main row in Table 2). The yields obtained are the highest observed in absolute terms and the variability is the lowest. This indicates that when there is abundant precipitation, maize yields are generally very high regardless of the sowing strategy and the variability is contained, thus reducing the value of weather information. However, DSSAT's performance in extremely wet years may be unreliable due to the persistent soil moisture, which can lead increased pest and disease outbreaks. Delaying the sowing process, as part of the combined strategy, may assist in avoiding over-watering and potentially widen the gap reported in this study between traditional farmers and weather-informed farmers.

Moreover, our use of the GHACOF precipitation classification scheme is consistent with other studies, but there is still considerable variability within each category that warrants further investigation, especially during wet years. For example, in 1997 we observed extraordinary precipitation (more than 700mm in March-April-May) that would require a tailored approach compared to the other wet years (Appendix, Figure 6). In that case, the higher yield for this year is obtained sowing at the end of the sowing window, specifically from March 27 to 31. This leads in a 12% increase compared to the combined strategy shown in previous framework, which detects the sowing date nearly one month earlier[29]. With advancements in weather forecasting expected in the future, it is plausible that improved farmer strategies can be developed to address extreme years, further widening the gap with traditional sowings.

Looking at the performance of specific cultivars across different growing seasons, Figure 4 shows that STUKA has the highest overall potential yield, but also exhibits significant variability (Appendix, Table 4). H612 is the most stable throughout the period, with a relative standard deviation of 37%. TMV1 shows the most significant reduction in variability and an increase in relative yield. Overall, all three cultivars show the same upward trend in yield as more weather forecasts are used.

In dry years, H612 has the worst yield percentage deviation among all the weather-informed strategies and does not show any reduction in variability. On the other hand, TMV1 proves to be the most responsive to weather-informed sowing strategies. This suggests that while all cultivars respond well to these strategies under low precipitation conditions, some performs notably worse than others in increasing yields and/or reducing variability. In normal years, STUKA demonstrates the best performance in terms of average yield increase,

[29] To determine this difference, we utilized the DSSAT crop model for each day within the sowing window (16 February – 31 March), considering the maximum attainable yield for each cultivar. For the sake of simplicity, we omit the complete results.

whereas H612 shows the most significant reduction in variability with -31%, -40%, and -48% (Appendix, Table 4). Overall, when comparing normal growing seasons to dry ones, all cultivars show greater stability in yields, as evidenced by the more compact box plots in Figure 5. In wet years, H612 shows a significant reduction in variability with percentages of, -53%, -63% and -62%, while there is no statistically significant variation in yield for any of the cultivars. This lack of significance may be attributed to the small sample (n=13) rather than non-significant differences.

## Robustness checks

We conduct severe robustness checks to ensure the validity of our results and to demonstrate that the results obtained are not due to chance. We compare the sowing strategies presented in Table 1 to i) a strategy based on 20mm of cumulative precipitation in 10 days, ii) a strategy which assumes that the next growing season will always be dry, (iii) normal and (iv) wet and a (v) random sowing date sowing strategy. The random sowing date strategy uses a randomly selected date to sow the maize for each year per 1,000 replications to reject the hypothesis that choosing a casual date within the sowing window gives better results than the weather informed strategies. Table 3 presents a comparison between the weather-informed sowing strategies presented in Table 1 and these alternatives.

Table 3 Robustness checks

| Farmer strategy | Yield (kg/ha) | % diff from 10-day | % diff from Seasonal | % diff from 10-day + Seasonal |
|---|---|---|---|---|
| 20mm in 10-day | 2'002 | -9.66* | -13.15** | -14.81*** |
| Always "dry" | 2'176 | -1.80 | -5.60*** | -7.40*** |
| Always "normal" | 2'235 | +0.86 | -3.04* | -4.89*** |
| Always "wet" | 2'235 | +0.86 | -3.04* | -4.89*** |
| Random sowing date* | 1'773 | -20.00 | -23.08 | -24.55 |

Notes: * in "Random sowing date" we compute 1'000 reps considering the "whole period" (37 years) and therefore we cannot find the bootstrap confidence interval for mean of paired difference as the others.

Using a more conservative precipitation threshold of 20mm in 10 days, the farmer will wait longer compared to a threshold of 10mm in 10 days. This alternative sowing strategy mimics a more risk averse farmer who wants to ensure that there will be abundant precipitation on his field. However, this approach will result in a reduction of maize yields of about 10% compared to the 10mm threshold sowing strategy, and even greater reduction compared to seasonal and combined cases, -13% and -15% respectively. Therefore, using a more conservative sowing strategy with a 10-day forecast will not improve the performance compared to either the traditional strategy (2,054 kg/ha) or any other weather-informed approaches.

The assumption that the next growing season is always dry is a very conservative approach, which implies that the farmer sows at the beginning of the season every year, on 16th February. When compared the results of this alternative strategy with the 10-day strategy, the yield is slightly less but not statistically significant. This suggests that the short-term weather forecast strategy presented in Table 1 could be replaced by this alternative approach. However, when compared to only seasonal and the combined cases, being too conservative significantly reduces the yield. Put differently, if the farmer act as the next growing season is always dry, he will be successful 31% of the time (11 years out of 35), and he ends up being too conservative 69% of the time. Therefore, by choosing to be too conservative instead of using the seasonal forecast, the farmer experiences an average loss of 5.6% over the entire period. Despite these negative results, it is worth noting that this alternative strategy may be comparable to the traditional farmer strategy, as the latter achieves on average only 2,054 kg/ha.

As the seasonal sowing strategies presented in Table 1 are similar for normal and wet years, these sowing strategies can be commented together respect to the alternatives. Assuming that the next season is always normal or wet achieves results that are quite comparable to the 10-day strategy but inferior if compared to seasonal and combined cases. When compared to 10-day sowing strategy, the result of this alternative is quite obvious, considering that the majority of seasons are normal or wet. Therefore, predicting the seasonal forecast correctly 70% of the time will result in better maize yields than a yield obtained with 100% accurate 10-day forecast. Comparing this alternative sowing strategy to the always correct seasonal information, the incorrect prediction of dry years only has a negative effect on yield of -3.04%. Although this may seem to be a modest result, the magnitude of this error is significant if we consider that seasonal forecasts in this alternative sowing strategy are incorrect only 30% of the time. The difference in yield is greater and statistically significant when compared to the combined sowing strategy, around -5%. This approach is therefore a valuable alternative to traditional and 10-day sowing strategies.

Finally, comparing the weather informed sowing strategies with the random sowing date alternative, we find that none of the weather informed sowing strategies have a lower yield performance. Random sowing of maize results in yield reductions ranging from -20% to -25% compared to the weather-informed sowing strategies. This result confirms that our findings are not due to chance and supports the hypothesis that sowing according to both short- and long-term weather forecasts can significantly improve yield compared to random sowing.

## Conclusions

This study demonstrates that using weather forecasts, as opposed to a traditional sowing strategy, allows farmers to significantly increase maize yields and decrease variability by merely adjusting the sowing date. The importance of weather forecast is particularly evident during dry seasons, when precipitation is scarce, and anticipating the sowing process provides a significant advantage. In addition, all simulated strategies based on weather forecasts dramatically reduce the probability of crop failures, which is a major concern in arid and semi-arid regions (Bussman et al., 2016). This highlights the critical role of weather services, especially as the number of dry years is predicted to increase in Tanzania and much of sub-Saharan Africa in the coming decades (Haile et al., 2020). Conversely, the value of weather forecasts is lower during normal and wet seasons when abundant precipitation reduces the negative impact of non-optimal choices. In these cases, weather forecasts could be more useful for other agronomic decisions such as fertilizer strategy (Asseng et al., 2016), or in limiting losses, as excessive precipitations can be highly detrimental to crops (Li et al., 2019).

The most effective strategy for increasing yields is to use combined weather forecasts. However, using either 10-day or seasonal forecasts alone still produces positive results. The different results from the 10-day and seasonal forecasts can be seen as a trade-off between sophistication and length of information, with simpler but longer-term information being more valuable than shorter but more sophisticated information. Higher precipitation thresholds reduce performance, and a random sowing test ensures that the results from the forecast-based sowing strategy are never due to chance. However, when comparing the 10-day sowing strategy with some alternative approaches (always dry, normal or wet in Table 3), we found no statistically significant difference that would make it replaceable. Nevertheless, the reduction in variability it offers may still make it preferable to strategies with higher expected yields as in contexts such as sub-Saharan Africa, stabilising crop yields over time is often preferred to maximising returns (Roudier et al., 2016). On the other hand, the effectiveness of the seasonal and combined strategy in increasing yields outperformed any alternative strategy, and these results remained consistent across all the robustness checks.

This finding is in contrast with the results of Roudier et al. (2016), who found that short-term forecasts were more important than seasonal forecasts for millet growers in Niger. This difference may be attributed to the significantly longer life cycle of maize (around 120 days) compared to millet, which in some cases has a maturity of only 80 days.

The heterogeneous yield performance of each cultivar may offer some future options for forecast-based sowing strategies. Although all three cultivars show similar patterns across growing seasons, some are particularly effective in mitigating year-to-year weather variability as their performance is quite stable across contrasting seasons. On the other hand, other cultivars have higher yield performance but may be more affected by weather variability as their performance varies widely between different growing seasons.

The results of the present simulation should be viewed in light of the assumptions we made, which may not fully capture the complexity of real-world farmer conditions. Firstly, we assumed that farmers receive seasonal forecasts at the beginning of the sowing window every year. However, in the case of GHACOF seasonal bulletins, this information is often distributed later, sometimes not until the first days of March, which can diminish the value of forecasts, particularly in dry years. This highlights the importance of receiving timely weather forecasts, as information received too late in the decision-making process becomes useless (Mjielde et al., 1988). Secondly, we assumed that farmers are able to sow on a specific day with all the necessary agricultural inputs immediately available. However, sowing is often a slower process than assumed in this study for Tanzanian farmers' due to their low technological level and difficulty in accessing inputs such as fertilizers, seeds, and labour force. Thirdly, we assume that weather forecast is 100% accurate[30]. However, the accuracy of information can greatly influence farmers' decisions and the perceived value of using such information. In

[30] In Appendix, the Figure 5 shows the probability of each state of the nature predicted by seasonal forecasts issued by GHACOF, for example.

developing countries, farmers show a high level of risk aversion, which can lead them to prefer more conservative options or disregard new information in favour of traditional practices (Meza et al., 2008). This risk aversion can make it difficult for farmers to fully trust and utilize new technologies, such as meteorological services. Moreover, the decision-making model adopted by farmers plays a significant role in determining the potential value of weather services: if farmers primarily rely on indigenous knowledge, the potential value of weather services may be limited (Radeny et al., 2019).

Weather forecasts are an accessible and widely disseminated tool that can help farmers adapt to climate change, especially in light of the expected increase in weather variability. However, the effectiveness of weather forecasts depends on farmers' prior knowledge of how maize responds to different weather conditions, including dry, normal and wet years. Only with this understanding farmers can effectively use weather forecasts to make informed decisions and optimise their farming practices. Although we only consider one of the most basic adaptation strategies, the results of this study are comparable to other adaptation strategies in the same area (e.g. Thornton et al., 2009; Hellin et al., 2012; Cairns et al., 2014; Kassie et al., 2015; Gummadi et al., 2020; Ahmad et al., 2020; Volk et al., 2021). These results are particularly promising when additional agronomic operations are optimised using weather forecasts (e.g. Shtienberg and Elad, 1997; Asseng et al., 2016; Rodriguez et al., 2018; Morari et al., 2021), but also for not strictly related agronomic practices such as labour allocation (Yegbemey et al., 2021).

To conclude, despite its potential contribution to reduce the negative effective of weather variability, and climate change as well, the use of weather forecast in agriculture is still overlooked, both by farmers and by scholars. Then, to fully support agricultural decision-making, policy makers should implement targeted information programs that offer farmers a comprehensive understanding of the potential impacts of their actions on the agricultural production process. It is crucial for policymakers to address technological constraints that may limit the value of weather forecasting information, even if it is 100% accurate. Only by addressing these constraints can we effectively leverage the benefits of weather forecasting services to support agricultural production and decision-making.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the results reported in this work.

# Appendix

Table 4 Absolute (kg/ha) and relative differences maize yields from traditional sowing rule and standard deviation.

| | | All years | | | | Dry | | | | Normal | | | | Wet | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Trad | 10-day | Seasonal | 10-day + Seasonal | Trad | 10-day | Seasonal | 10-day + Seasonal | Trad | 10-day | Seasonal | 10-day + Seasonal | Trad | Weather | Seasonal | 10-day + Seasonal |
| TMV1 | Yield (kg/ha) | 1662 | 1846 | 1915 | 1952 | 1064 | 1376 | 1507 | 1535 | 1642 | 1887 | 1911 | 1950 | 2231 | 2236 | 2292 | 2338 |
| | % diff from TRAD | | *11.07*** | *15.22**** | *17.45**** | | *29.32* | *41.63** | *44.27** | | *14.92* | *16.38**** | *18.76*** | | *0.22* | *2.73* | *4.80* |
| | Standard deviation (kg/ha) | 750 | 590 | 599 | 604 | 637 | 531 | 600 | 587 | 597 | 573 | 587 | 595 | 550 | 323 | 342 | 353 |
| | % diff from TRAD | | *-21.33* | *-20.13* | *-19.47* | | *-16.64* | *-5.80* | *-7.85* | | *-4.02* | *-1.68* | *-0.36* | | *-41.27* | *-37.82* | *-35.82* |
| H612 | Yield (kg/ha) | 1961 | 2054 | 2114 | 2165 | 1345 | 1504 | 1518 | 1568 | 1914 | 1982 | 2123 | 2216 | 2571 | 2605 | 2651 | 2662 |
| | % diff from TRAD | | *4.74* | *7.80*** | *10.40**** | | *11.82* | *12.86* | *16.57** | | *3.55* | *10.92* | *15.78** | | *1.32* | *3.11* | *3.54* |
| | Standard deviation | 733 | 617 | 641 | 601 | 523 | 559 | 670 | 610 | 683 | 468 | 413 | 357 | 399 | 186 | 149 | 151 |
| | % diff from TRAD | | *-15.83* | *-12.55* | *-18.01* | | *6.88* | *28.11* | *16.63* | | *-31.48* | *-39.53* | *-47.73* | | *-53.38* | *-62.66* | *-62.16* |
| STUKA | Yield (kg/ha) | 2540 | 2757 | 2885 | 2933 | 1605 | 1930 | 2152 | 2151 | 2439 | 2763 | 2846 | 2944 | 3500 | 3510 | 3596 | 3638 |
| | % diff from TRAD | | *8.54*** | *13.58**** | *15.47**** | | *20.25* | *34.08* | *34.02* | | *13.28*** | *16.69**** | *20.71**** | | *0.29* | *2.74* | *3.94* |
| | Standard deviation (kg/ha) | 1127 | 921 | 943 | 926 | 870 | 758 | 839 | 841 | 811 | 715 | 841 | 749 | 829 | 533 | 561 | 540 |
| | % diff from TRAD | | *-18.28* | *-16.33* | *-17.83* | | *-12.87* | *-3.56* | *-3.33* | | *-11.84* | *3.70* | *-7.64* | | *-35.71* | *-32.33* | *-34.86* |

Notes: the leftmost column is relative to all years (1984-2020) whereas the last three columns are relative to Dry, Normal, and Wet years. The stars next to the yield percentage difference are calculated by bootstrapping 10'000 repetitions with replacement: (*) significant at 90% confidence interval, (**) significant at 95% confidence interval, (***) significant at 99% confidence interval. The sample size used depends on scenario: "All years" n=35; "Dry" n=11 "Normal"; n=12; "Wet" n=12

Figure 5 GHACOF seasonal bulletin for precipitations, March-April-May 2020.

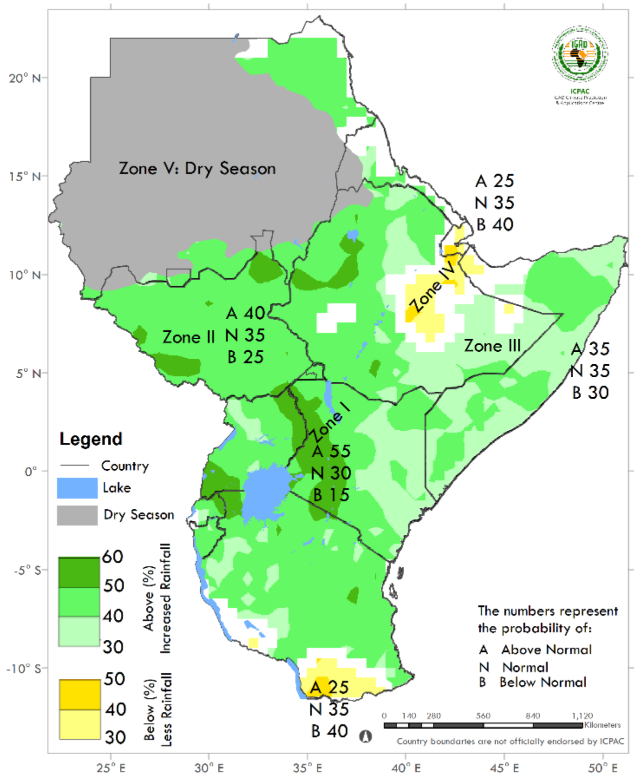
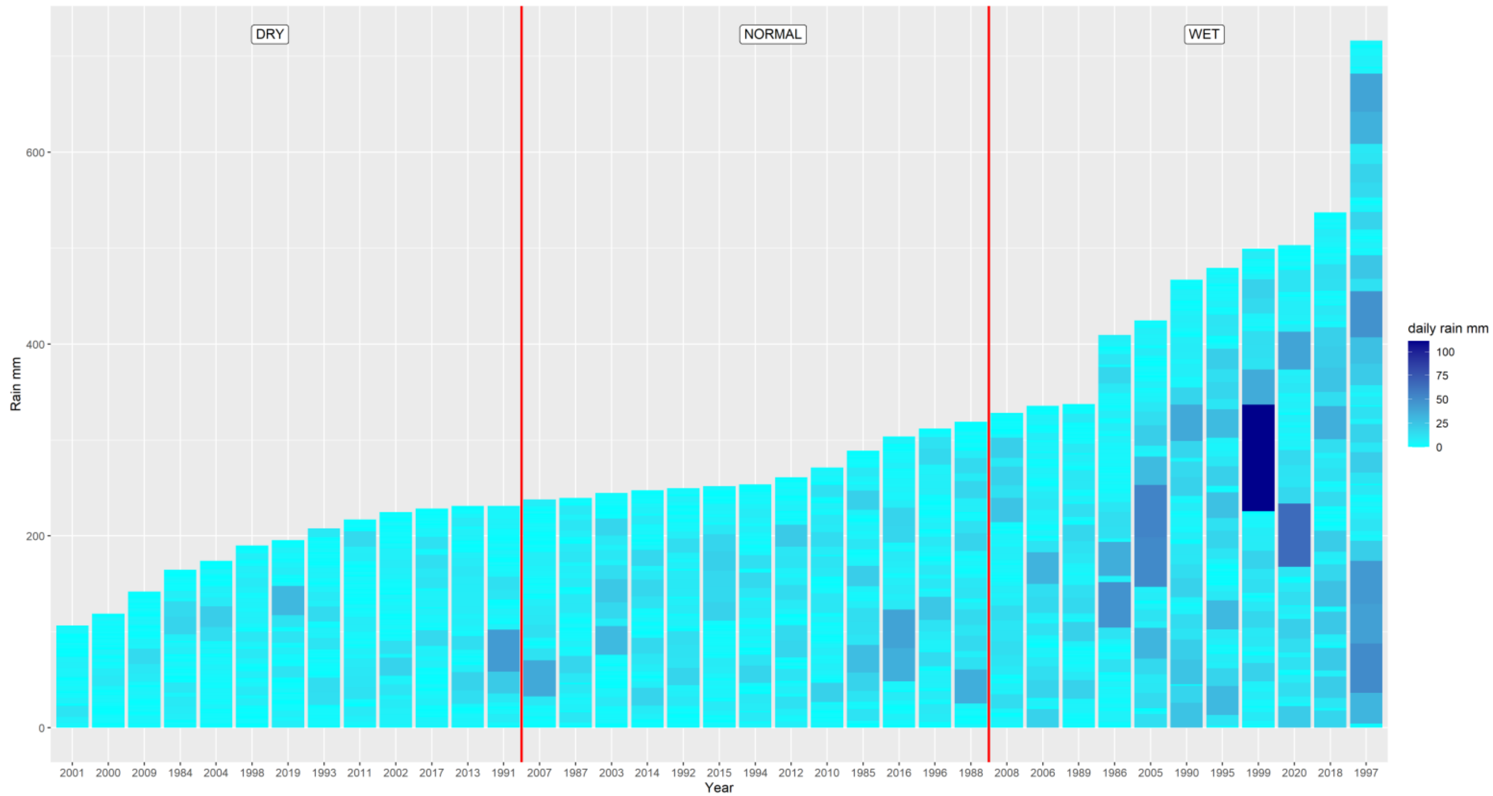



Figure 6 Cumulate precipitations in March-April-May 1984-2020.




Notes: colours and "brick height" mean daily precipitations intensity composition within each year.

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# The environmental impact of livestock adaptation to climate change


## Abstract

The livestock sector is a major contributor to global greenhouse gas (GHG) emissions through enteric fermentation and manure management. However, it is also highly susceptible to the effects of climate change, including rising temperatures, changing precipitation patterns and increased atmospheric $CO_2$ concentrations, which can affect mortality rates and feeding systems within the sector. Given its importance as an economic resource worldwide, it is crucial for the livestock sector to adapt to these new climatic conditions. Surprisingly, there is a lack of global assessment regarding the impacts of livestock adaptation in the existing literature. In this study, we use an agricultural economic model to observe farmers past choices in terms of intensity of livestock grazing on agricultural land, and project the future impact of adaptation in terms of GHG emissions. Under a medium development scenario for the period 2041-2060, we find a slight global increase in direct methane emissions (+0.14%) respect to 2010 levels. However, this overall increase is the result of significant differences between agricultural areas. In colder and wetter countries, agricultural conditions are expected to improve due to climate change, allowing for higher livestock grazing intensities. Conversely, agricultural conditions are projected to deteriorate in warmer and drier countries, resulting in reduced livestock grazing. These results highlight potential conflicts in the future for developed countries in the northern hemisphere with GHG reduction targets. On the other hand, developing countries in the tropics and subtropics, which have the greatest need for livestock production, may face increasing challenges due to climate change.



Keywords: Climate change, Global, Agriculture, Livestock, Adaptation, Agricultural economic model, Cattle, Sheep, Greenhouse gas emissions, Projections.

# Introduction

The livestock sector accounts for nearly 40% of the global agricultural gross domestic product and is a major source of employment for rural households (Thornton et al., 2010). It also accounts for 8% of global human water usage (Schlink et al., 2010) and plays a crucial role in the global dietary balance by providing 17% of kilocalories and 33% of protein consumption (Rosegrant et al., 2009). As populations and living standards are expected to grow in the future, particularly in developing countries, the pressure on the livestock sector will increase (Wright et al., 2012; UN, 2013). However, this sector both contributes to and is affected by climate change. The impacts, whether positive or negative, can vary significantly depending on local climatic and environmental conditions (Thornton et al., 2010).

The livestock sector is a significant contributor to global GHG emissions, accounting for more than 14% overall (Gerber et al., 2013; Caro et al., 2014). The primary sources of these emissions are associated with the feed production process, accounting for 45%, while enteric fermentation and manure management contribute about 50%. Among all livestock species, cattle are the largest contributors, accounting for 65%, while small ruminants such as sheep account for 6.5%. The emissions mainly consist of methane (CH4), which is over 25 times more effective than carbon dioxide ($CO_2$) in warming the atmosphere. Nitrous oxide ($N_2O$) and $CO_2$ from feed production and land use change also play a significant role (Opio et al., 2013).

Climate change affects the livestock sector, particularly grazing livestock, through rising temperatures, increased atmospheric $CO_2$ concentrations, and changes in precipitation patterns (Thronton et al., 2009 and Rojas-Downing et al., 2017 for a review). For example, rising temperatures in warmer regions can lead to increased mortality in grazing livestock, but they may also increase the growth rate of certain plant species, thereby increasing the availability of herbage in pastures. The effects of increased $CO_2$ levels can have both positive and negative consequences, as they can stimulate forage growth rates but potentially reduce their nutritional quality. Changes in precipitation patterns may lead to longer dry seasons or droughts. These effects may be amplified when combined with rising temperatures, as livestock may will require two or three times more water (Nardone et al., 2010).

The livestock sector needs to adapt to climate change, and there is a body of literature focused on understanding how it can respond to the new conditions. Adaptation strategies can be categorized into breeding, management, policy and institutional changes (see Rojas-Downing et al., 2017; Cheng, McCarl and Fei, 2022). Our focus is on the management system, which includes practices such as livestock diversification (Martin et al., 2020) and adjusting animal grazing intensity. However, it is important to note that the adaptation process may lead to unintended consequences and this vicious circle has been already noted in the literature. For instance, the adaptation can stimulate the shift between different agricultural land uses increasing water pollution (Fezzi et al., 2015; Bussi et al., 2017), or increasing agricultural land at the expense of forests, with negative implications for GHG emission reduction (Cohn et al., 2014; Lungarska and Chakir, 2018).

So far, there has been a lack of a global environmental assessment of the impact of livestock adaptation in the literature, despite the significant importance of this sector in both generating and being affected by climate change. However, there are a few studies in the literature that consider the intensity of livestock grazing in relation to climate change. For instance, Fezzi and Bateman (2011) found that adjusting the number of grazing animals per agricultural area is one way for farmers in the U.K. to maximise profit under new conditions. Similarly, Diaz-Solis et al. (2009) found that adjusting stocking rates can help reduce the impact of drought on cow-calf in Mexico, while Mu et al. (2013) found that cattle stocking intensity decreases as the Temperature-Humidity Index (THI)[31] rises and precipitation decreases in the U.S. summer. Adjusting livestock grazing intensity according to the new climatic conditions is also a way to avoid overexploitation and irreversible vegetation change of rangelands, especially in the case of semi-arid areas of the planet (Behnke and Scoones, 1993; Illius et al., 1998; Van de Koppel et al., 2002; Díaz-Solís et al., 2006).

Adaptation in the livestock sector also has the potential to contribute to the achievement of GHG emission reduction targets. Scholars such as Thornton and Herrero (2010) found that improved livestock management practices in tropical areas could contribute 7% of the global agricultural mitigation potential by 2030. Cohn et al (2014) suggested that intensifying livestock production on traditional lands can help mitigate deforestation and associated GHG emissions. In addition, Havlík et al (2014) highlighted the potential for significant emission reductions by transitioning to more efficient and less land-intensive livestock systems. However, it's important to note that livestock mitigation policies should be complemented by land use and

[31] The Temperature-Humidity Index (THI) is a measure that considers the combined effects of ambient temperature and relative humidity and is a useful and simple way of assessing the risk of heat stress (Dikmen and Hansen, 2009).

land-use change policies, which have been shown to be 5-10 times more effective in reducing GHG emissions than livestock-only policies (Hong et al., 2021).

Many developed countries have set ambitious goals for reducing GHG emissions, such as the Global Methane Pledge where over 120 countries have committed to reducing methane emissions by 30% by 2030, primarily in the livestock sector. This is in line with the European Union's target of reducing GHG emissions, particularly from livestock, through the implementation of the Effort Sharing Regulation (ESR) and the European Green Deal (EC, 2021). Similarly, New Zealand's Emissions Trading Scheme (ETS) aims to reduce methane emissions from ruminant by 24-47% by 2050, as outlined in the Zero Carbon Amendment Bill (New Zealand Government, 2019). It is therefore necessary to understand how, where and to what extent adaptation in the livestock sector aligns with these policies in order to maximise benefits and reduce areas of conflict with policies aimed at supporting adaptation.

In this study we model the relationship between livestock grazing intensity and climatic conditions on a global scale using an agricultural economic model. After estimating the parameters, we project how farmers will adapt to future climate changes and the resulting consequences in terms of methane emissions. Taking 2010 as the reference year, we project the effects of climate change globally with a spatial resolution of 5 minutes (about 10 km at the equator) using an ensemble of General Circulation Models (GCMs) for the period 2041-2060 and Socio-Economic Path 245 (SSP245). We found that methane emissions will increase by +0.14% overall, with significant differences between countries. Our study demonstrates that colder and wetter countries will experience improved agricultural conditions due to climate change, allowing for higher livestock grazing intensities. Conversely, warmer and drier countries will experience worsening agricultural conditions resulting in lower livestock grazing intensity.

The results of this work contribute to several strands of literature. It is the first to provide a quantitative and spatially explicit representation of where and to what extent the livestock sector will be affected by climate change on a global scale. This has implications for literature (and policies) addressing deforestation caused by livestock expansion in regions such as South America (Cohn et al., 2014; Oliveira Silva et al., 2016, da Siva et al., 2017). It also has implications for development policy in sub-Saharan countries and other underdeveloped nations (Ehui, 2000; Upton, 2004; Herrero et al., 2013; Bruhn, 2019) where there is a pressing need to increase productivity in the sector to address malnutrition and poverty. This work also contributes to the modelling of the interaction between climate change and livestock.

## Data

We use the spatial Gridded Livestock of the World (GLW 3) data from Gilbert et al. (2018) to model cattle and sheep grazing intensity of cattle and sheep, as they are the most representative ruminants globally for GHG emissions and presence (FAOSTAT, 2013).[32]

The aim of this study is to model how farmers determine livestock grazing intensity in agricultural land based on climatic conditions. To achieve this, we exclude observations that may represent landless farming or intensive livestock production systems, as these systems are often independent to local climatic conditions and can therefore introduce bias in the analyses. We use grazing intensity thresholds to identify these farming practices (Robinson et al., 2011). Specifically, we remove observations with more than 4 cattle per hectare and 20 sheep per hectare following previous approaches (e.g. Fezzi et al., 2015).

Similarly, we exclude irrigated agricultural areas and mixed irrigated livestock systems from the analysis, as they may also bias the results. Livestock production in these areas may be too positively influenced by irrigation infrastructure that is not strictly related to local climatic conditions. We use the complementary Livestock Production Systems dataset (Robinson et al., 2011) and the Global Map of Irrigated Areas v5.0 (Siebert et al., 2013) to exclude any mixed irrigation systems that may be erroneously included in the dataset.

To quantify livestock intensity on agricultural land, we incorporate the land use data from the European Space Agency (ESA) (available at http://maps.elie.ucl.ac.be/CCI/viewer/index.php). We consider two land use categories, cropland and grassland, to calculate the total agricultural area for each georeferenced tile. These land use categories include sub-classifications such as: a) rainfed cropland, b) mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%), c) mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%), d) mosaic herbaceous cover (>50%) / tree and shrub (<50%). The agricultural land per tile is then calculated by adding the areas of categories "a," "b," "c," and "d."

[32] The cattle intensity data encompass both beef cattle and dairy cows and we cannot distinguish them. Then, for the sake of simplicity, we will only refer to cattle hereafter.

The climatic variables, temperature and precipitation, are obtained from WorldClim (Fick and Hijmans, 2017) for the reference period of 1970-2000 and the future period of 2041-2060. These variables represent the mean annual temperature and total annual precipitation. To project the impact of future livestock intensity on global GHG emissions, we employ an ensemble of 12 General Circulation Models (GCMs) using the SSP245 scenario (a full list of GCMs can be found in the Appendix), which represents the intermediate sustainable scenario (IPCC, 2021).

Soil and terrain characteristics are derived from the IIASA/FAO (2010) web portal (available at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). The soil type variables include three categories: fine, medium, and coarse texture, which serve as proxies for soil quality. Additionally, we consider slope by including eight variables that represent the percentage within each georeferenced tile, ranging from flat terrain (1$^{st}$ category: slope ~ 0%) to very steep terrain (8th category: slope > 45%). We also control for elevation using the World Digital Elevation Model (ETOPO5) provided by the European Environment Agency.

Population density is obtained from the Gridded Population of the World, Version 4 (GPWv4), which represents the average number of people per km$^2$ for each georeferenced tile in 2010. We also incorporate the presence of main roads as a control variable using the spatial explicit road data provided by Meijer et al. (2018). Table 1 summarize all the data sources and uses.

Table 1 Data source, description and use.

| *Name* | *Description* | *Use* | *Reference* |
|---|---|---|---|
| *Gridded Livestock of the World* | *Number of cattle and sheep for each georeferenced tile in 2010* | *We use this data to compute the livestock grazing intensity* | *Gilbert et al., 2018* |
| *Livestock Production Systems* | *Livestock production system* | *We use this data to delete from the analysis all the mixed-irrigated livestock production areas* | *Robinson et al., 2011* |
| *Global map of irrigated areas v.5.0* | *Percentage of irrigated land within each tile* | *We use this information to delete from the analysis all the irrigated agricultural areas* | *Siebert et al., 2015* |
| *European Space Agency land use* | *Global land use data, 5-min of global resolution, 2010* | *We compute % of grassland and cropland for each georeferenced tile at global level* | *http://maps.elie.ucl.ac.be/CCI/viewer/index.php* |
| *Soil and Terrain characteristics, IIASA/FAO* | *Soil texture and slope* | *We account for these characteristics in regression analysis* | *https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/* |
| *World Digital Elevation Model* | *Terrain elevation* | *We account for this characteristic in regression analysis* | *ETOPO5, European Environment Agency* |
| *Gridded Population of the World* | *Average number of people per km$^2$, 2010* | *We account for this characteristic in regression analysis* | *CIESIN, 2018* |
| *Road and Highways* | *Km of main roads, 2010* | *We account for this characteristic in regression analysis* | *Meijer et al., 2018* |
| *WorldClim* | *Historical climatic values for temperature and precipitation (1970-2000) at 5-min of global resolution.* | *We use average historical temperature and precipitation in the regression analysis* | *Fick and Hijmans, 2017* |
| *WorldClim* | *Future climatic values for temperature and precipitation (2041-2060) at 5-min of global resolution.* | *We use these projections for the expected climate change impacts.* | *Fick and Hijmans, 2017* |

In assessing livestock GHG emissions, we focus on methane emissions from enteric fermentation and manure management. We intentionally disregard the other 50% of emissions from the feed system, which also includes the dynamics of land use and land use change. Our goal is to disentangle the effect of climate change on livestock grazing intensity, while keeping agricultural land use and other variables constant. To this purpose, we use the default emission factors provided in Chapter 10 of the IPCC Guidelines on Emissions from Livestock and Manure Management, as reported in Table 2 and Table 3 (IPCC, 2006). These resources provide the default emission factors in kg $CH_4$ head$^{-1}$ yr$^{-1}$ (annual methane emissions per head) for both sheep and cattle. The direct methane emissions from enteric fermentation have mixed effects depending on the region, as summarized in Table 2[33]. Manure management, on the other hand, depends on both the development status and temperature, with livestock raised in warmer and richer countries producing more methane compared to cooler and poorer regions (Table 3). For cattle, we have calculated average emissions between dairy cows and beef cattle, as we are unable to differentiate between the two in the livestock data. Hereafter, for the sake of simplicity, we will refer to methane emissions as the only GHG emission from the livestock sector.

Table 2 Enteric fermentation emission factors.

| Animal | Region or developing status | CH4 emission factors kg (head$^{-1}$ yr$^{-1}$) by region or developing status |
|---|---|---|
| Cattle | North America | 90.5 |
| | Western Europe | 87 |
| | Eastern Europe | 78.5 |
| | Oceania | 80 |
| | Latin America | 64 |
| | Asia | 57.5 |
| | Africa and middle east | 38.5 |
| | Indian subcontinent | 42.5 |
| Sheep | Developed countries | 8 |
| | Developing countries | 5 |

Source: own elaboration from table 10.10 and 10.11 of IPCC guidelines for livestock emission (IPCC, 2006).

[33] It depends on the quality of feed intake, and livestock produced in developed countries produce more methane than those raised in developing ones.

Table 3 Manure management emission factors.

| | Region or developing status | CH4 emission factors kg ($head^{-1}$ $yr^{-1}$) by average annual temperature (°C) | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ave. annual temp. | | ≤10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | ≥28 |
| Cattle | North America | 24.5 | 25.5 | 27 | 28 | 29.5 | 32.5 | 33.5 | 35 | 36 | 38 | 40 | 41.5 | 43.5 | 45.5 | 47.5 | 50 | 53.5 | 56 | 57 |
| | Western Europe | 13.5 | 15 | 16 | 17.5 | 18.5 | 22 | 24 | 26 | 28 | 30.5 | 33 | 35.5 | 38 | 41 | 45 | 48 | 53.5 | 57.5 | 59 |
| | Eastern Europe | 8.5 | 9 | 10 | 10.5 | 12.5 | 14.5 | 15.5 | 16.5 | 17 | 18.5 | 20 | 21 | 22.5 | 24.5 | 26.5 | 28 | 31.5 | 34 | 34.5 |
| | Oceania | 12 | 12.5 | 13 | 13.5 | 13.5 | 14.5 | 15 | 15 | 15 | 15.5 | 15.5 | 15.5 | 15.5 | 15.5 | 16 | 16 | 16.5 | 16.5 | 16.5 |
| | Latin America | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.5 | 1.5 | 1.5 |
| | Africa | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Middle east | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 2 | 2 |
| | Asia | 5 | 5.5 | 5.5 | 6 | 6.5 | 7 | 7.5 | 8 | 8.5 | 9 | 9 | 10.5 | 11 | 12 | 12.5 | 13.5 | 14.5 | 16 | 16 |
| | Indian sub-continent | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 3.5 | 4 | 4 |
| Sheep | Developed countries | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.37 | 0.37 | 0.37 |
| | Developing countries | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.20 | 0.20 | 0.20 |

Source: own elaboration from table 10.14 and 10.15 of IPCC guidelines for livestock emission (IPCC, 2006).

## Theoretical framework and Method

The theoretical agricultural production model we adopt to model farmers' decisions is derived from a strand of research in agricultural economics and has been previously used in the literature (Fezzi and Bateman, 2011; Fezzi et al., 2015). We assume that farmers choose livestock intensity in order to maximize profits, considering environmental characteristics, climate, costs and prices, and a variety of other constraints.

For estimation, we specify the empirical profit function per unit of land as a Normalized Quadratic. We indicate with $w_n$ the numeraire good, with $\mathbf{x} = (\frac{p}{w_n}, \frac{w}{w_n})$ the vector of normalized input and output prices, with $\bar{\pi} = \frac{\pi}{w_n}$ the normalized profit function per unit of livestock, with $\mathbf{z}^*$=(z) the vector of fixed factors, which include policy, environmental and climatic conditions. The profit function is then defined as:

$$\bar{\pi} = \alpha_0 + \sum_{i=1}^{m+n} \alpha_i x_i + \frac{1}{2} \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} \alpha_{ij}\, x_i x_j$$

Output (livestock) intensities, that are the main focus of our analysis can be derived via Hotelling's Lemma. For instance, if $x_i$ indicates the normalized price of cattle, the equation corresponding to cattle intensities ($Y_i$) can be derived as:

$$\frac{\delta\pi}{\delta x_i} = Y_i = \alpha_i + \sum_{j=1}^{m+n} \alpha_{ij}\, x_j$$

and we allow the parameter $\alpha_i$ to be a function of the environmental, climatic and physical characteristics of the farm as:

$$\alpha_i = \alpha_{i0} + \sum_{n=1}^{k} \alpha_{ij}\, z_j^*$$

The variable vector $z^*$ includes physical environmental characteristics such as altitude, slope, soil texture, population, major roads and climatic variables (average annual precipitation and temperature). We control for any unobserved variables such as prices, costs and policy constraints that vary with space by including spatial fixed effects. These fixed effects are created by overlapping a spatial grid cell of 2°x2° at the global level. We do not use administrative boundaries because of the different extent of the latter among countries[34]. Climatic variables are represented by linear regression splines, both for total precipitation and mean annual temperature. Accordingly, we capture the non-linear relationship in the precipitation function breaking at 300, 600, 900, 1,200 and 1,800 mm of precipitation and temperature at 8, 15 and 25 °C. Finally, we consider an interaction effect between precipitation and temperature to consider the non-independent behaviour of the main climatic variables.

For the econometric specification we use a Tobit model that is suited in presence of censored data (Tobin, 1958). This approach is necessary recalling that in the profit maximization problem, the optimal livestock densities per each animal must be equal to the livestock intensities shadow prices of alternative uses. Then, censoring from below at 0 implies that the corresponding livestock intensity shadow price is lower than those of alternative uses. The observed livestock intensity $Y_i^*$ is therefore specified as $Y_i$ = 0 if $Y_i^* \leq 0$ and $Y_i$ = $Y_i^*$otherwise.

To avoid spatial autocorrelation, we estimate the model using a sample of the entire dataset, avoiding sampling contiguous cells. This is defined by selecting one georeferenced tile every fourth grid cell along both the latitude and longitude axes (Fezzi and Bateman, 2011) (Appendix, Figure 5).

To obtain an estimate of the GHG emissions we multiply the livestock densities by the agricultural land extent within each grid cell. We assume that each tile is equal to 10x10km, i.e. 100km$^2$ (10'000 hectares). Moreover, in creating our projections we assume that all the parameters except temperature, precipitation and livestock intensities will remain fixed at reference level.

## Estimation results

In Table 4 we report the main results of regression analysis, whereas in Figure 1 we show the estimated impact of precipitation and temperature on cattle and sheep grazing intensity.

[34] For example, the average size of administrative regions in Southeast Asian countries such as Cambodia, Laos, Vietnam and Thailand is 7,500 km$^2$, while the average size of administrative regions in the United States and Canada is more than 300,000 km2

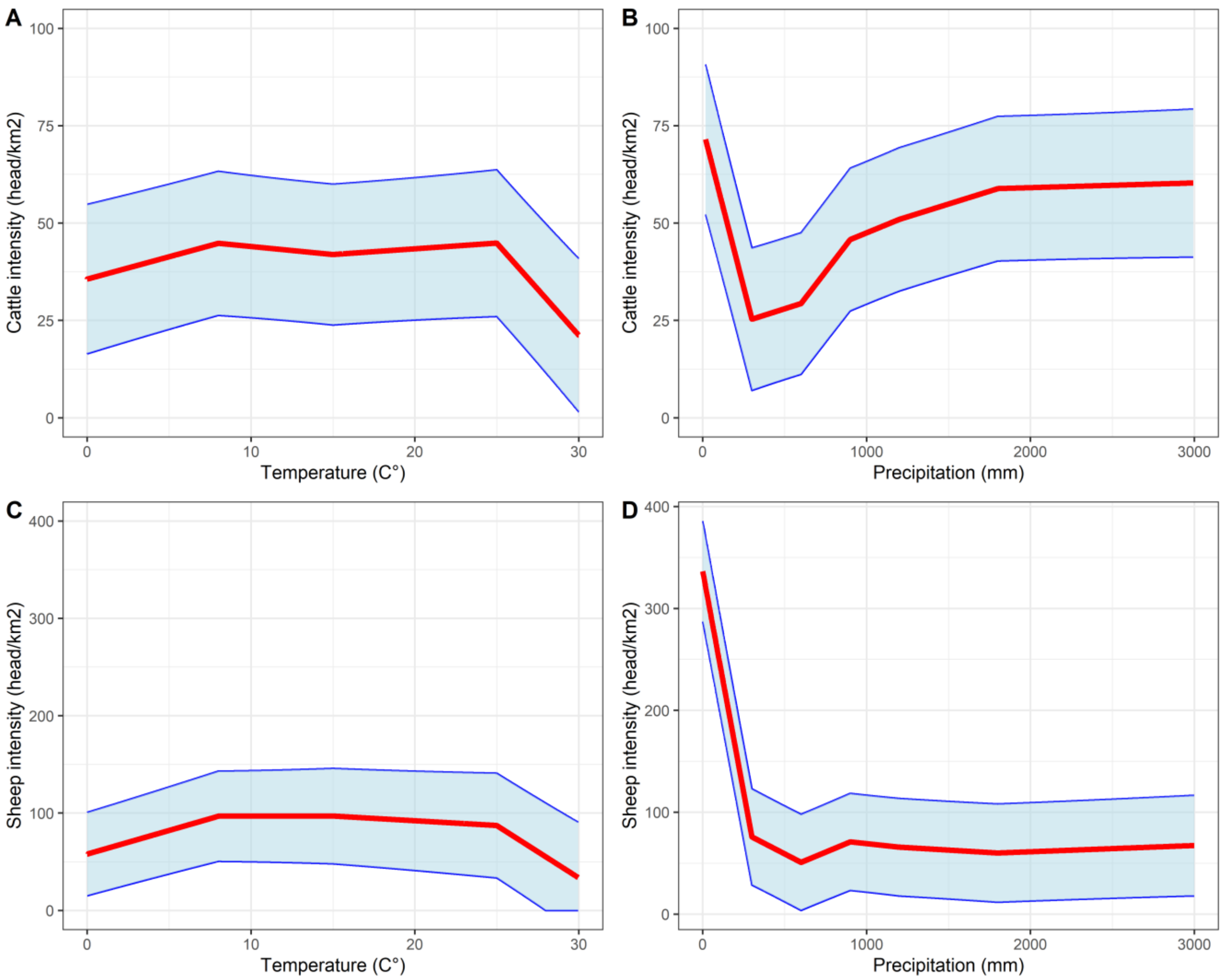
Table 4 Livestock densities model's estimates

| | Cattle head/km$^2$ | Sheep head/km$^2$ |
|---|---|---|
| Prec * Temp | -0.000201* | -0.000208 |
| Temp | 1.313*** | 5.031*** |
| Temp > 8 °C | -1.561*** | -4.832*** |
| Temp > 15 °C | 0.706 | -0.995 |
| Temp > 25 °C | -5.021*** | -9.771*** |
| Prec | -0.161*** | -0.866*** |
| Prec > 300mm | 0.177*** | 0.786*** |
| Prec > 600mm | 0.0414*** | 0.150*** |
| Prec > 900mm | -0.0375*** | -0.0843*** |
| Prec > 1'200mm | -0.00417 | 0.00785 |
| Prec > 1'800mm | -0.0119*** | 0.0157 |
| 0% < Slope < 0.5% | -0.0287 | -0.0553 |
| 0.5% < Slope < 2% | -0.211*** | -0.253*** |
| 2% < Slope < 5% | -0.216*** | 0.0203 |
| 5% < Slope < 10% | -0.178*** | -0.492*** |
| 10% < Slope < 15% | -0.0623 | 0.156 |
| 15% < Slope <30% | -0.00812 | -0.235* |
| 30% < Slope <45% | 0.418*** | 0.161 |
| 250mt > Elev < 500mt | 0.332 | 6.107*** |
| 500mt > Elev < 1'000mt | -0.692 | 11.52*** |
| 1'000mt > Elev < 1'500mt | 2.156 | 15.60*** |
| 1'500mt > Elev < 2'000mt | -6.909*** | 9.579* |
| Elev > 2'000mt | -11.11*** | 3.308 |
| Fine soil | -0.598 | -8.150*** |
| Medium soil | -0.773 | -6.649*** |
| Main roads | -0.0311*** | -0.0358*** |
| Population | -0.00841*** | -0.0243*** |
| Constant | 60.18* | 313.9*** |
| Ret. fix effects | YES | YES |
| Var | 2'611.2*** | 19'006.5*** |
| Pseudo R-sq | 0.037 | 0.028 |
| N°† | 118'202 | 127'955 |

*Notes: * p<0.05, ** p<0.01, *** p<0.001.*

†: *The number of observations differs between the two estimated models because we used different grazing density*

Figure 1 Estimated impact of total precipitation and average temperature during the whole year on livestock and sheep densities.




Notes: red lines indicate estimated relations, blue lines and shadow area indicate the 95% asymptotic confidence intervals. All other explanatory variables are fixed at the sample means.

We see an inverted U-shaped relationship between livestock grazing intensity and mean temperature for both animals. Although both animals are sensitive to temperature, they show a good range of adaptability. Significant variations in density are only observed at extreme temperatures. This can be attributed to the wide range of breeds considered within each animal category, including both cattle (dairy) and sheep, which are well adapted to local climatic condition. For example, there are more than 1,000 recognised breeds of cattle worldwide (Felius, 1995). Farmers increase livestock density with increasing mean temperature in extremely cold regions (Temperature < 8 °C). This is probably because in cooler areas, as the average temperature increases, there is more forage available for grazing livestock and farmers can rely on longer growing seasons. At very low mean temperature (Temperature ~ 0 °C), sheep appear to suffer more than cattle. However, their density increases more rapidly, as indicated by the relatively lower starting points in Figure 1 (around 50 head/km$^2$ for at 0 °C) and the larger temperature parameter (+5.03). This can also be attributed to the higher average number of sheep flocks compared to cattle (Figure 1: A, C). With increasing temperatures (Temperature > 8 °C), the presence of both species stabilises, but rapidly decreases when the mean temperature exceeds 25 °C. Above this temperature, both livestock intensities decrease, although cattle appear to be more sensitive. This is evident from the significantly steeper negative slope of the estimated relationship line in Figure 1 (A) compared to sheep. The sheep grazing intensity also decreases above 25 °C, but to a lesser extent.

Precipitation is even more important than temperature in explaining global grazing livestock density, as evidenced by the magnitude of the parameters and shapes of the estimated relationships in Figure 1 (B, D), which appear to be more reactive compared to temperature response. In regions with extremely low precipitation, the presence of cattle and sheep is very high, which can be attributed to the difficulty of cultivating crops. Sheep, in particular, seem to be more resistant than cattle in very dry areas, which explains their massive presence in arid and semi-arid regions, such as sub-Saharan Africa (Gilbert et al., 2018). As average precipitation increases, the density of both species decreases rapidly. This may be due to the improvement of agricultural conditions for other purposes such as cropping; both precipitation parameters are negative and statistically significant. Then, density then starts to increase again after 500-600 mm of average annual precipitation, especially for cattle. On the other hand, sheep densities continue to decrease at higher levels of precipitation (up to 600 mm) and then remain stagnant, indicating that even under more favourable precipitation conditions sheep are not very an attractive option for farmers. On the contrary, "Precipitation > 300 mm" and "Precipitation > 600 mm" are positive and statistically significant for cattle densities up to 1,200 mm. However, at very high precipitation levels (Precipitation > 1,800 mm), livestock densities for both species become relatively stable, and the estimated relationships become flatter. This means that a marginal increase in precipitation thereafter has practically no effect on livestock densities, although cattle density remains significantly high. This suggests that in high precipitation areas, where cropland may become less profitable, livestock may be a valuable alternative again. From these results, it seems that cattle (and dairy cows) play a more important role as precipitation increases, while sheep seem to be better suited as a buffer strategy in extremely dry conditions as their density does not significantly increase from 300mm. Additionally, the interaction term between precipitation and temperature is negative for both species (although not statistically significant for sheep), indicating that wetter and hotter areas reduce livestock grazing density.

The slope of the land is a key factor in determining the presence of cattle and sheep. When interpreting the results in Table 4, it is important to consider the omitted categorical variable "Slope ≥ 45%", which represents very steep terrain. The statistical significance varies more among the terrain categories only for sheep. Flatter agricultural land is more suitable for arable farming than livestock, as it allows for easier work with tractors and the use of large plots for intensive farming. Conversely, hilly land is more suitable for livestock farming (Ravi et al., 2023), which explains why, especially cattle, are more prevalent in slopes between 30% and 45%. These results may also reflect the exclusion of landless and intensive livestock farming from the analysis, as these types of farming are often located in flatter agricultural areas.

Elevation is also an important factor in determining the presence of livestock. Cattle are more commonly found at lower elevations, while sheep tend to graze at higher elevations. Once again, it is important to consider the omitted categorical variable “Elevation <= 250mt” when interpreting the results.

Soil quality is another important explanatory variable for livestock intensity. Finer soils are less likely to support high livestock densities compared to coarse soils, which are more suitable for grazing than for cropping. Additionally, the presence of roads and population density have a statistically significant impact on reducing livestock presence.

## Future projections

After estimation, we assess the fit and predictive ability of our model by performing out-of-sample prediction tests (Appendix, Table 6, Figure 6, and Figure 7). Our model captures a significant portion of the variability in the original data, as evidenced by our lower RMSE (Root Mean Squared Error) compared to the original standard deviation (Appendix, Table 6). We also observe the goodness of fit of our models by plotting the spatial patterns between the observed cattle and sheep densities in 2010 and the predicted densities for the same year using the estimated parameters shown in Table 4 (Appendix, Figure 6 and 7). The main difference between the maps is that our map distributes livestock density more evenly and smoothly across the given geographical area, in contrast to the original layer which shows concentrated density peaks.

Figure 2 shows the total difference in GHG emissions from 2010 to 2041-2060 in the SSP245 scenario, using the estimated parameters outlined in Table 4. Overall, global methane emissions could increase by more than 150 thousand tonnes in 2041-2060, i.e. an increase of about +0.14% compared to 2010. However, there are great differences between countries. Regions with hot and dry climates, such as the tropics and subtropics, may experience a decrease in emissions, due to worsening grazing conditions for livestock. Conversely temperate and continental areas are likely to see an increase in agricultural suitability for livestock, leading to an increase in GHG emissions. Notably, there is a clear distinction between North American continent, Europe, Russia and China and the tropical belt countries. Specifically, the U.S. is interested by contrasting effects with southeast states (e.g. Florida, Georgia, and Arkansas) negatively affected by climate change while west and northern states (e.g. Washington and Oregon) positively affected. Similarly, in the European continent, southern countries (e.g. Italy, France, Greece) are predicted to suffer more than northern countries such as Germany, U.K. and Poland. These differences are even more pronounced in the case of the Asian continent, where China and Russia are expected to increase livestock grazing densities and hence GHG emissions, while India and the whole of South-East Asia are expected to reduce grazing densities consistently. Canada, South Africa, Argentina and the Scandinavian countries, which have significantly lower temperatures and/or higher precipitation, appear to benefit almost entirely from climate change, while hotter and/or drier regions such as Central America, Brazil and sub-Saharan Africa will be severely affected.

Figure 2 Difference in total livestock methane emissions in 2041-2060 respect to 2010, scenario SSP245

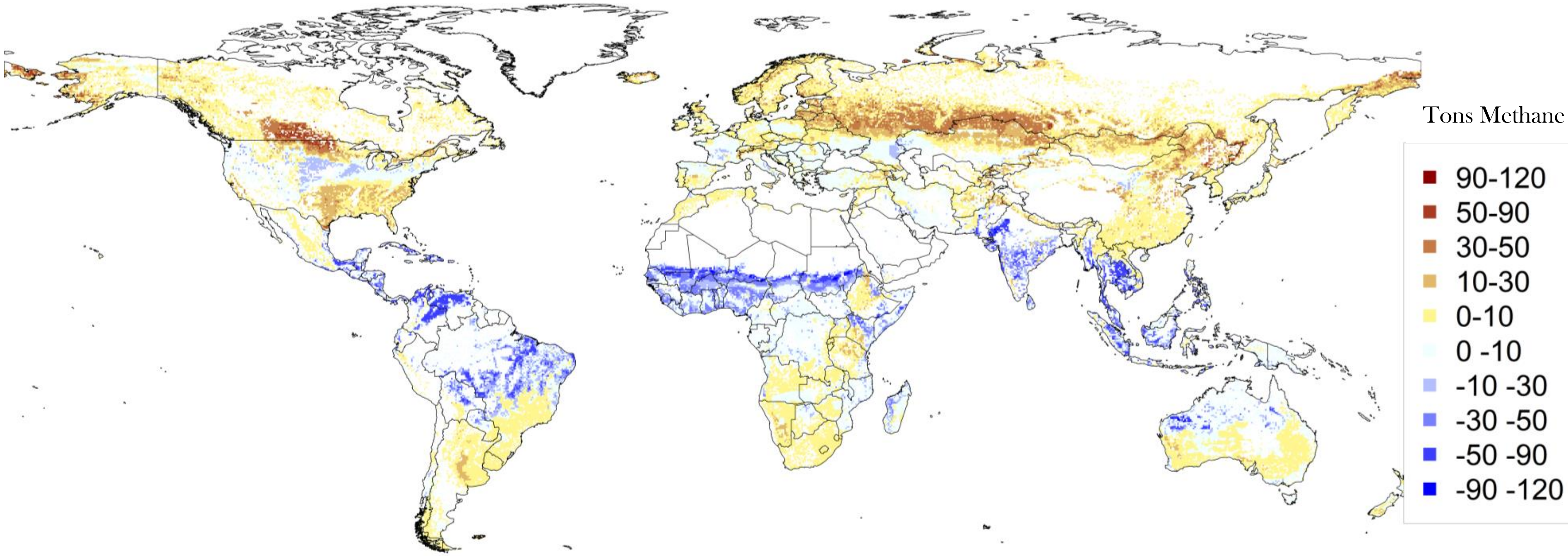


Table 5 shows the mean livestock grazing intensity per animal and total emissions by macro regions for the reference period 2010 and the projected period of 2041-2060. In 2010, economically developed regions such as North America, Europe and Oceania have higher densities of grazing cattle compared to regions such as Africa, Asia and the Middle East. North America has the highest cattle grazing rates at 16.54 head per $km^2$. Conversely, poorer and warmer regions tend to have higher densities of grazing sheep, with the Middle East reaching a peak of 44 sheep per $km^2$. On the other hand, when considering total GHG emissions, Latin America emits the most GHGs, due to the combination of high livestock intensities and huge agricultural extension. Looking at the differences in the 2041-2060 period, almost all developed regions, except Oceania, are expected to experience an increase in livestock grazing intensity and total GHG emissions. By contrast, all other areas are projected to face a decrease in both livestock grazing intensity and GHG emissions. The largest increase in GHG emissions is expected in Eastern Europe, where the combination of increased precipitation and temperatures (Appendix, Figure 8) will lead to 25% increase in GHG emissions. Conversely, the African continent shows a reduction in emissions of over 10%, confirming that countries in the tropical and subtropical belt may face the highest costs from climate change in terms of livestock suitability.

Table 5 Mean livestock intensity and total emissions in 2010 and 2041-2060.

| | Mean cattle grazing intensity 2010 (head/km$^2$) | Mean sheep grazing intensity 2010 (head/km$^2$) | Tot emissions from livestock 2010 (thousands of tonnes, methane) | Mean cattle grazing intensity 2041-2060 (head/km$^2$) | Mean sheep grazing intensity 2041-2060 (head/km$^2$) | Tot emissions from livestock 2041-2060 (thousands of tonnes, methane) |
|---|---|---|---|---|---|---|
| North America | 16.54 | 8.64 | 15'025 | 19.36 | 16.53 | 16'148 (+7.47%) |
| Western Europe | 9.14 | 7.25 | 7'921 | 10.66 | 11.67 | 8'116 (+2.46%) |
| Eastern Europe | 12.02 | 8.55 | 7'912 | 15.21 | 17.77 | 9'926 (+25.45%) |
| Oceania | 15.68 | 29.19 | 5'942 | 14.02 | 25.02 | 5'770 (-2.89%) |
| Latin America | 11.26 | 14.24 | 28'589 | 10.24 | 13.25 | 27'030 (-5.43%) |
| Africa | 8.64 | 19.8 | 16'409 | 8.05 | 17.85 | 14'638 (-10.8%) |
| Middle east | 6.76 | 44.29 | 1'935 | 6.28 | 42.5 | 1'906 (-1.5%) |
| Asia | 6.47 | 22.06 | 15'004 | 6.39 | 22.10 | 15'411 (+2.71%) |
| Indian sub-continent | 4.56 | 7.30 | 5'905 | 4.31 | 6.62 | 5'484 (-7.13%) |

Notes: percentage differences for total GHG emissions are in brackets below the absolute value.

As mentioned in the "Data" section, emissions from manure management are temperature-dependent (Table 3), and livestock raised in warmer (and richer) countries emit more GHGs than those raised in colder (and poorer) countries. Therefore, in addition to showing the final effect given by the sum of the change in livestock density and the increase in temperature (and precipitation variation), we distinguish between the two effects in Figure 3 and Figure 4 to better observe the contribution of each in determining the final result.

Figure 3 shows the effect of climate change on livestock emissions, specifically focusing only on the variation in temperature while keeping all other parameters and livestock densities constant in 2010. Global emissions will increase by over 500 thousand tonnes of methane, representing an increase of approximately +0.55%. This increase is primarily attributed to rising temperatures in colder countries, specifically Europe, North America and China (darker areas). Intuitively, it is logical to anticipate only positive changes, as the average annual temperature is predicted to rise worldwide (Appendix, Figure 8).

Figure 3 Differences in livestock methane missions in 2041-2060 caused only by temperature variation, keeping constant the livestock density in 2010.

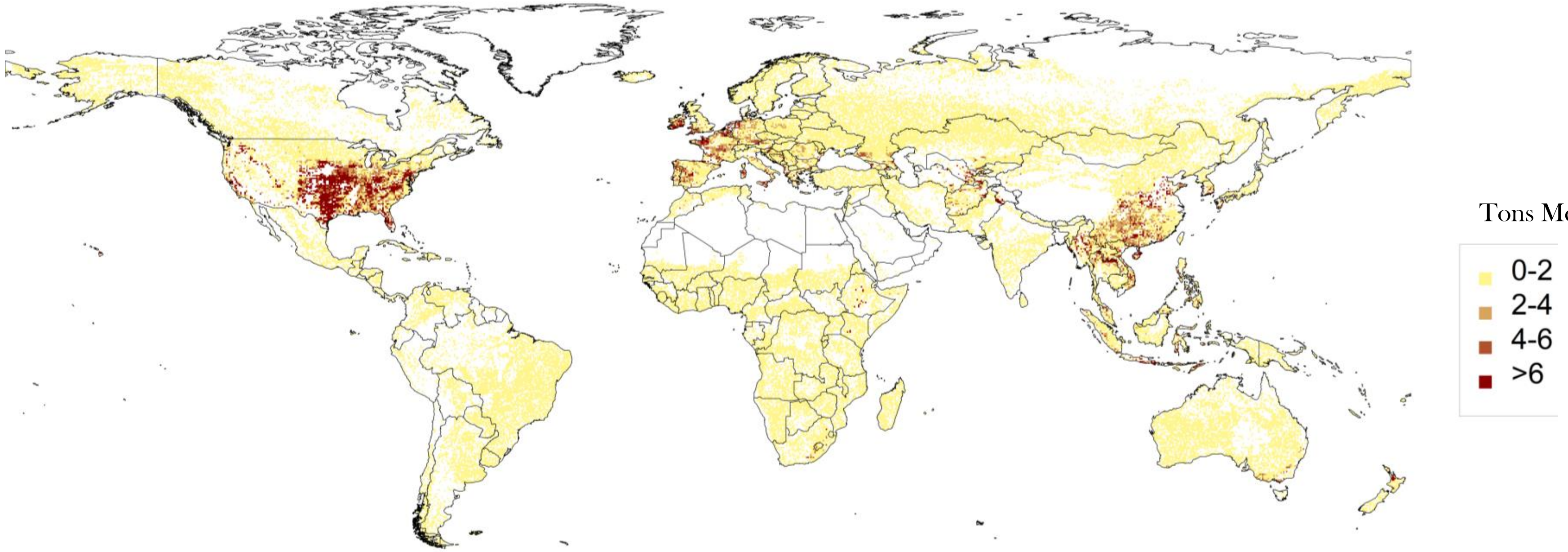
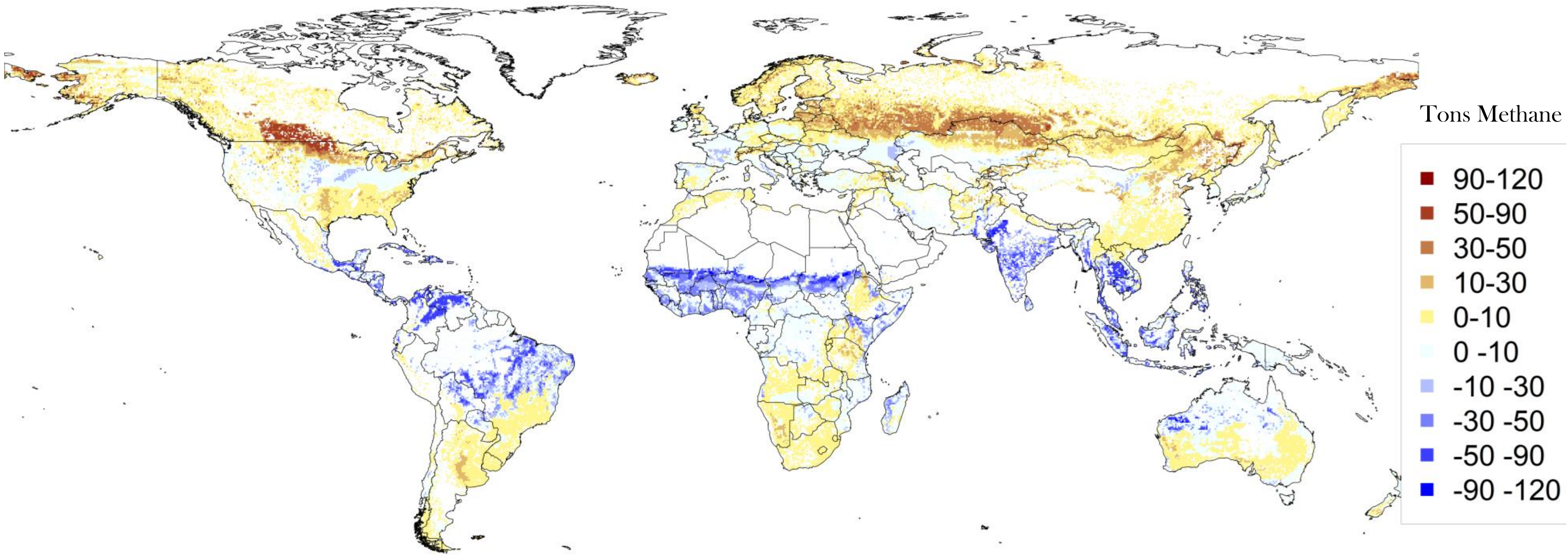


Figure 4 shows the differences in 2041-2060 of methane emissions from changes in grazing livestock density only (using the parameters estimated in Table 4), while keeping the manure management emission factors at 2010 levels. Most tropical and subtropical areas, where temperatures are very high and precipitation very low (Appendix, Figure 8), projected methane emissions could decrease due to the expected reduced capacity of agriculture to sustain grazing livestock. Conversely, in colder and/or wetter countries, as indicated by the parameters in Table 4, emissions could increase as environmental conditions improve and farmers potentially increase grazing livestock. Globally, emissions decrease by more than 400 thousand tonnes of methane, resulting in a reduction of about -0.4%. This map is quite similar to Figure 2, as the density of grazing livestock is the most influential driver of changes in GHG emissions.

Figure 4 Differences in livestock methane missions in 2041-2060 caused only by livestock intensity variation, keeping constant manure management emission factors in 2010.



## Discussion

The results presented above are consistent with other studies in the same strand of literature that consider the direct effects of climate change on livestock (see Thronton et al., 2009 and Rojas-Downing et al., 2017 for a review). Our findings regarding the effect of temperature confirm earlier studies by McDowell (1972) and Hahn (1999) which found that the optimal temperature range for livestock suitability is around 5-25° C. Within this temperature range, the authors observed no significant problems with feed intake and physiological processes in livestock. However, it is important to note that optimal temperature range for livestock can be influenced by adapted breeds. Hahn et al. (1992) and Sirohi and Michaelowa (2007) found that extreme temperatures, especially in summer, rapidly reduce agricultural suitability for livestock, as also evidenced by the temperature relation we found in Figure 1 (A, C). The work by Howden et al. (2008) also supports our main findings, as they reported that temperature increases between 1 and 5 °C could induce high mortality in grazing cattle, which are more affected by climate change than confined animals (Rotter and van de Geijn, 1999). According to our results, this is particularly true in regions where the temperature baseline is already high, such as tropical countries.

Mu et al. (2013) found similar findings related to the impact of direct heat stress on livestock. They discovered that as the summer temperature-humidity index (THI) increases and precipitation decreases in the U.S., the number of livestock decreases. They also observed that farmers tend to favour cropland over pasture as temperature and precipitation increase. Mu et al. also predict that these changes will be more pronounced in the central and southeastern regions of the U.S., confirming the spatial patterns shown in Figure 2. Although they examine a very different area for both climatic and socio-economic reasons, Seo et al. (2009) predict similar effects in sub-Saharan Africa, where warmer and drier climate will favour livestock over crop production. Their findings show that by 2100 cattle numbers will decline, but ruminants such as goats and sheep will increase. This result can be explained by the fact that sheep are better adapted to lower precipitation and higher temperatures than cattle, as shown in Figure 1.

Our results show that in regions with poor precipitation, the presence of livestock is very high, which can be attributed to the challenge of cultivating crops. This result is in line with previous research on the role of livestock in arid and semiarid regions, where pastoralism and agropastoralism are major sources of livelihood (McCown, Haaland and Haan, 1979; Ogutu et al., 2008; Serè et al., 2020; Mudzengi et al., 2020). On the contrary, the density decreasing we observe after this initial peak in Figure 1 (B, D) may be due to the exclusion of landless livestock from the analysis. In these intermediate conditions, livestock are likely to be raised in confinement, as farmers profit more from intensive cultivation than from grazing livestock on pastures.

The demand for livestock products in developing countries is expected to double in the coming years due to rising living standards and population growth (Garnett, 2009; Alexandratos and Bruinsma, 2012). Our projections show that many of these countries, particularly those in the sub-Saharan belt, will experience a significant deterioration in livestock grazing conditions. Although we consider a medium development scenario and a relatively short time horizon, we anticipate that these countries will struggle to meet the increasing demand for meat and dairy products. This increase in demand is expected to pose significant challenges, particularly in terms of the cost of livestock production, which could affect the balance between productivity, food security and environmental protection (Wright et al., 2012). To meet the growing demand, farmers may face pressure to intensify production through methods such as landless and intensive farming, potentially leading to increased resource use, deforestation and associated GHG emissions. The potential expansion of landless or intensive farming practices is not only environmentally damaging (Steinfeld et al., 2006), but also requires substantial investment (McDermott et al., 2010), making these practices less viable for the poorest. However, Havlík et al. (2014) argue that less land-intensive livestock systems can reduce deforestation and GHG emissions, suggesting that there may be some trade-offs between the two forces. This may be critical in areas such as the Amazon, where deforestation caused by livestock expansion threatens the sustainable use of local and global resources (e.g. Hecht, 1993; Barona et al., 2010). Our projections suggest that the intensity of livestock grazing in the Amazon will worsen, and that a landless livestock production system could potentially be more beneficial for livestock production and reducing GHG emissions. This interpretation is consistent with de Oliveira Silva et al. (2016), who argue that beef production could reduce GHG emissions in Brazil if decoupled from deforestation.

By contrast, grazing conditions are likely to improve in more developed areas, with mixed implications for GHG mitigation plans and livestock producers. For example, our projections suggest that grazing conditions will improve in the U.K. and Canada, allowing for more livestock to be grazed per unit of land. This may conflict with the GHG mitigation plans, such as Canadian Greenhouse Gas Offset Credit System Regulations, and the UK Net Zero Growth Plan, to which these countries have committed. On the other hand, our findings support recent consumer trends for livestock-related products, particularly in Europe. Due to ethical and environmental concerns, a growing proportion of European consumers tend to favour environmentally friendly livestock production systems, such as grazing animals on pasture and rangeland, over landless intensive production (Stampa et al., 2020; Canavari and Coderoni, 2020). The improved expected grazing conditions can therefore be beneficial for inland and continental parts of Europe, including Germany, Austria, Poland and the Czech Republic. Increasing grazing livestock in a sustainable way can also be an important economic and environmental resource for marginal lands, also known as "high nature value grasslands", in the European Union (IEEP, 2007).

There are some limitations to our work that need to be considered when commenting on the final results. Firstly, we have chosen to exclude landless production and/or mixed irrigation systems from our analysis. This implies that even if environmental conditions reduce the capacity of agricultural land to support high livestock grazing rates in some areas, farmers may still be compelled to adopt intensive livestock production. In these areas, the presence of livestock, and therefore GHG emissions, may still increase. Moreover, landless and intensive agriculture is known to be highly polluting as well (Steinfeld et al., 2006), further increasing the negative environmental externalities of this sector on the surrounding environment. Secondly, we have only modelled cattle and sheep grazing densities. However, several other animals such as pigs, goats, horses, poultry and buffalo also have an important impact on GHG emissions. Including these animals in the assessments is necessary to obtain a complete picture of GHG emissions from the livestock sector as a whole (Vergè et al., 2009; Marino et al., 2016; Dennehy et al., 2017). Thirdly, we keep some key variables constant at their 2010 levels in our projections but some of them are likely to vary in the future. Both enteric fermentation and manure management emissions are strongly influenced by a country's economic status, and it is possible that some countries may achieve higher levels of economic development in the future, resulting in higher quality livestock feed intake and higher GHG emissions. The extent of agricultural land is expected to increase in the future, particularly in the northern hemisphere, due to changing climatic conditions that will make these areas more suitable for agricultural purposes and therefore also for livestock (Zabel et al., 2014; Di Paola et al., 2018). Lastly, we only model 50% of total emissions, disregarding other sources such as emissions from the feed production process, land use, and land use change. Gerber et al. (2013) estimate that emissions from feed production, processing and transport account for about 45% of livestock-related emissions. Within this category, 25% of total GHG emissions are attributed to land use change. The conversion of grassland to arable land leads to increased GHG emissions into the atmosphere. Extensive research has focused on understanding the different impacts of these conversions, not only in terms of GHG emissions (e.g. Searchinger et al., 2008; Wright and Wimberly, 2013; Zhang et al., 2021). In regions where improvements in grazing conditions, and thus an increase in livestock intensity, could be observed in the future, a higher rate of conversion from grassland to cropland could also be observed.

## Conclusions

The livestock sector is one of the largest contributors of GHG emissions to the atmosphere. At the same time, it is affected both directly and indirectly by climate change. It is also a sector of great economic significance, as it is crucial for ensuring global food security and economic development. Consequently, understanding how famers will adapt to climate change in the future is fundamental for developing appropriate policies that allow economic and environmental sustainability to coexist.

This work highlights how different livestock species respond non-linearly and differently to the same climatic conditions and suggests that future impacts of adaptation to climate change may vary across climatic regions. Countries with higher baseline temperatures are likely to experience worsening climatic conditions, leading to a potential reduction in livestock grazing intensity and GHG emissions. Conversely, countries with low baseline temperatures may experience an improvement in climatic conditions for agriculture, leading to an increase in grazing potential and, consequently, GHG emissions. However, in areas with very low precipitation, livestock intensity and emissions are likely to increase, as livestock may be the only viable alternative to agriculture. The overall result is a global level of GHG emissions that remains virtually unchanged. This result is achieved by compensating losses in tropical and subtropical areas, where most developing countries are located, with an increase in the northern hemisphere, where most developed countries are present.

This final result, combined with those of the first chapter, lead to a critical scenario for tropical countries. Higher average temperatures will lead to declining crop yields and poor grazing conditions for livestock. At the same time, the literature suggests that arable land will be converted to grassland under these conditions. This scenario highlights the need for these regions to invest in new technologies and agricultural practices that can meet increasing demand in the face of worsening climatic conditions. Given the strong correlation between livestock density and arable land suitability, this work provides a compelling indication of the future dynamics of GHG emissions from the agricultural sector as a whole. Ignoring these emissions could lead to a less accurate future picture.

In this article, we focus on the potential impact of livestock sector adaptation on GHG emissions. However, livestock farming has many other impacts on the environment, including water quality and availability, biodiversity and recreation (Hooda et al., 2000; Alkemade et al., 2017; Rojas-Downing et al., 2017). The theoretical framework and methodological approach used in this work could therefore be used to investigate many other aspects of agricultural sector adaptation externalities.

In conclusion, this work emphasises the importance of policies that support adaptation while being mindful of their different impacts on economic, environmental, and climatic conditions. This approach is necessary to ensure efficient and harmonized outcomes.

## Declaration of Competing Interest

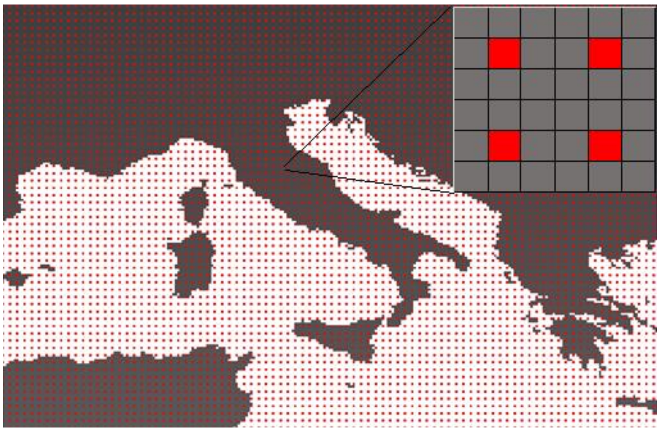
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the results reported in this work.

Appendix

List of 12 General Circulation Models (GCMs) used in future climate projections: hadgem3-gc31-ll, cmcc-esm2, giss-e2-1-h, miroc6, access-cm2, canesm5, ec-earth3-veg, fio-esm-2-0, mpi-esm1-2-hr, inm-cm4-8, mri-esm2-0, ukesm1-0-ll.

Figure 5 below show an example of sampling approach. Only tiles on land are used.

Figure 5 Spatial sampling approach.



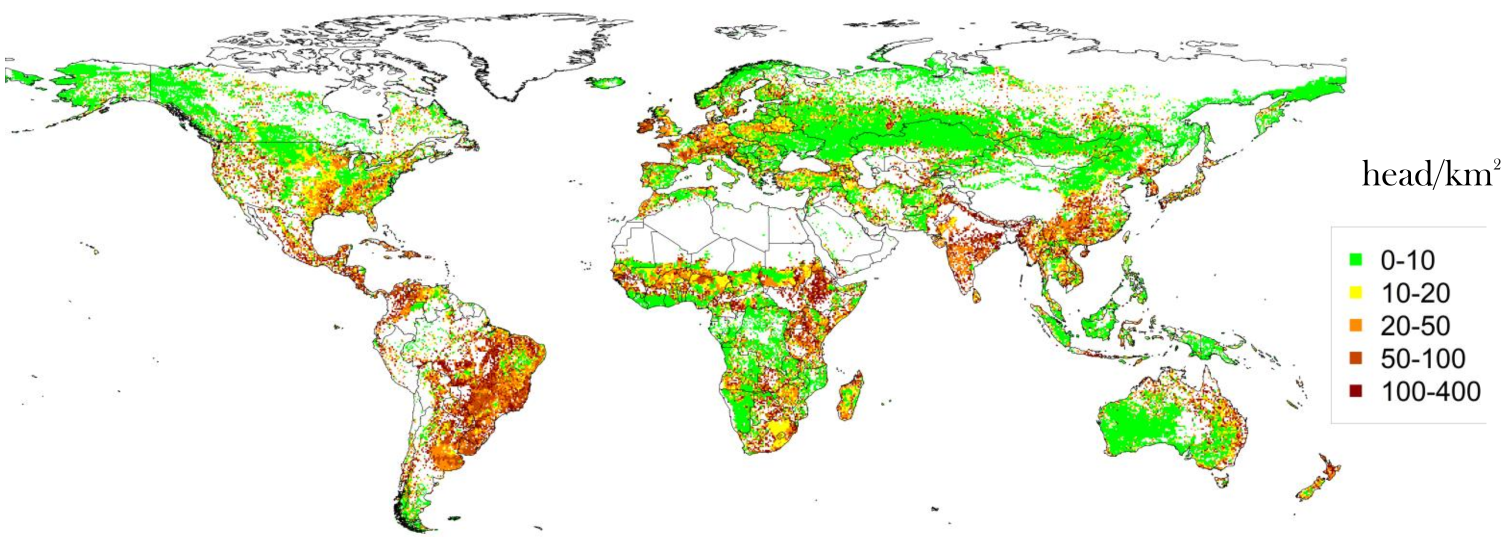
In table 6, we calculate the root mean square error (RMSE) statistics for the estimated livestock number. We compare this measure with the standard deviation of the observed livestock density data for the same reference year 2010. Since only about 10% of these data are used to estimate the model, this test mainly consists of out-of-sample predictions. Our model's ability to capture the variability in the original data is demonstrated by a significantly lower RMSE compared to the observed standard deviation.

Table 6 Livestock densities models: predictive performance.

| Cattle | | Sheep | |
|---|---|---|---|
| RMSE estimated cattle $km^2$, 2010 | 52.55 | RMSE estimated sheep $km^2$, 2010 | 142.89 |
| SD observed cattle $km^2$, 2010 | 62.86 | SD observed sheep $km^2$, 2010 | 166.40 |

In general, our model closely follows the spatial patterns for cattle (Figure 6) on all continents except for inland Russia, sub-Saharan Africa and parts of Australia, where it seems to overestimate the presence of cattle. Similarly, for sheep (Figure 7), our model appears to slightly overestimate density in Australia and the African continent, particularly in sub-Saharan and South Africa, while it is accurate in all other areas.

Observed cattle intensity 2010




Predicted cattle intensity 2010

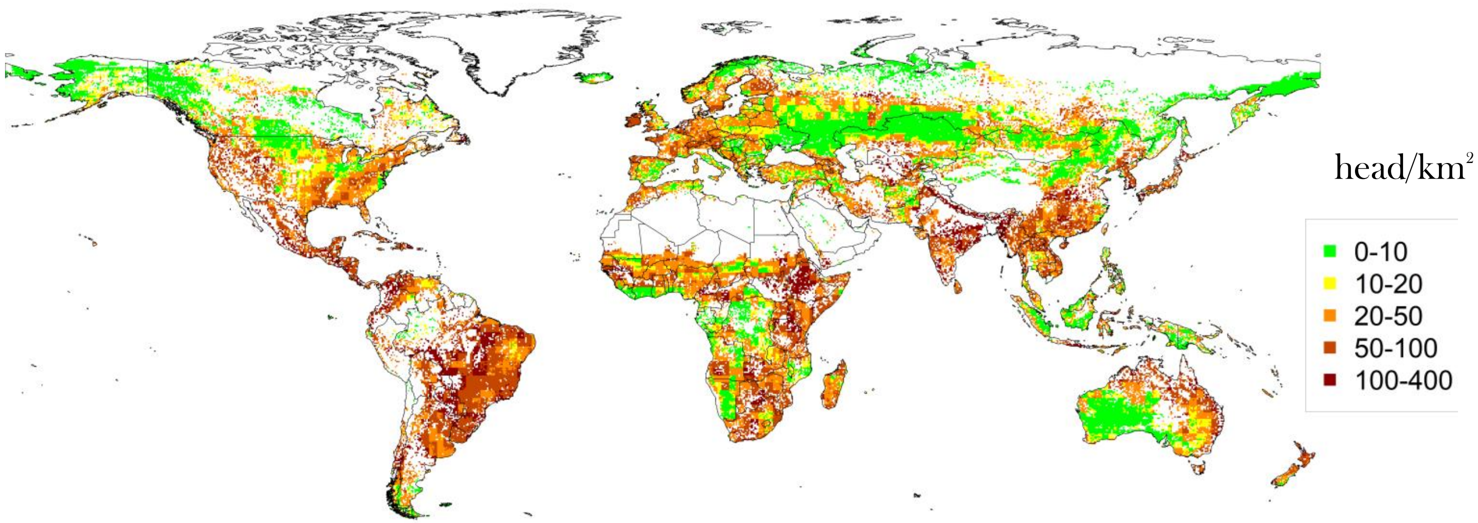



Figure 6 Observed (upper) and predicted (lower) cattle intensity in 2010.

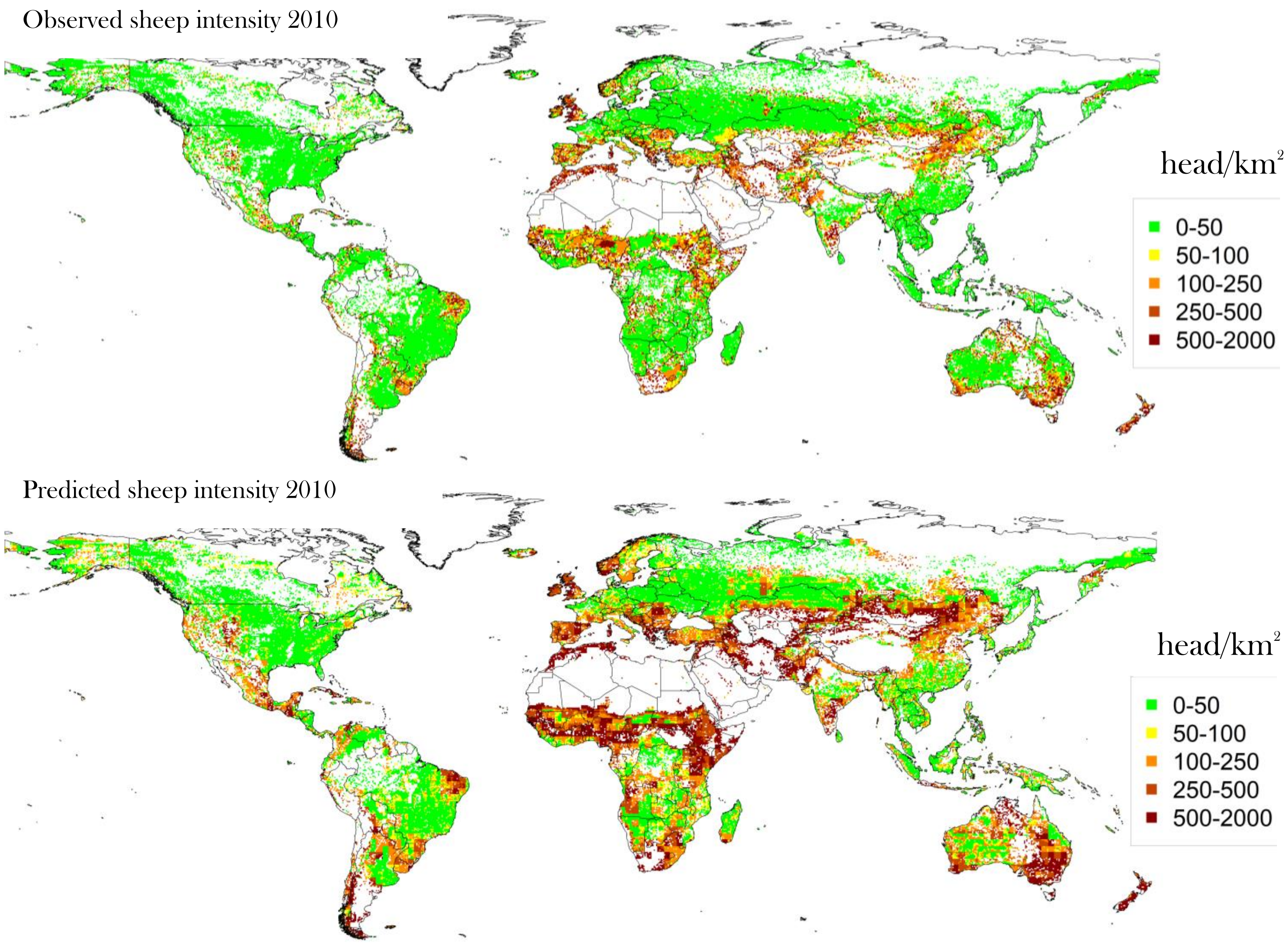
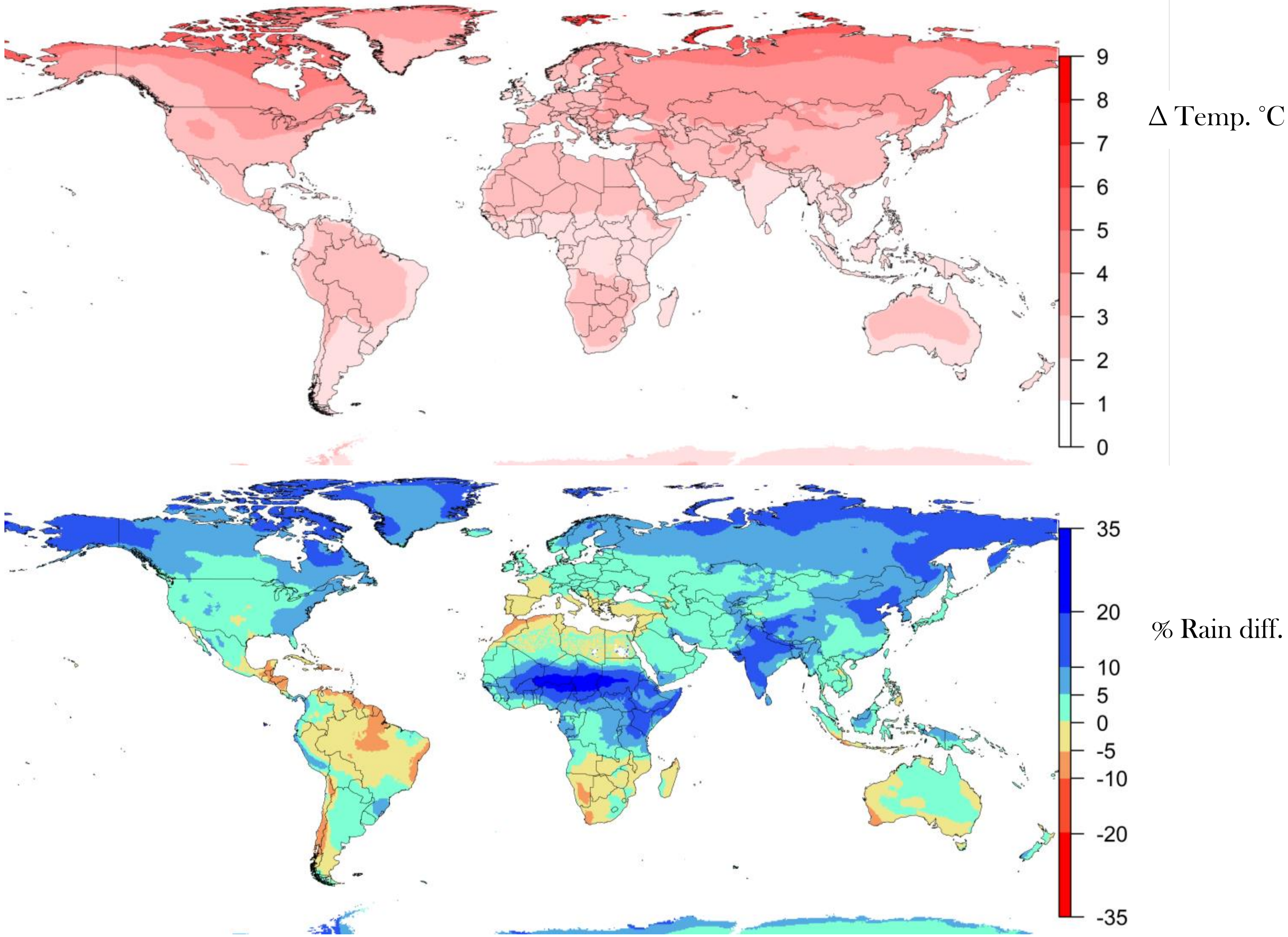



Figure 7 *Observed (upper) and predicted (lower) sheep intensity in 2010.*

Figure 8 Difference in average temperature from 1970-2000 to 2041-2060 (upper) and average precipitation (lower), SSP245.



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