Assessment of Projected Climate Change Impact on A Parametric Agricultural Insurance Product

Master Thesis

Author(s):
Iliopoulou, Georgia

Publication date:
2022-04-19

Permanent link:
https://doi.org/https://doi.org/10.3929/ethz-b-000569448

ETH ZURICH

MASTER'S THESIS

Assessment of Projected Climate Change Impact on A Parametric Agricultural Insurance Product

Author:
Georgia ILIOPOULOU

Supervisors:
Prof. Dr. David N. Bresch
Dr. Alessio Ciullo
Dr. Samuel Eberenz
Sagarika Roy
Dr. sc. Stefanos Mystakidis

Department of Environmental Sciences,
Department of Management, Technology and Economics
&
Swiss Re Institute

April 19, 2022

Acknowledgements

I would like to acknowledge and express my deep gratitude to my supervisors Prof. David N. Bresch, Dr. Alessio Ciullo and Dr. Samuel Eberenz who enabled me to complete this paper. Their help and recommendations aided me in completing all stages of the writing process.

I warmly thank Dr. sc. Stefanos Mystakidis, for the trust he has shown me from the beginning, entrusting me with this topic, his scientific guidance, his suggestions, his perseverance, his interest and his support. I am grateful to Swiss Re Agri-Reinsurance Team and especially to Mrs Sagarika Roy, who gave me the opportunity to perform research on a topic in which I had a strong personal interest and supported me with feedback during the whole process.

Last but not least, I would like to give special thanks to my family as a whole for their unwavering support and understanding through my research journey at the ETH Zurich.

~ To Philippe, who was always by my side and reminded me that:

"Chase your dreams. ***Life is short, and it's up to you to make it sweet****. If you want something, don't wish for it. Life is too short to wait."~*

Abstract

Agricultural production is a key pillar of food security (Swiss Re, sigma No 1/2013). One of the most highly rated risks that may dynamically impact agriculture, is climate change. Climate change may threaten agriculture's inherent diversification benefits due to winter and summer crops and/ or geographic spread. This thesis investigates the changing risk landscape at a higher granularity compared to other relevant research (keeping in mind the limitations at the regional scale). The following method within the CLIMADA environment is mainly used to assess the climate's impacts on crops: process-based crop growth models. To achieve the goal of the thesis, CLIMADA combined with output from AgMIP and ISIMIP will be used for the overall analysis. The main questions to address are how climate change impacts the 'tailish' behavior of agricultural portfolios and how climate change threatens portfolio diversification benefits caused by the geographic and seasonal (i.e., winter vs summer crops) diversification of each portfolio. As a consequence, the impact of projected mid-term climate change on the interannual yield variability, the trend and ultimately the severity of different cat event (e.g., 1-in-100-year) scenarios will be analyzed. Primary data collection methods and especially quantitative methods - time series analysis - can be reliably implemented to get the possible desired results. However, some results as well as limitations and observable weaknesses can be effectively stated throughout the research of this paper.

Table of Contents

Chapter 1: Introduction

1.1 Agricultural production and climate change

The relevance of agricultural production stands on its long way to promote global food security (Adenium 2004, Sigma 3013, Pawlak and Kołodziejczak, 2020), offer income to farmers, and employment opportunities for the younger generation (Johnston and Mellor, 1961, Meijerink and Pim, 2007, de Janvry and Sadoulet, 2010). Moreover, agricultural production plays a vital role in a country's economy by contributing to the growth of the national GDP through exports (Rezaei, Siebert & Ewert, 2017). Agricultural production systems are undergoing rapid shifts in response to climate change, technological changes, socioeconomic developments, population growth, and commodity demand (Ruane & Rosenzweig, 2019). Over the past 50 years, agriculture benefited from the so-called Green Revolution (Saini, 1976, Evenson and Gollin, 2003), mainly due to increasing investments in crop-related research and improved agromanagement practices. A few examples of such practices include the installation of water resources infrastructures, applying pesticides and herbicides, the proliferation of mechanical equipment, introducing dwarf and hybrid crop varieties, etc. (Tester & Langridge, 2010, Ruane & Rosenzweig, 2019). Recent agricultural production trends include: introducing complicated technologies such as aerial images, temperature and moisture sensors, robotics, and GPSD technology to facilitate crop growth monitoring, thereby promoting precision agriculture. Other emerging trends include the growing horticulture and floriculture, rising productivity, diversification of the sector, growing investments, and application of modern techniques, among others witnessed in the global economy (Ruane & Rosenzweig, 2019).

Climate change (e.g., the rise in mean temperature, the amplified surface warming at high altitudes and different latitudes, changes in precipitation variability and extremes, etc.) is essential for agriculture. It poses significant risks but also gives opportunities to food production systems. It is well known that variations in precipitation, average temperature, and atmospheric CO2 concentration impact crops both negatively and positively (Leng & Hall, 2020). For instance, increased atmospheric CO2 concentration, air temperature, and soil moisture up to optimal conditions promote crop productivity through enhanced photosynthesis and growth rates (Muller et al., 2021). Nevertheless, in recent years, crop production systems suffered several shocks caused by unprecedented regional extreme weather events. For instance, a severe drought in 2012 in the USA caused significant shortfalls in maize and soybean production and was ranked as the most costly and catastrophic season for agriculture since 1988 (Rippey, 2015). Similarly, the Russian heatwave in 2010 led to the decline of wheat grains yields due to increased wildfires and water deficiency for plant growth, making the Russian government ban exports (Barriopedro et al., 2011). Another climatic shock includes the Argentina drought in 2018, which emanated from water scarcity due to unprecedented intense heatwaves and rising temperatures, making the Argentina government call for an agricultural emergency (Aon, 2018). The Argentina drought of 2018 devastated the productivity of summer crops such as maize and soybeans yields (Bert et al., 2021).

In the past, technological advances and improved agromanagement practices have outweighed the adverse effects of climate change on crops in several countries (Hoffman et al., 2017, Rezaei et al., 2017; Aggarwal et al., 2019). However, it remains uncertain whether the technological options to adapt to a changing climate will continue to help at the same pace in the future as in the past.

Empirical evidence shows yield stagnation or slowdown in high and low input agricultural production systems (Brisson et al., 2010, Ray et al., 2012, Fuglie, 2018, Schauberger et al., 2018). Besides, the societal pathways will highly govern the future trends in agricultural production and climate change depending on how different regions across the globe will follow (Ruane & Rosenzweig, 2019). These pathways include the actions and policies adopted by national areas on the net global greenhouse gas emissions, developed adaptation technologies, measures instituted to curb aerosol emissions, and procedures created to impact the land use patterns.

A plethora of scientific papers has been written, investigating the response of crop yields to historical and future climatic conditions across various spatial scales, using a variety of methods and data products (e.g., Challinor et al., 2014, Rosenzweig et al., 2014, Trnka et al., 2014, Lesk et al., 2016). In the past, climate change favored crop growth and development in some regions of the planet. For instance, cereal crops in Australia and China benefited from warmer minimum temperatures (Nicholls, 1997, Yang et al., 2015, Tao et al., 2017). Soybean yields in USA, Brazil and China responded positively in elevated atmospheric CO_2 concentration (Sakurai et al., 2014). Nevertheless, various lines of evidence indicate that projected climate change will cause adverse effects on crops across several regions in the world. More specifically, these effects will manifest through weather and climate extreme events such as droughts (Zipper et al., 2016), extreme heat (Lobell et al. 2013, Asseng et al., 2015), excess rainfall (Rosenzweig et al., 2002), severe frost (Zheng et al., 2015, Unterberger et al., 2018, Lamichhane, 2021), etc.

According to Muller et al. (2021), different crop varieties respond differently to climate changes; for instance, C4 plants, e.g., maize and sorghum, are more vulnerable to an increase in CO2 and temperatures compared to C3 plants such as potatoes, wheat, and peanut. As a result, climate change impacts crop yields in various dynamics. Increased mean temperatures lead to accelerated plant growth causing early maturity. Early plant maturity means that the plant has not gained sufficient biomass, and as a result, it leads to a decline in the overall yields. Consecutively, increased temperatures drive the shifting of suitable crop growing seasons. For instance, warmer temperatures extend the crop growing seasons in regions that are currently exposed to cold temperatures while at the same time restraining growing seasons in areas with high temperatures.

On the other hand, extreme temperatures increase heat stress on a plant triggering leaf loss and eventual mortality (Ruane & Rosenzweig, 2019). Furthermore, scorching temperatures make a plant lose its photosynthetic activity. On prolonged exposures, this fact leads to leaf loss and eventual plant growth failure, which can cause a loss of crop yields. In addition, extreme events such as heatwaves during the crop flowering stage may lead to pollen sterility and the ultimate defeat of yields (Muller et al., 2021). This fact is happening because pollen sterility translates to a low grain number. Also, it is essential to note that the impacts of heatwaves will vary depending on the crop development stage.

Additionally, extreme temperatures over the land degrade the agricultural soil by lowering the moisture content for supporting crop growth (Leng & Hall, 2020). This ultimately provokes a decrease in agricultural productions. Also, extreme droughts make agricultural lands unsupportive for crop growth leading to loss of agricultural yields.

Conversely, elevated levels of CO2 impact crop yield from multiple perspectives. For instance, increased concentration of CO2 facilitates photosynthesis leading to increased productivity (Ruane

& Rosenzweig, 2019). In addition, having elevated concentrations of CO_2 in the environment facilitates stomatal gas exchanges, which work to reduce transpiration rates, thereby enhancing water retention in a plant. Increased water usage efficiency in a plant life leads to increased crop yields. Consecutively, high concentrations of CO_2 in the atmosphere may lead to a decline in a plant's nutritional content. According to (Muller et al., 2021), crop yields grown in rich CO_2 conditions contain lower nutritional value as they have low nutrients such as proteins, zinc, and iron.

Decreased precipitation means scarce water to support plant growth. This condition induces plant water stress and eventual mortality (Ruane & Rosenzweig, 2019). For instance, in cases of excessive transpiration rates, plants reduce gas exchange activity to conserve water for photosynthesis and production. Excessive water loss and lack of water to replenish the lost water leads to automatic wilting and mortality. However, increased precipitation reduces water stress for plant growth, leading to increased yields.

On the contrary, more severe storm surge causes plant damage by knocking down and uprooting crops leading to loss of yields. Furthermore, shifting climate zones will affect agricultural production by disrupting the timing and potential extent of damaging agricultural diseases, pests, and weeds (Muller et al., 2021). Moreover, inland flooding due to heavy precipitations reduces crop yields through waterlogging, which induces unfavorable wet field conditions for plant growth.

1.2 Approaches to assess climate and climate change impacts on agricultural yields

Assessing the future impact of climate change on agricultural yield is essential in developing crop resilient methods and approaches, which are critical to improving food security in the future. Consequently, the assessed future crop yields due to climate change play a crucial role in enhancing the pricing mechanisms of the agricultural insurers for profitability and resilience. Over time several approaches have been proposed in the scientific literature, assessing climate and climate change impacts on crops. These are primarily based on:

1. Process-based crop growth models (CGMs)
2. Empirical models
3. In-situ manipulation experiments, performed, for example, on open fields or under closed chamber environments

Owing to the complex nature of assessing future climate change impact on crop production, the problem might require exploring the potential of multimethod analyses (Zhao et al., 2017, Ciscar et al., 2018). The following subsections present a short overview of the three main approaches, including their advantages and limitations and a few application examples.

1.2.1 Process-based CGMs

A process-based CGM can be defined as a collection of tens of thousands of equations describing several processed within the crop-atmosphere-soil system (Bootie et al., 2013, Jones et al., 2016). Specifically, CGMs incorporate simplified functions describing the interactions between crop growth, development, and yield in response to soil and weather conditions, genetic characteristics, and crop management, among other factors impacting crop production (Bootie et al. 2013, Jones et al., 2016). For instance, by simulating CO2 physiological effects under future climate conditions, these models help assess climate change implications on crop growth, development, and final harvest yields (Supit et al., 2012, Jones et al., 2016). Input data to a process-based crop growth model include daily minimum and maximum temperature, rainfall, and solar radiation. Additional input data relate to agro-management practices (e.g., planting date, planting density, planting depth, cultivar type, nitrogen, irrigation amount etc) and soil characteristics (e.g., clay, sand, carbon, nitrogen content etc) (Jones et al., 2003, Stöckle et al., 2003).

Point-based CGMs have participated in several intercomparison studies in Europe (Palosuo et al., 2011, Roetter et al 2012), north America (Camargo and Kemania 2016, Ahmed et al 2017), southern America (Battisti et al., 2017), Asia (Soltani and Sinclair, 2015, Husain et al., 2018) and Africa (Akinseye et al., 2017). Asseng et al. (2018] analyzed results from a suite of 30 CGMs at different locations around the world and identified a strong negative response of winter wheat to warming temperatures.

Although CGMs were initially developed to be applied at individual sites, the increasing need to use CGM output in a variety of applications across large scales (Holzworth et al., 2015), promoted the development of spatially explicit application methods (Balkovic et al., 2013, Elliott et al., 2014, Ewert et al., 2015, Shelia et al., 2019). In the context of assessing future climate change impacts on food production, notable work is currently done within the Global Gridded Cop Model Intercomparison (GGCMI; Elliott et al., 2015), as a contribution to the Agricultural Model Intercomparison and Improvement Project (AgMIP;Rosenzweig et al., 2014) and the Inter-Sectoral Impacts Model Intercomparison Project (ISIMIP; Warszawski et al., 2014)., Simulations of major crops (i.e., maize, wheat, rice and soybean) performed within GGCMI, revealed a contrasting yield response to projected climate change between the tropics (yield reduction) and mid/high latitudes (yield increase) (Rosenzweig et al., 2014). Moreover, Jaegermeyr et al. (2021), by using output from a more recent model ensemble, found that significant breadbasket regions will experience distinct anthropogenic climate risks very soon compared to the previous anticipations. Improved crop model sensitivities and warmer climate projections reveal a maize productivity shift from +5 to -6 % (SSP126) (Jaegermeyr et al., 2021).Similarly, a study conducted by Muller et al. (2021) on cereal crops in the Saran region in Africa using AquaCrop, which is FAO process-based crop model, found that temperature rise posed a significant impact on the crop production such that increase in precipitation there would be still a net loss of agricultural yield between 2025 to 2050.

One of the key strengths of process-based crop models is that they are based on the physical relationships that govern crop growth and development and as result they are applicable in a wide range of environmental conditions globally (Jones et al., 2017, Roberts et al., 2017). In addition, CGMs can factor out the effect of technology on yields, thus facilitating the assessment of the pure climate impact on crops (Asseng et al., 2015). In the context of climate change impact studies, CGMs are powerful tools for understanding the implications of climate variations on future agricultural productivity (Supit et al., 2012). Moreover, they can translate the climate change signal from CMIP-type of earth system models into a yield change signal that is more relevant to the agricultural sector (Rosenzweig et al., 2014, Lobell and Assseng, 2017).

Despite their strengths, CGMs suffer from limitations that can be attributed to uncertainties in a) input data (e.g., weather, soil etc); b) model structure (e.g., processes simulated) and c) parameters (e.g., cultivar-specific parameters) (Tao et al., 2018). Notably, the effect of some processes or perils influencing crop growth and development in the real world (e.g., the effect of hail, fire, pests, diseases, weed species etc) cannot be adequately represented or not even represented at all by current CGMs (Supit et al., 2012, Jones et al., 2017). Another limitation of process-based crop models lies in their uncertainty to predict future crop yields on farmer-managed fields, which are subjected to a wide range of climate and weather scenarios.

1.2.2 Empirical models

Technology evolution has led to the introduction of big data in agricultural systems, thereby promoting the application of machine learning techniques in assessing, among others, the impacts of projected climate change on agricultural production systems (Van Kloppenburg et al., 2020, Muller et al., 2021). Such approaches can give insights into future crop responses to climate change. The core function of a ML method is to learn from a variety of input data (a.k.a. training data) and predict a target variable under conditions different than those used in training (Liakos et al., 2018). In the context of agricultural modeling (Basso and Liu, 2018), examples of training data typically include:

1. Agro-climatological indicators (e.g., yield, precip, temp, etc.).

2. Remote sensing-based retrievals (e.g., solar-induced chlorophyll fluorescence (SIF), the Enhanced vegetation index (EVI), the Normalized difference vegetation index (NDVI), the Fraction of absorbed photosynthetically active radiance (fAPAR) etc).

3. Soil properties (e.g., field capacity, plant wilting point etc.).

A study conducted by Cai et al. (2020) revealed that combining remote sensing-based and climatic data can facilitate the achievement of high-performance agricultural production projections at a standard deviation of 0.75. The complexity of the underlying ML approach, can vary markedly, ranging from relatively simple linear or multilinear regression models to more sophisticated methods based on artificial neural networks, support vector machines, random forests, etc. (Gonzalez-Sanchez et al., 2014, Liakos et al., 2018, Benos et al).

Leng & Hall (2020), followed a multimethod approach to model historical maize yields based on a simple linear regression model, a more complex machine learning-based model and a processed-based CGM. The complex machine learning-based model explained more than 93% of the historical yield variability, followed by the simple linear regression model (51 %) and the process-based CGM (42%). The machine learning-based model was then used to assess mid-term climate change impacts on maize yields in USA. The results of the study revealed a ca. 13% maize yield decline in a 2degC warmer world. The strength of machine learning approaches lies in their potential in minimizing reporting errors when predicting the future crop yield due to climate change. This approach incorporates many algorithms and satellite data in its simulation, increasing its prediction accuracy. When compared to CGMs, machine learning approaches give more accurate results of the spatial distribution of crop yields across large areas (Lobell & Burke, 2010, Leng & Hall, 2020). In addition, they have less requirements on input data, parameters and computational resources compared to process-based CGMs (Lobell & Asseng, 2017, Leng and Hall, 2020).

A known limitation of any empirical-based method is that its validity is bound within the environmental space used for the development training (Lobell & Asseng, 2017, Jones et al., 2017). In other words, empirical models might be unable to predict e.g., yield responses to climatic conditions beyond the ones observed or used for training. Moreover, machine learning-based methods were found to underestimate the variability of the yearly yield for short spans, thus making them inaccurate for analyzing climate impacts on crop yields for short spans (Leng & Hall, 2020). Furthermore, the effect of agricultural management practices, pests and weed control is challenging to be represented.

1.2.3 In-situ manipulation experiments

In-situ manipulation experiments can provide complementary insights on agricultural yields' response to climate change (Ainsworth and Long, 2005, Frei et al. 2020). In such experiments, crops are grown under controlled environments (e.g., open fields, greenhouses, controlled environment chambers or open-top chambers) and are exposed to water, temperature, light or nutrient stress, as well as to varying atmospheric CO_2 and O_3 concertation (Ainsworth and McGrath, 2010, Asseng et al., 2015, O'Leary et al., 2015, Ainsworth and Long, 2021). In-situ manipulation experiments can help quantify the biological crop responses to different climate change levels, thereby giving a precise forecast of the crop yields (Ettinger et al., 2019). Active warming methods may include, forced air heaters, infrared heaters, soil warming cables etc. (Shaver et al. 2000; Williams et al. 2007; Aronson & McNulty 2009, Frei et al. 2020). In addition, precipitation manipulations are incorporated through water additions or reduction, snow removal, etc., to help observe the interactive impacts of precipitation and temperature separately from the dynamic environmental changes (Price & Waser 1998; Cleland et al. 2006; Sherry et al. 2007; Rollinson & Kaye 2012, Ettinger et al., 2019). Notably, Free-Air CO_2 Enrichment (FACE) technology played a pivotal role in conducting experiments where crops are artificially exposed to varying atmospheric CO_2 concentration (Long et al., 2004).

Zhao et al. (2016), used results from 46 field warming experiments to study the response of wheat yield to temperature in China's wheat belt. The analysis revealed a contrasting response of wheat yield to temperature between the North/Northwest (negative effect) and Southern East China (positive effect). A FACE experiment conducted in Germany, shed light on the response of maize under wet and dry conditions (Manderscheid et al., 2014). The results of the experiment showed that elevated atmospheric CO_2 concentration boosted yields by 41% compared to ambient conditions, in response to reduced stomatal conductance and leaf transpiration.

The main advantage of any manipulation experiment is that several environmental factors can be controlled. Thus, the effect of individual growth drivers can be separated and quantified (Ainsworth and McGrath, 2010). The strengths of In-situ manipulation experiments include revealing observable crop resilience on the anticipated climate change patterns (Frei et al. 2020). This is essential to help policymakers understand the actual impacts, thereby prompting them to adopt resilient adaptation measures to promote crop growth under the simulated crop growing conditions in the future (Ettinger et al., 2019). One of the main limitations of the in-situ manipulation experiments is that they are not scaled for global usage, and the findings and applicability are limited to few geographical zones. In addition, this approach has no clear and distinct procedures to address the worldwide variation of the anticipated future agricultural yields to a lack of uniformity in crop growing conditions (Frei et al. 2020). Environmental conditions in some types of manipulation experiments (e.g., indoor growth-chambers and experiments) might not mimic those observed on open fields (Sudhakar et al., 2016, Ainsworth and Long, 2021), thus introducing significant spread in the resulting responses (de Graaff et al., 2006).

1.3 The role of agricultural insurance

Agriculture/insurance plays a crucial role in protecting the insured parties from low crop yields and prices, thereby hedging them against weather and climate risks in agricultural production through a risk transfer mechanism (Pawlak & Kołodziejczak, 2020). Risk transfer in the context of Agri/reinsurance refers to the proactive transference of risks of agricultural production assets to Agri/reinsurance companies and capital markets. Through risk transfer, agriculture re/insurance can offer indemnification against economic loss from damage due to adverse natural phenomena along the whole value chain in both mature and emerging markets (Sigma, 2013, Shields, 2015). According to Meijerink, Gerdien & Roza (2007), Agri/insurance plays a significant role in risk management, supporting food distribution, thereby reducing poverty vulnerability. This fact is achieved by availing numerous incentives to corporations and farmers, fueling food sector investments. In addition, it acts as an enabler for advanced developments of distribution channels, transportation networks, logistics, and warehouses. Notably, Agri/insurers, through microinsurance, provide health and life protection to households and low-income farmers. Another role of agriculture insurance includes lessening global food insecurity by providing risk protection and facilitating agriculture productivity and output (Meijerink, Gerdien & Roza, 2007).

As a result, farmers can focus on improving their farm production levels, thereby boosting global food security. Some of the risks covered by insurance include market/price risks due to price volatility, operational risks, e.g., input shortages, theft, fire, equipment failure, accidents, etc. Other roles of agriculture insurance include creating risk awareness to farmers and encouraging them to adopt the fundamental risk mitigation measures, offering market-based solutions to farmers, providing credit services for farmers, reducing investment fluctuations as a result of extreme events as well as providing the practical risks transfer against the effects of catastrophic events (Goswami, 2021). In addition, agriculture insurance helps stabilize and protect farmers' earnings, thereby promoting poverty alienation.

Worldwide agriculture insurance premiums were estimated at $23.5 billion in 2011 compared to $8 billion in 2005. This fact showcases an average growth rate of about 20% between 2005 to

2011. During the same period, agriculture insurance premiums quadrupled in emerging markets with an aggregated annual growth rate of 30%. According to Hess, Hazell & Kuhn (2016), India, China and Brazil emerged as the critical growth drivers contributing about 62% of the total agricultural insurance premiums by 2011 from the emerging markets. In 2018, the three countries accounted for approximately $13billion of the insurance premiums in the worldwide markets. China led with an estimated insurance premiums market estimated at $8 billion in 2018, followed by India with around $4 billion, and the Brazilian market accounted for about $1.1 billion in the same year (Hess, Hazell & Kuhn (2016)).

In 2020, the global market size of agriculture insurance premiums was estimated to be $34.05 billion, with an anticipation that it will reach $53.02 billion by 2027, thereby growing at a CAGR of 6.1% between 2020 to 2027 (Goswami, 2021). The Asia-Pacific and North America regions generate 82% of the global premium volume, followed by Europe (13%), Latin America (4%) and Africa (1%). Crop insurance is by far the most developed subline of the Agri business, with a global market share of 83% in terms of the annual gross written premium (Hohl, 2019).

The three main types of agricultural insurance products include indemnity, index, and revenue (Iturrioz, 2019). Indemnity-based insurance products are categorized into multiple perils and named peril agriculture insurance. According to Pawlak & Kołodziejczak (2020), the named-peril insurance covers single perils such as fire, frost, hail, or a storm event. The sum insured is determined depending on the aggregated agricultural value, e.g., fertilizers and seeds. On the other hand, the multi-peril crop insurance (MPCI) covers multiple risks which can trigger widespread losses, e.g., flooding, drought, and diseases. The sum insured is determined based on the value of the insured crop, and the yield shortfall is compensated based on the pre-agreed threshold (Ali, Abdulai & Mishra, 2020).

Revenue insurance products refer to those which incorporate price risk and production in determining the gross crop revenue (Iturrioz, 2019). These agricultural insurance products are used to offset losses in revenue caused by shortfalls in production and price. However, their availability is limited to the US.

In recent years, parametric (a.ka., index-based) insurance has gained traction, mainly in emerging markets such as Vietnam, India, and various African countries (Iturrioz, 2019). In contrast to a traditional indemnity-based insurance solution, a parametric insurance product bases payout on an index used as a proxy to the underlying and not on the actual physical loss suffered on the ground (Hohl, 2019). An example of index insurance products includes weather insurance products where weather parameters are used to determine the compensation payout. Other index-based insurance products include area-yield insurance, whose compensations are based on the output yield shortfall relative to the historical threshold yield (Iturrioz, 2019). The area yield insurance product is prevalent in various markets, including India, the US, Brazil, Canada, and Mexico. Moreover, other examples of index insurance products include drought insurance on pasture lands, forest fire index, and area-yield index. Notably, “index-based" insurance and "peril" insurance are not suitable for Agri/insurance under the changing climatic conditions as the two assumes a constant and uniform risk factor when basing their pricing mechanism to cover the insured risks of losses of farm outputs which might not be the case in the projected future climatic condition.

Index-based crop insurance solutions offer several advantages compared to indemnity-based products. A few examples include the ease of administration, the fast claims settlement process (no loss adjuster is involved), the lower price (again because no loss adjuster is involved), the minimization of the moral hazard (a farmer cannot influence the production of a whole area) and adverse selection, etc. However, the main limitation of any index-based insurance product relates to the so-called basis risk. Basis risk can be defined as the difference between the loss calculated by the index and the actual loss suffered on the ground (Sigma, 2013). The basis risk cannot be fully eliminated, but measures are usually taken to minimize it (e.g., by better understanding the underlung and the key processes driving crop growth and development, by evaluating the index and quanfiying the unexplained part of uncertainty etc).

Examples of other Agri/insurance sublines include the livestock insurance, which covers swine, cattle, and poultry against death due to fire, non-epidemic diseases, accidents, and natural perils. Others are aquaculture insurance which covers & offshore fish, among other aquatic farms; and forestry insurance which covers commercial plantations against storm and fires losses; and finally, the greenhouse insurance, which covers greenhouse structures against natural risks (Iturrioz, 2019).

In most markets, costing and pricing of crop insurance products is based on historical data available over relatively short time periods (e.g., between 10 to 20 years, source discussions with Swiss Re's agro underwriters). Even in markets where long timeseries are available (e.g., USA, Argentina, Brazil) their representativeness in a future (e.g., warmer) world might be questioned. Additionally, there is significant variability in projected future crop yields under different climatic scenarios in another geographical region, which leads to un-harmonious crop yield projections. Furthermore, climate change is adding a dynamic component to the risk landscape by introducing for example more intense and frequent climate extremes and novel types of compound events (e.g., Seneviratne et al., 2012, Zscheischler et al., 2018, Fisher et al., 2021). Such events may exhaust policy limits and cause catastrophic losses along the whole agriculture supply chain, thus ultimately affecting the profitability of agri re/insurance portfolios (Duncan and Myers, 2000). Hence, more research is needed to reinforce the existing risk modeling frameworks, which can help give insightful and harmonious data on the projected climate change and its potential risks to crop productivity. This will help provide a solid base point for pricing and costing of future agricultural assets by the Agri-insurance companies, thereby minimizing the extent of risk losses. Furthermore, to avoid future losses in the Agri-insurance business, the insurance companies will require to adopt diverse risk assessment methods that accommodate future climate change impacts on various agricultural portfolios.

1.4 Purpose and structure of the master thesis

This purpose of this thesis is twofold. The first is to review the scientific literature and document existing approaches for assessing climate and climate change impacts on crops. The second is to use a newly developed module within the CLIMADA weather and climate risk assessment framework (https://gmd.copernicus.org/articles/12/3085/2019/gmd-12-3085-2019-metrics.html) and model output from the GGCMI project, with the aim to quantify climate changes impacts on crops through the lens of an agricultural insurance product. For this reason, different yield indices

(AYIs) are structured and costed at different regions in continental Europe for a historical and future time horizon.

1.5 Market Overview

1.5.1 Challenges Facing Agri/Insurer due to climate change

Due to the dynamic climate, numerous hurdles face the agricultural insures, which induces pricing complexities in the agriculture sector. These challenges include lack of regulatory frameworks or supportive policies, lack of quality and accurate pricing data, unawareness of insurance premiums to farmers, and affordability problems among farmers in the emerging markets. This fact inhibits agricultural insurance penetration in emerging markets. Earlier on, the pricing and costing of the various crop insurance products were based on historical data of between the past 15 to 20 years. However, these historical data on climate patterns are no longer reliable for forecasting future risks on crop yield due to the diverse shifting of climate patterns (Ruane & Rosenzweig, 2019). As a result, the main challenge caused by changing climate is induced pricing complexities to Agri/ insurers due to lack of adequate data that can be used to accurately base future pricing to help adequately cover the projected risks on future agricultural yields (Ruane & Rosenzweig, 2019).

More research is needed to reinforce the existing crop modeling frameworks, which can help give insightful data on the projected climate change and its potential risks to crop productivity. To avoid future losses in the Agri insurance business, the re/insurers will require to adopt diverse risk assessment methods that accommodate future climate change impacts on various agricultural portfolios.

This introduction presented a literature review of the main methods applied for assessing climate and climate change impacts on crops (see 1.2-1.4). Following the introduction, chapter 2 presents the data and methods used for the analysis. The results are then presented in chapter 3 and a discussion on limitations, conclusions and the road ahead are presented in chapter 4.

Chapter 2: Data and Methods

This chapter describes the data used in the analysis, presents a short overview of the CLIMADA platform and introduces the method to calculate the area yield indices over the areas of interest.

2.1 Data

2.1.1 Gridded crop model output

The thesis hazard data has been derived from the interaction of various models. Analytically, a climate -historical or future- scenario triggers a climate model that feeds a crop model for the final output. Thus, crop growth models run global gridded simulations using harmonized and bias-adjusted input data from climate models. Concerning the future climate scenarios, ssp126 and ssp585 were used. Ssp126 represents a significant reduction in green gas emissions by the end of the century. Ssp585 represents a rising green gas emissions scenario. In the present analysis, ten different crop models and five different climate models were used:

Crop Models

- *crover lpjml*
- *cygma1p74 pdssat*
- *epic-iiasa pepic*
- *isam promet*
- *ldndc simplace-lintul5*

Climate Models

- *crover*
- *cygma1p74*
- *epic-iiasa*
- *isam*
- *ldndc*

2.1.2 CLIMADA

CLIMADA is a probabilistic climate risk assessment tool that offers a framework for individuals to combine hazard, exposure, and vulnerability and impact data in calculating risks (Aznar-Siguan and Bresch, 2019, Bresch and Aznar-Siguan, 2021). Through this model, probabilistic impact data can be created from event sets and climate change impacts assessed. Also, adaptation measures can be evaluated to see how the impact changes vary (Bresch, 2017). As a result, this model can be extended to cover agricultural risks losses under the projected future climate changes. Furthermore, since the CLIMADA is not limited to particular exposure/impacts types of hazard types, it is suitable in predicting the risks of future crop yields concerning changing risk landscape, among other problems, as it is highly customizable.

The three components combined together calculate the severity term which is the main attribute for a risk function. The hazard factor poses the level of threat in terms of both the intensity and the frequency of weather-related events, and the exposure describes the presence of people, ecosystems, and assets exposed to a specific hazard. The extent of the affected exposure by a hazard, known as vulnerability, is parameterized by appropriate impact functions. CLIMADA has the advantage of customization, providing the user with the feature of using his own data for the analysis. In the present thesis, the hazard is the relative deviation of the simulated crop yield per grid cell from a historical mean value and the exposure is the total crop yield in a specific region. The thesis hazard-exposure data was imported in CLIMADA to get as output the total impact of the hazard in crop production, taking advantage of the CLIMADA features.

Here, the graphs show, per year, the change in production. These changes have as baseline the value indicated on the graph next to the baseline exposure. For example, in the first graph (Ain case), in the year 1850 the production is (approximately) -300 compared to baseline (64216 - 300). Production in some places falls below -2000, but with an upward trend in recent years. The results of the code, as it is understood from the above, express the fluctuation of production per year compared to a baseline (from the set of historical events). The blue line is the plotted results contained in the csv files. The gray line is a statistical term known as the moving average (known as the rolling method in python).

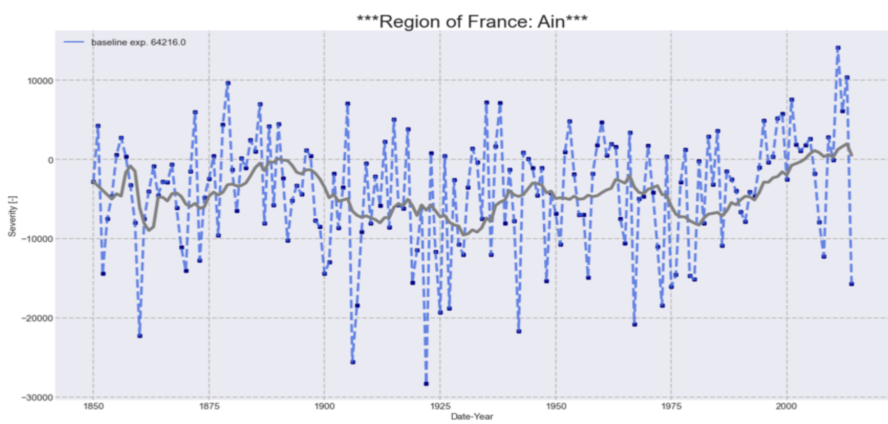

Figure 1: Production Change per year in Ain (France)

2.2 Methods

2.2.1 Calculation of an area yield index

An area yield index bases payout on the shortfall in the realized yield of an administrative area, relative to its average historical yield. If the actual yield of an area falls below a predefined threshold, then every policy holder receives a payment independent of the actual individual loss (https://www.swissre.com/reinsurance/property-and-casualty/reinsurance/agro.html). In this thesis, AYIs are calculated using simulated crop production output from all CGMxCMIP combinations. Figure 2 illustrates an example of a structure of an AYI for winter wheat in France. The grey line corresponds to the raw model output. For the purpose of this analysis, all model output were detrended using Gaussian-kernel detrending with a bandwidth of 5. The blue line corresponds to the detrended production timeseries. The benchmark production (orange line) is defined as the multi-year average production. The deductible and limit for this structure are set at specific percentages of the benchmark production, respectively. Hence, the trigger (yellow line) is at 0.15*1231714.44=1046957.27 t and the exit (purple line) at 1231714.44*(1-(0.4-0.15)) = 554271.50 t. The loss for each year is then calculated based on the following formula:

$$Loss_i = MIN(MAX(Trigger - P_i; 0); Trigger - Exit)$$

where $Loss_i$ and P_i correspond to the loss and production for a given year (i), respectively.

The average loss across all years, divided by the so-called layer (difference between exit and trigger) defines the burning cost on-line (BCOL):

$$BCOL = \frac{\frac{\sum_i^N Loss_i}{N}}{(Exit - Trigger)}$$

where N corresponds to the number of years.

The BCOL is indicative of both the product premium and payback period or the frequency of the loss. In the example shown in Figure 2, BCOL for the whole period is at 3%. This means that, on average, every 1-in-30 years the index would result in 100% payout. In this analysis, BCOL is calculated for a historical (1986-2015) and future (2016-2045) time period for two emission scenarios (SSP1-2.6 and SSP5-8.5). The possible impact of climate change is then assessed by comparing the future and historical values of BCOL across the whole multi-model ensemble. The AYI is calculated for winter wheat and maize at four Level 1 regions located in France (Aquitaine and Rhône-Alpes for maize and Centre and Picardie/Nord-Pas-de-Calais for winter wheat) and Germany (Niedersachsen and Bayern for both crops).

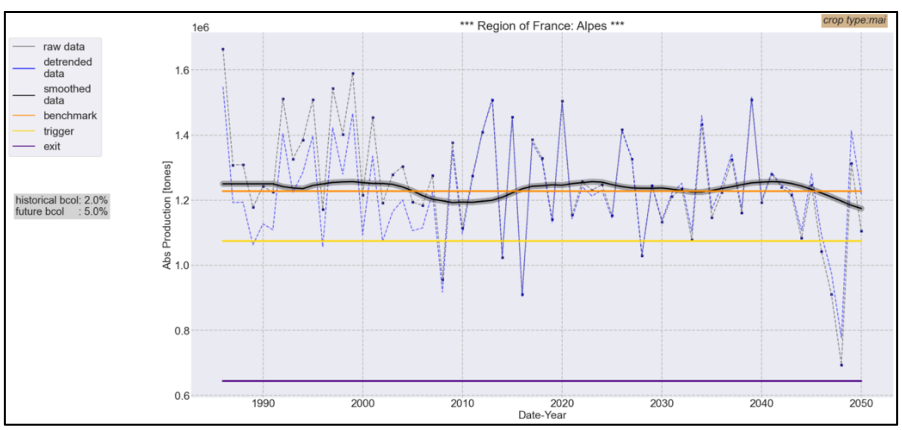

Figure 2: Example of area yield index in the Region Rhone-Alpes (France)

Chapter 3: Results

Observed statistics already showing signs of yield stagnation in many countries of the world. In addition, it can be observed that the increased frequency of extreme events at the global scale resulting in catastrophic losses for agri re/insurance (e.g., drought in USA,heat wave in Russia, frost in France in and Switzerland in 2021 etc.). This change of the risk landscape creates challenges for all the major players along the agriculture supply chain, including the agri-insurance sector. Consequently, it is imperative to understand the dynamic risk landscape and discover options to quantify projected climate change impacts on crop yields.

To determine a possible relation between different crops, and thus the long-run relationship between climate change factors and other control variables, a correlation analysis was performed allowing the detection between different indices for the agricultural risk insurance and also its proximity to the linear type. The results of the correlation analysis between 1985-2050 showed various behavioral characteristics concerning the volume of the crop production that was produced with respect to the climate change over time on the examined areas. More specifically, large deviations are found in the point of entry (trigger) of the concerned crop production risk insurance which corresponds in the long run, to the volatility of the crop volume.

Three main indicators were compared to obtain the results from this analysis:

- the historical occurrence of the crop volume (1985-2022),
- the projected mean temperature rise based on two different future scenarios (ssp585, ssp126 for 2022-2050) as already described
- and the burning cost on line variation which acts as the key risk indicator and helps in putting insurance literature towards the context of potential spatial patterns in agricultural systems.

In order to obtain and identify the most important time characteristics and thus reduce volatility, only the detrended characteristics after the appropriate regression analysis were taken into account making the experiment's ex-post approach more deterministic. For the same reason, the insurance's trigger and exit points were set at specific percentages from the benchmark line accordingly to achieve homogeneous treatment across the different models. In this way, the results across different regions are comparable. As mentioned, the Burning Cost on Line ratio (BCOL), was set as a dependent variable so that different scenarios could be generated from CLIMADA's regression analysis for each region. Thus, it was decided to select two different scenarios for each example close to the average point of each variation which exceeds however the 3% BCOL since the impact of the aggregated losses and thus the risk would have been insignificant in this case. Lastly, the produced simulations, concerned both historical and future scenarios with 2022 being the cut-off year.

3.1 Area yield index for maize

Maize is cultivated widely throughout the world, and a greater weight of maize is produced each year than any other grain. Almost all countries within the European Union (EU) enhance maize production. In the 27 EU Member States (MSs), the area of grain maize and silage maize covers about 8 million hectares and 5 million hectares, respectively. To achieve this, the largest maize producers are France, Romania and Germany (European Commission). Consequently, considerable research has been conducted in Europe regarding the feasibility of substituting of growing these crops and thus excess of data available allowed to perform accurate measurements. In the 75 analyzed crop years (1985-2050) in the French regions of Aquitaine and the Alpes, similar patterns were observed as shown in graph (1) below:

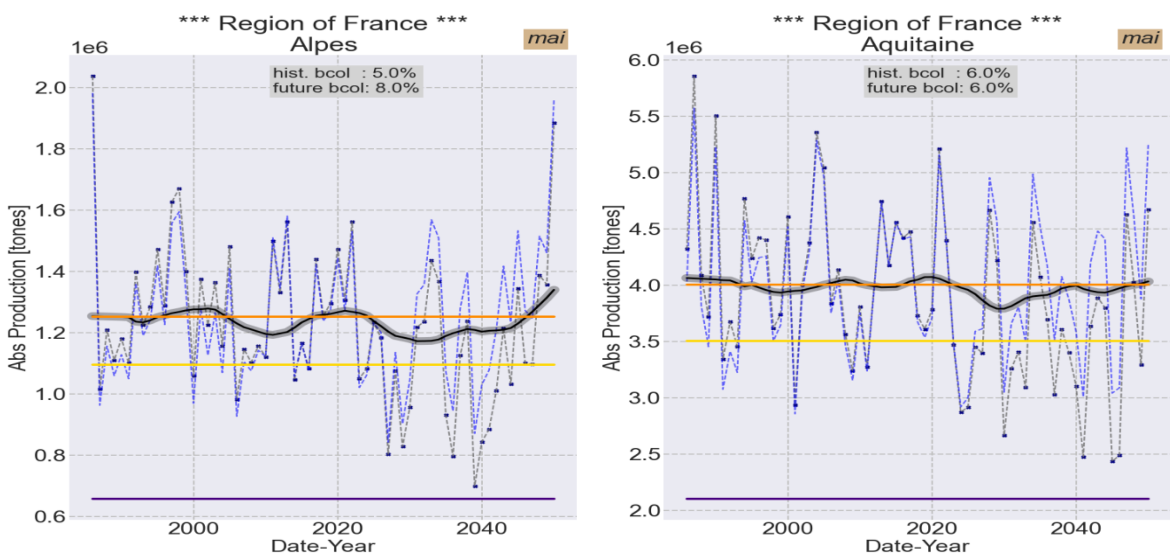

Figure 3: Graphs of 8% and 6% BCOL under two different future scenarios in the regions of Alpes and Aquitaine

The historical data for the period of 1985-2016, show that the turnovers of the farming product did not occur to any risk event. This trend came to a halt between 2020 and 2023. From 2023 to 2030 farmers of both regions are expected to incur losses as the production was dropping from its historical averages until 2020. The mass of the detrended data falls down the benchmark line and approaches the trigger line. The most pronounced deficit projected to occur between 2027-2029 in Alpes and between 2023-2025 in Aquitaine, where the loss of production will reach 35% and 30% compared to benchmark line respectively. After 2030, the mass of detrended production gets higher and ends over the benchmark line in both regions.

More specifically, were recorded 10 years under which liable deficit events have been fully compensated, giving approximately on average 1 payment every 6 years for both regions. Consequently, the probability of payments calculated at 0.17. Concerning the retention and thus the risk absorption from the policy holder/farmer it was observed from the graph that the duration lasted for 8 years for Alpes and 5 years for Aquitaine. The calculated burning cost on line parameter for Alpes is greater than Aquitaine, as the deficit period is intensified. However, Alpes modeling shows an increased production trend after 2040 in contrast to Aquitaine, where the trend seems to be nearly constant.

The same model analysis was performed to understand the pattern characteristics in the German regions of Niedersachsen and Bayern. In this way, the compared samples could be judged and identify possible differences in the model's data support and the existence of an effect in the populations they represent. Consequently, the analysis is straightforward and robust when independent samples are compared.

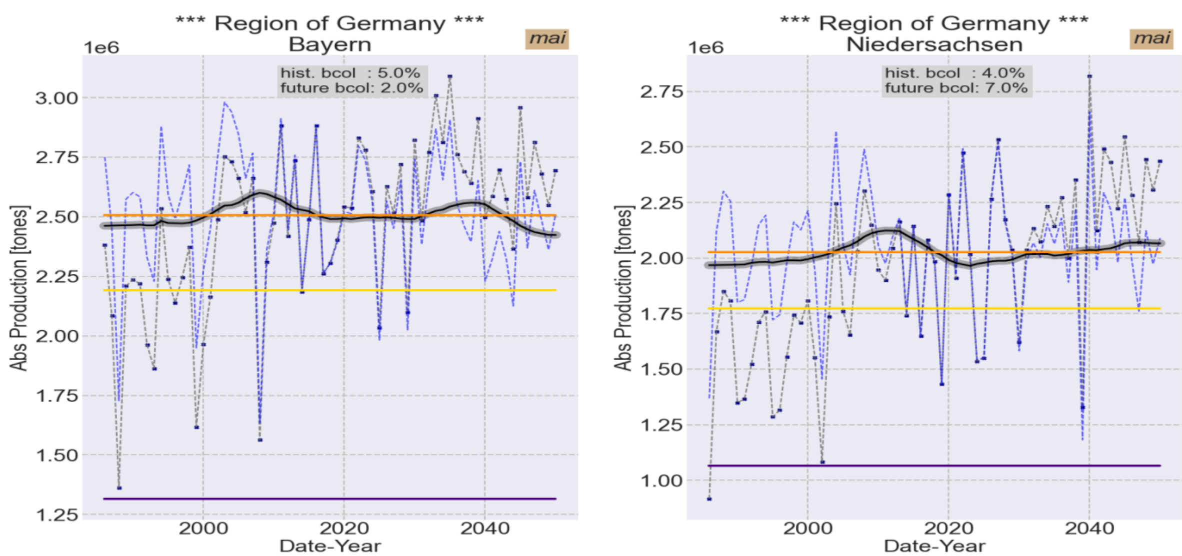

Figure 4: Graphs of 5% and 7% BCOL under two different future scenarios in the regions of Bayern and Niedersachsen

The historical data indicated that the yield performance increases overtime which aids to offset the low production made by retainer/farmer over the historical period until 2000 in Bayern and 2005 in Niedersachsen. However, during this time period the farmers were covered by the insurance. Consequently, it can be observed that the insurance coverage is triggered approximately 1 payment every 6.5 years for the first region and 1 time every 7 years for the second. Probabilistically, it corresponds to 0.23 and 0.27 likelihood that insurance coverage needed. After historical period, it is observed that the mass of the detrended production data is under the benchmark line between 2017 and 2030 for Bayern and between 2017 and 2025 for Niedersachsen. At these periods, there is increased risk for farmer. Concerning the policy holder payment, the deficit in production is small in Bayern and thus the farmers should not covered by the insurance, in contrast to Niedersachsen, where the burning cost online is higher and there are more detrended data lower of the trigger line. After 2040, in Bayern the trend falls again, raising the risk for the farmers. In comparison to France, the smoothed lines of the regions of Germany are higher compared to benchmark lines, and the data density bellow the trigger line is lesser, making wheat a robust choice for agricultural production in Germany.

In France, the smoothed line of detrended data is generally lower than Germany, meaning higher risk for farmer and insurance. However, after 2045 it is observed an increased trend in production for both Alpes and Aquitaine and the data get higher than benchmark line. In Germany, at the same period, it is observed decreased trend in Bayern and constant trend in Niedersachsen. It is evident that the microclimatic conditions of each region might alter the same type of crop that is typically planted there obliging farmers to shift to crops that are currently grown in warmer areas. Conversely, if the higher temperature exceeds a crop's optimum temperature, yields will tend to decline.

3.2 Area yield index for winter wheat

Currently, wheat is the most important staple cereal for millions of people around the world skyrocketing its demand which is forecasted to increase strongly in the future as a result of global population growth and changes in the dietary. Hence, increasing wheat production is one of the most important challenges that agriculture faces nowadays, especially as there has been a global decrease in the growth of wheat volumes since the decade of 1990s, potentially threatening global food security (European Commission). Moreover, the European Union (EU) acts as a key player in this context, since it is the largest wheat producer and supplier in the world, with wheat yields above the world average. However, many Member States (MSs), observe that their wheat yields are plateauing and as a consequence, this lack of yield improvements may put the future wheat consumption at a severe risk.

In order to assess the accuracy and suitability of the developed model, new winter wheat data were processed to estimate the actual yield risks in historical and future scenarios. The new crop addition allowed to quantify the difference between maize and wheat yields and thus to approximate the insurance coverage. Consequently, the exploration and the impact of asymmetric information (different crops) was processed in France and Germany allowing retainers/farmers to get valuable information concerning their decision to contract insurance, risk exposure and decide which is the appropriate crop production to be planted.

The new added wheat scenarios in two French regions are presented in the graph below:

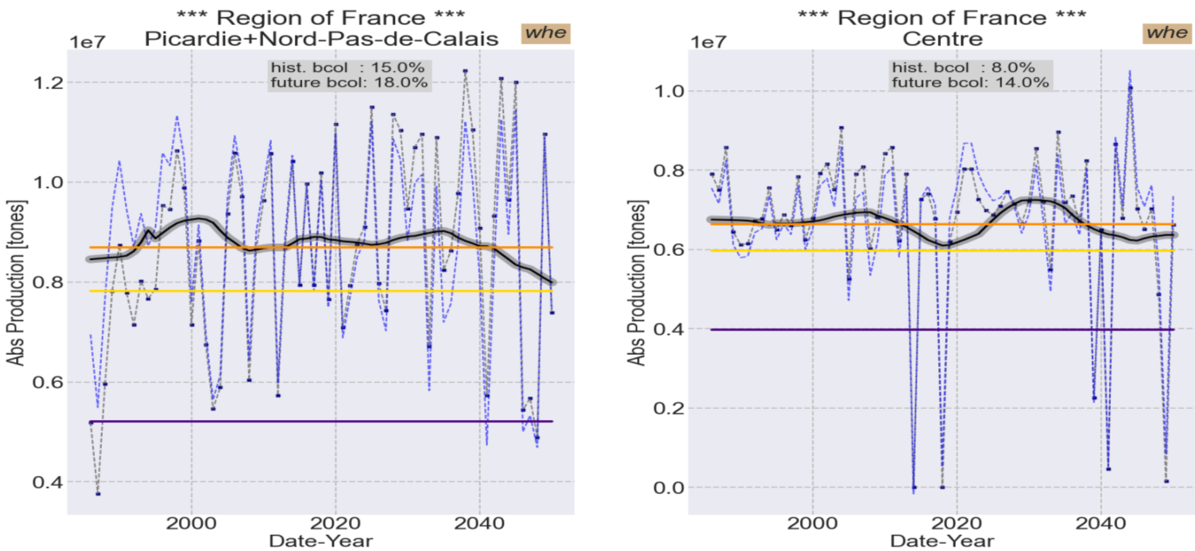

Figure 5: Graphs of 18% and 14% BCOL under two different future scenarios in the regions of Picardie + Nord Pas-de-Calais and Centre

As shown in Graph 5, similar characteristic with maize production in Germany were observed especially in the Picardie + Nord Pas-de-Calais region. However, the graphic comparison between the two French areas revealed that different trends were followed even if their average production volumes were almost similar and there is a close proximity in terms of geographical location.

Analytically, the biggest difference was observed in the historical scenarios (1985 to 2015) where the starting trend in yield is positive for the region of Centre in which 0.7 tons of wheat was produced while for the region of Picardie + Nord Pas-de-Calais it started with the less than desired volume of wheat production resulting to 0.9 tons respectively. Moreover, the historical data in the region of Centre, indicated the yield's small increase of the performance overtime throughout the historical period until 2015. It is noted that that during these 30 years of production there were stable positive yields without major increases or decreases which allowed the retainers to plan accordingly. During the rest 27 years, major instabilities can be observed. Wheat production started to underperform with a downwards trajectory which did not allow the farmers to get covered by the insurance since the production volume was kept between the trigger and the benchmark production outputting 0.6-0.7 tons of crops in the time period of 2013-2020. This decrease, however, was quickly compensated in the time period of 2020-2037 where a continuous increase in the yield is observed especially after passing the benchmark line in 2025 with maximum output of production 0.75 tones. The simulation ended with a decrease in the production volume from 2037 and thereafter where the production volume is in between the benchmark and the trigger line and thus the farmer is not compensated. In contrast, the production volume in France's Picardie + Nord Pas-de-Calais performed much more stable and positive in the historic scenario. It started from a less than expected production volume from the risk absorption zone (1985-1992), with continuous positive yields until 2043 maxing out in 2005 with an all-time high output of 0.9 tons of production. In addition to that, the smoothened data line moved in parallel with the benchmark production with very small fluctuations allowing the minimization of risk for 30 years.

Since 2035 and thereafter, a distinctive reversal in production volume is observed from the forecasting models in both regions. In the Picardie + Nord Pas-de-Calais region, a continuous negative output was observed surpassing the benchmark point for the rest of the simulation with some sign of recovery in the last five years of the simulation. Similarly, Centre followed the same negative trajectory for the rest of the scenario with less than expected returns to the retainers without triggering the insurance coverage though. However, the main difference of this continuous decrease was projected to fall within the below the sharing boundary, and thus the farmers will probably get compensated after 2050. Therefore, there was not any insurance coverage in both French regions, allowing the insurance companies to achieve high return with almost no risk in wheat production.

It must be noted that in the Centre scenario, many points of abnormal distance from other points were found (e.g.: 2014, 2018, 2042, 2048). These data points were zero or close to zero values which might slightly distorted the overall scenario described above even if only the smoothen data were considered which is the best way to discard the ‘outside the other values ’and avoid wrong projections.

The last scenario of this section and its analysis concerned Germany and the especially the production of winter wheat in the regions of Bayern and Niedersachsen. Again, the historical and future scenarios plotted together, and their graphical representation is illustrated below in Figure 6:

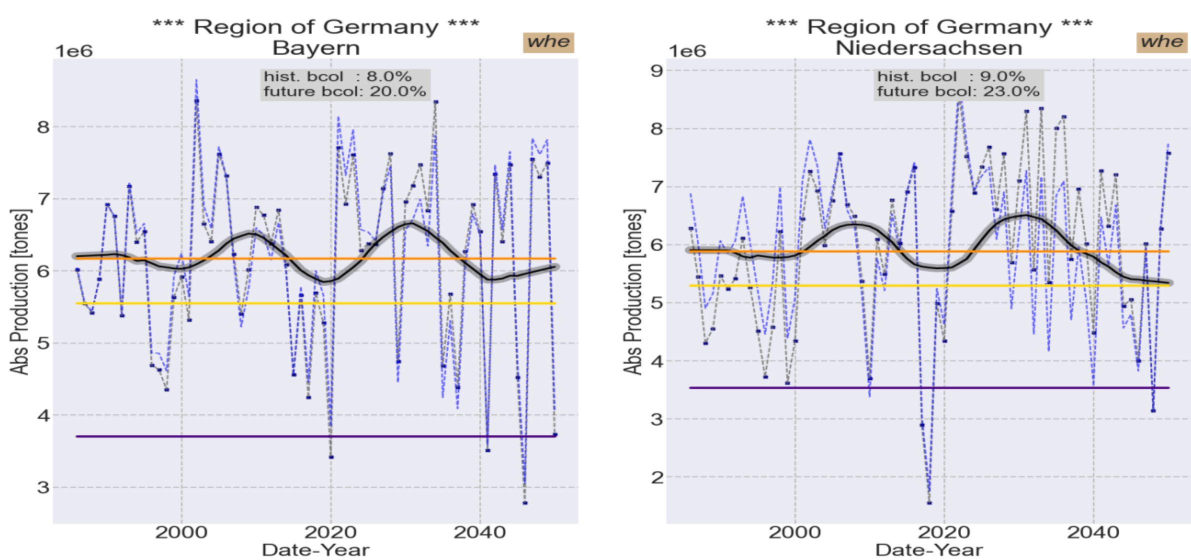

Figure 6: Graphs of 20% and 23% BCOL under two different future scenarios in the regions of Bayern and Niedersachsen

In Germany’s regions again, many fluctuations were recorded following similar occurrence of events. In Bayern region, the observation of the historical data indicated high variance in the wheat production volume outputting on average 6 tons of wheat during the period of 1985-2025. This volume was almost matching the benchmark line from the time period of 1985-2005 with some not significant crosses of the line in both positive and negative terms. This average output came to a halt, for a short period of 10 years (2005-2015) in which positive crop yields were observed. A similar pattern was followed in Niedersachsen region. The most profound difference, however, was that the production volume was even more stable with almost negligible risk absorption giving stability to the farmers. This positive yield ended and the steadily decreasing trend in average volume of production transferred the losses to the retainers during the time period of 2015-2025 without triggering the insurance in both regions. The remaining trajectory of the simulation followed a semitonical pattern, mirroring the previous trends and thus, it returned back to positive volumes in 2025-2037 with maximum output of 6.7 tones of production in both regions. lt became slightly positive for the next 5 years until their return to below the benchmark line again until 2024. Similarly, Bayern region phased an extended period of crop yield.

The simulation for Bayern region ended however, with a deficit for the remaining period 2037-2050 without triggering the insurance coverage with signs of recovery at the end of the simulation. A similar trend as Bayern, was forecasted for the Niedersachsen area with a continuous decrease of the trend's gradient resulting that the crop yields to reach their minimum level by 2050 producing 5.2 tons of wheat. In 2050s, the production volumes are almost equal with the trigger line and thus the insurance will probably get triggered in the following years.

3.3 BCOL over three warming scenarios

A boxplot, also known as a box and whiskers diagram, is a graphical representation of the distribution of a set of quantitative data in a way to promote the comparability between different variables (Galarnyk, 2021). The boxplot displays the median, quartiles, and extremes of the data. The width of the box is proportional to the interquartile range, and the whiskers extend to the most extreme data points within 1.5 times the interquartile range. In a boxplot, each of the data points is represented by a rectangle. The length of the rectangle is proportional to the value of the variable. The length of the whiskers represents one and a half times the interquartile range. Notably, the boxplot is composed of 5 elements: the median, the 25th percentile, the 75th percentile, the upper whisker, and the lower whisker (McGil et al., 2019). The median is the middle value in the data set, while the 25th and 75th percentiles are the values at which 25% and 75% of the data are below, respectively. The boxplot can be used to identify outliers and clusters. An outlier is an observation (data point) that is distant from other observations, while a cluster is a group of observations that are relatively close to each other (Galarnyk, 2021). Example of these additional information that can be added to the box plot include a description of statistic distribution of data values.

Figures 7 and 8 show the burning cost on line (BCOL) in percent over three warming scenarios for a total of eight regions in France and Germany. The first scenario is equivalent to the historical data with 0.5°C global mean temperature difference from the preindustrial area. The second scenario assumes a 1.5°C global mean temperature difference and the future SSP126 scenario. The third scenario assumes a 1.5°C global mean temperature difference and the future SSP585 scenario.

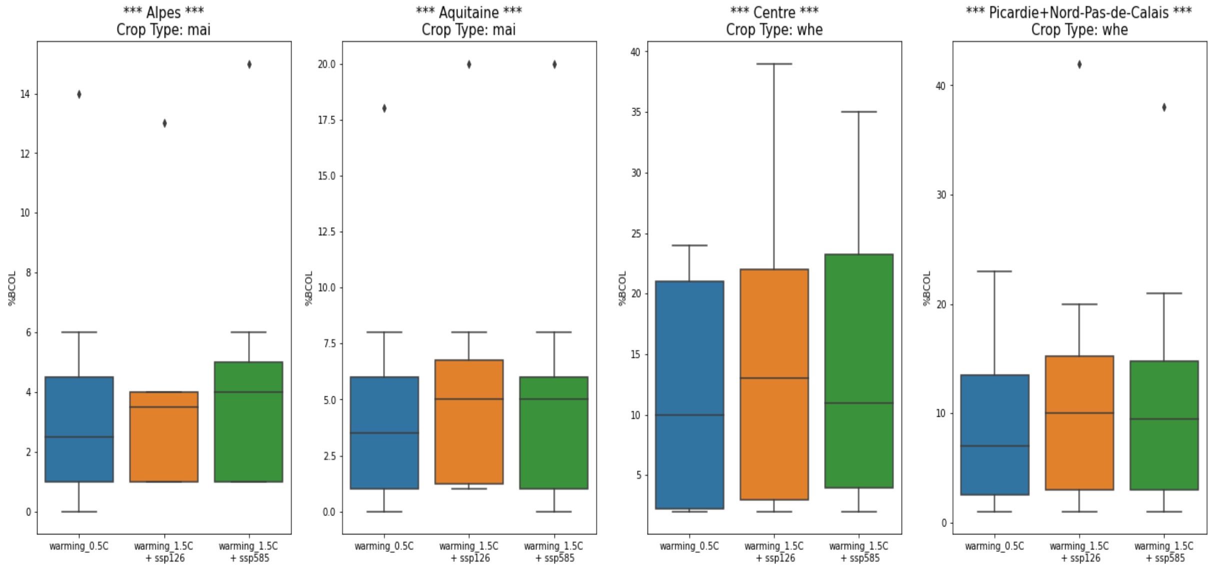

Figure 7: Graphs of BCOL in percent over three warming scenarios

Figure 7 shows the results for the Alps, Aquitaine, Centre, and Picardie / Nord pas de Calais. For Alpes, we see that the median BCOL increases from the first scenario at 2.5% to 5% in scenario 2 and 4.0% in scenario 3. The volatility of BCOL, represented by the spread of the boxplot, decreases from scenario 1 to 2 but increases again from scenario 2 to 3. Thus, the results imply that the uncertainty in BCOL is the lowest in scenario 2. In summary, scenario 3 is the most unattractive from an insurance perspective in the long run, while scenario 1 is the most special. In Aquitaine, the median BCOL for scenario 1 is 3.3%, for scenario 2 and 3 5.0%. However, the volatility increases from scenario 2 to 3 in the lower area. Thus, more attractive BCOL values seem more likely and scenario 3 is preferrable, while scenario 1 is the most attractive. In Centre, the median BCOL value for scenario 1 is 10%, 13% for scenario 2 and 11% for scenario 3. The volatility in scenario 2 is slightly higher than the one in scenario 3, and both are significantly higher than in scenario 1. While scenario 1 is the most attractive, scenario 3 is more attractive than scenario 2 in this region. In Picardie / Nord pas de Calais, the median values are 7% for scenario 1, 10% for scenario 2 and 9% for scenario 3. The volatility is highest for scenario 1, decreases in scenario 2 and slightly increases in scenario 3. Again, scenario 1 is the most attractive while scenario 2 is the most unattractive. In summary, for all regions except for Alpes, scenario 3 is slightly more attractive than scenario 2, while scenario 1 is the most attractive for all regions in France.

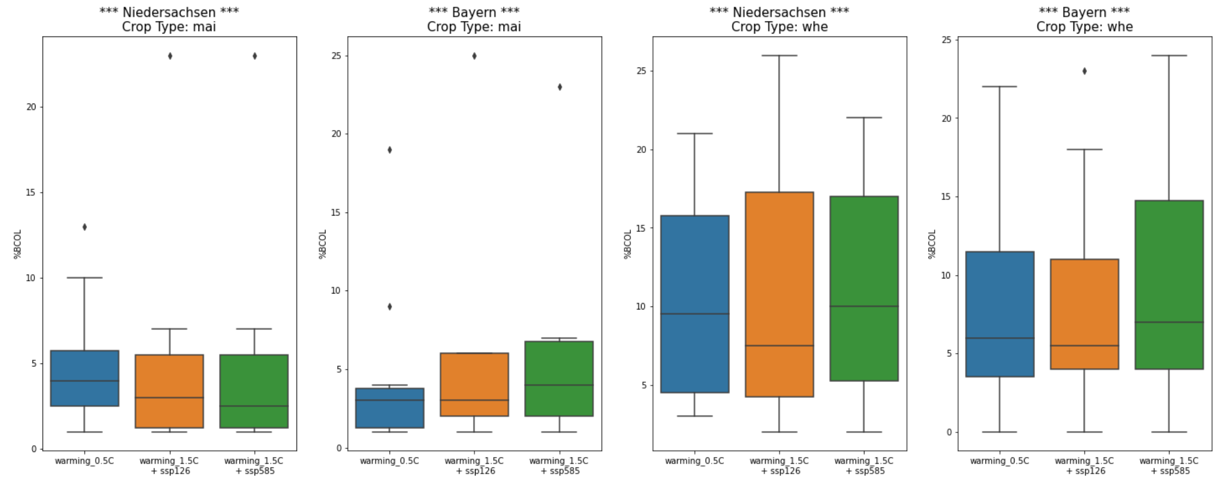

Figure 8: BCOL in percent over three warming scenarios

Figure 8 shows the results for the Niedersachsen with maize, Bayern with maize, Niedersachsen with wheat and Bayern with wheat. For Niedersachsen with maize, the median BCOL value for scenario 1 is 4.3%, for scenario 2 3.5% and for scenario 3 2.5%. The volatility of scenario 1 is highest, while the ones of scenarios 2 and 3 are comparable. Thus, scenario 3 is the most attractive. For Bayern with maize, the median value in scenarios 1 and 2 is 4%, while the one for scenario 3 is at 4.5%. The volatility increases from scenario 1 to 2 to 3. Thus, scenario 1 is the most attractive, followed by scenario 2. In Niedersachsen with wheat, the median BCOL value is 9.5% for scenario 1. For scenario 2, it is 7.5% and for scenario 3 10%. The volatility in scenario 1 is the lowest, and the one in scenario 2 the highest. Despite the high uncertainty, the long-term attractiveness of scenario 2 is the highest, followed by scenario 1. Finally, for Bayern with wheat, the median value in scenario 1 is 5.5%, 5.3% in scenario 2 and 6.5% in scenario 3. The volatility is lowest in scenario 2, followed by scenario 1 and finally 3. Thus, scenario 2 is the most attractive from a risk perspective, while scenario 3 is the most unattractive.

In summary, figures show that in France, scenario 1 is consistently the most attractive. Apart from the Alpes, scenario 2 is consistently the most unattractive. In Germany, the results are less consistent. In Niedersachsen with maize, scenario 3 is the most attractive and scenario 1 the most unattractive, while in Bayern with maize, scenario 1 is the most and scenario 3 is the least attractive. For wheat, scenario 2 is the most attractive and scenario 3 the most unattractive in both regions.

Chapter 4: Discussion

4.1 Observations and main limitations of parametric modelling

A comprehensive review of the available data and its credibility is a fundamental step in the initial design and rating of all insurance schemes. In most of the cases, individual coverage is typically preferred by farmers. However, the data needed for deriving accurate insurance rates for each individual farmer, are almost never available. In such cases where there's a lack of data consistency at the individual level, two options are available. One way is to use aggregation of data in an attempt to measure all the different individual contract parameters. Alternatively, another approach is by considering coverage based upon historical observations and indices that reflect as close as possible the incurred losses by the farmers. Moreover, the availability and credibility of data in each region, are also the most important parameter in the production of a risk modelling tool. In such cases where significant availability and a big amount of reliable data is observed, one may decide to adopt nonparametric approaches when modeling yield risks in agriculture. However, such cases where not examined in this thesis and thus future work should be done to assess the differences and any possible correlation between parametric and non-parametric approaches in the examined areas. The most common case however, is where there's a limited availability of data. In such cases, parametric methods as those described above are preferable to simulate crop yields as accurate as possible. Consequently, this choice leads to a big tradeoff between bias and efficiency. When historical losses are available, crop yield modelling can become much more accurate when forecasting both the insurance risk and the production volume. In contrast, when rating an insurance scheme in absence of historical data available it relies to the sensitivity of the simulation scenarios and thus losses derived from crop yield models may differ depending on each scenario's parameters. This paper analyzed two different future scenarios under which agricultural insurance in crops can be forecasted. They rely on accurate statistical and actuarial developments in combination with empirical work based on historical experience.

Furthermore, the analysis of this thesis is based on CGM output. In the context of Agri re/insurance, any approach to assess climate impacts shall bring at least the following characteristics: a) global coverage b) the role of technology (i.e., changing agro management practices) vs. climate shall be separated ('as-if view) and c) plausible climate impacts can be translated into crop impacts (source discussion with Swiss Re's agro underwriters). Arguably, process-based CGMs meet these requirements. For instance, spatially explicit CGM configurations can simulate yields globally. In such simulations, the agromanagement practices are kept static, and the climate is the primary driver of variability (the role of technology is factored out). Moreover, CGMs were developed to quantify and translate climate impacts on crops (see 1.2.1). On the other hand, a mechanistic model explains the crop growth course using underlying physiological processes about the environment (see 1.2.1).

The thesis investigates the changing risk landscape at a higher granularity compared to other relevant research (Eberenz, 2021). In addition, climate impacts are assessed from an insurance product's point of view. This is a step beyond traditional practices, where assessments of climate risks end at the effects on pure yields.

Taking into consideration the above analysis and results, it is remarkably observed that a time series is a collection of events obtained from sequential measurements over time. In maize scenario, it can clearly been observed that in both of Germany's regions and the Centre of France there are many fluctuations and patterns that are being repeated. Partial periodic patterns are a valuable class of regularities that exist in a time series. In this way, the key critical property of these patterns is that conclusions can made on how they can start, stop, and restart anywhere within a series. Consequently, their crop yield characteristics can be categorized as regular patterns, patterns exhibiting periodic behavior throughout a series with some exceptions (e.g., maize production in Bayern) and recurring patterns, patterns exhibiting periodic behavior only for specific time intervals within a series (e.g., Niedersachsen). Thus, modelling the crop prediction using parametric approaches, could lead to partial periodic examination focusing on finding those patterns and their correlation with historical events. In this way, they provide valuable information pertaining to seasonal or temporal associations for a better understanding of crop production over time.

4.2 Conclusions within the Countries - Targets achieved & Future goals

As indicated in the previous sections, agricultural risk models for different regions of France and Germany were analyzed to forecast crop insurance, compensation, and risk absorption in order to quantify crop portfolio losses. In all the analyzed cases, crop losses were caused due to various parameters taken into account in the suggested models (e.g., adverse weather events, drought, flood, hail, frost, and windstorm). Estimating the likelihood and magnitude of future crop volumes and losses is still a significant challenge. Thus, the detailed patterns of crop volumes over a time period are a very important factor for decision making. For this reason, the key indices analyzed in the section above where grouped and plotted together and they are presented in the figure 9:

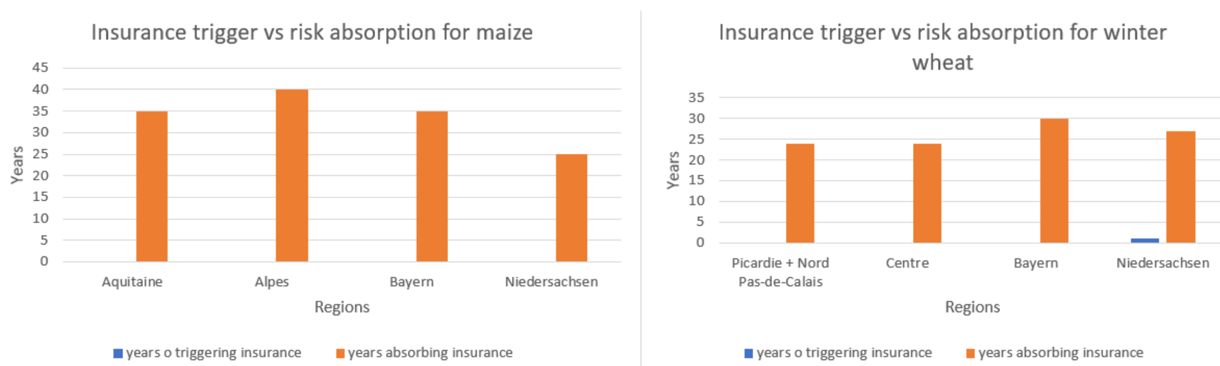

Figure 9: Insurance Trigger VS Risk Absorption

As it can be clearly observed in all cases, retainers/ farmers absorbed the vast majority of the risk when low crop yields occurred. This situation allowed the insurance companies to gain large amounts of revenues when charging premiums in exchange for insurance coverage. Especially for maize, the insurance was never triggered to compensate the retainers in the region. Consequently, the risk for the insurance companies was observed to be extremely low, allowing them to comfortably offer a customer a policy, knowing that its potential risk of paying out on that policy is very low. Similarly in maize production, low yields were absorbed as well by the farmers with only one year of compensation in the forecast model in the region Niedersachsen. Thus, it can be concluded that even if insurance coverage is a valuable tool for the risk mitigation of any crop production, in the cases analyzed it doesn't add any value for the farmers decided to grow winter wheat and maize.

Furthermore, low distortion and small variations of each year's yield, ensure production stability allowing farmers to minimize their income risk and thus, expand their businesses. Consequently, status change metrics illustrated in the figure above is another tool to assess the production in terms of risk:

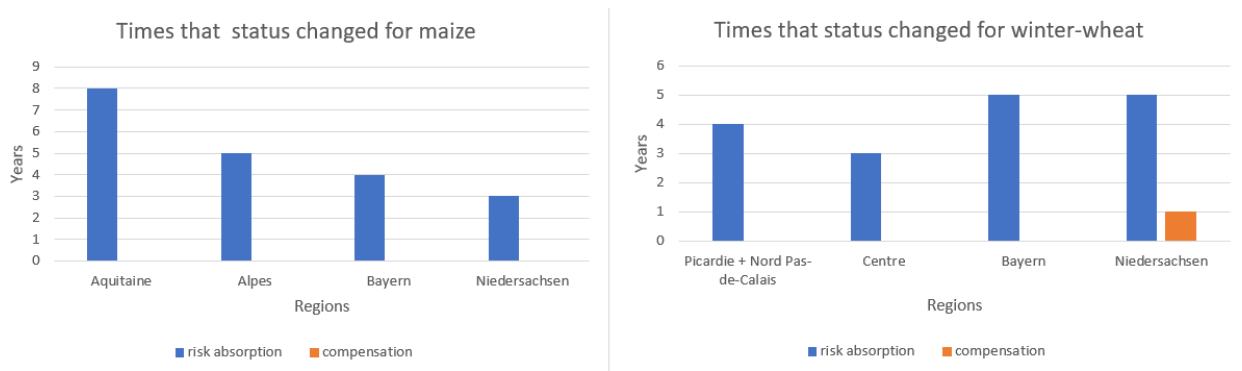

Figure 10: Times that status changed for maize/wheat

From the graphs plotted, the comparison of the times that status changed for wheat is explained and it can be concluded that in the 65 years analyzed, periods of positive and negative changes occured in all regions. In maize production, the most volatile region was Aquitaine where the insurance status changed 8 times (all for risk absorption). This volatility allowed smaller loss intervals before returning to positive volumes, meaning that farmers faced more opportunities when making decisions. The downside however is that, when a trend ends, losing yields will occur inevitably. In addition to that, useful patterns and strong trends cannot be identified maximizing the overall risk and uncertainty. In German other areas, the status changed less times giving the appropriate time to farmers to make the right decisions. Status change in winter wheat, followed a bit more predictable pattern than maize. The most volatile areas are in Germany this time, with 5 times status change in Bayern and 6 in Niedersachsen while less changes were observed in Centre and Picardie + Nord Pas de Calais with 3 and 4 changes respectively.

Europe ranked first in the world as to the imports and export amount of wheat and maize and other grain products. Among the best regions to grain harvest, certain areas in France and Germany were analyzed. To examine the changes in the structure of sown areas, clustering of data and future simulations from 1985 to 2050 were performed on the basis of parametric modelling and correlation analysis. Indicators for the assessment were the annual data, temperature and weather conditions on these areas of the two most common crops. As a result, two different clusters were obtained: the first cluster is the historical period from 1985 to 2015 inclusive, the second one, from 2015 to 2045. Winter wheat seems to rank first regarding the sown area size, which on average is bigger in terms of the total crop volume, especially in the forecasted future scenarios. Winter wheat sown area has decreased performance in the beginning of the historical scenarios in both France and Germany compared to maize production as shown in the graph and the analysis above which made the production of maize especially in the regions of Aquitaine and Alpes a better choice. This can be attributed to better microclimatic conditions for the certain seed or the introduction of specific technical agricultural equipment. Maize scenarios have undergone to more significant changes depending on the location. The average yields for different areas can correlate with each other but their trend is inversely proportional between France and Germany.

However, some limitations and observable weaknesses can be effectively stated throughout the research. Points to be addressed are:

1. Assumption about static vulnerability and exposure: IPCC defines risk as a function of hazard, vulnerability and exposure. The thesis is focused on the hazard part of the risk equation (e.g., changing climate risk). All other components are assumed static. Examples of vulnerability drivers could be the varieties planted or other agromanagement practices (e.g., fertilization, irrigation etc.) that can have a direct impact on crop growth and development. Exposure can be associated to e.g., insurance conditions, product structure, geographic portfolio spread etc. The thesis assumes that both vulnerability and exposure remain static, representative of today's world/situation. Assessments of risk and vulnerability are contingent upon a common interpretation of the words. According to Cardona et al, (2012), exposure and vulnerability are dynamic and vary across spatial and temporal scales based on social, economic, demographic, geographic, cultural, governance, institutional and environmental factors. Communities are variedly vulnerable and exposed depending on their education, wealth, gender, disability, ethnicity as well as health status. Lack of capacity to anticipate, resilience, cope or adapt to extremes are the causal factors of vulnerability (Cardona et al. 2012). Climate change exposure and vulnerability may be as a result of skewed development process connected to demographic changes, environmental mismanagement, failed governance and unplanned urbanization. According to the international Standards Organization, risk assessment can be defined as the process of comprehending the nature of risk and determining the level of risk (Cardona et al. 2012). Vulnerability and risk assessment comprise a variety of approaches and techniques, ranging from global or national evaluations based on indicators to qualitative participatory approaches at the local level. At the local level, risk assessment presents various challenges linked to unavailability of climate data as well as dynamic interplay and high complex between the capacities of individuals and communities and challenges that they face (Cardona et al. 2012).

2. Uncertainties in the global gridded crop growth model output: There are known issues with these data. First, CGMs inherit limitations and biases from the driving CMIP models. A positive aspect here is, that the gridded simulations use bias-corrected and statistically downscaled (from 1-2deg native grid to a 0.5deg grid) CMIP output as a climate forcing. Yet, the models might still not adequately represent regional climate extremes. There are also similar issues with the soil data. One of the main sources of uncertainty, relates to the local agromanagement practices and calibration of the cultivar-specific parameters. Since it is very challenging to calibrate locally a global CGM configuration, the modelers did several assumptions about the agromanagement

practices that may not reflect the situation in reality. Finally, processes influencing crops in the real world might not be well represented (e.g., pests, diseases) or not represented at all (e.g., the effect of hail, fire, frost etc) in CGMs. Another source of uncertainty in GGCMs include use of biophysical models, input data and set ups (Folberth et al., 2019). To cope with uncertainties arising from lack of global comprehensive data on cultivar distributions, crop management and coefficients for agro-environmental processes, usage of GGCM ensemble incorporating varying assumptions on set ups emerges as the only solution (Folberth et al., 2019).

3. AYI calculation for Level 1 regions: Typically, AYI is offered across small geographic areas. In view of the uncertainties in the data (see previous point), it is not safe to calculate AYIs at local scales. As a compromise, the analysis focuses on the Level 1 regions (a bit safer to analyze than e.g., the departments or grid points).

4. Role of internal climate variability in the near term: Internal variability of climatic system leads to a lot of uncertainty in projecting future climate. These uncertainties can be assessed from large ensembles of climate change simulations with a small perturbations in the initial atmospheric condition (Thompson et al., 2015). One of the main challenges when assessing climate impacts on the financial services sector (e.g., banking, investing, re/insurance etc) relates to the relatively short time horizon for decision making. For instance, agri re/insurance contracts are renewed every one to max three years. However, climate change impacts cannot be assessed on such short timescales. In the near term any signal is mainly dominated by the random internal climate variability. With the current data, the compromise is to look into a 30 year-long future horizon (i.e., from present-day to 2040's). Yet, even on this time horizon, robust climate signals might not be detectable.

Based on the above, it can be concluded that it is impossible to specifically diversify the potential risks of crop failures by means choosing the appropriate insurance and the appropriate crop production, because the results for different crops are greatly varying across different regions even if some trends could be observed. However, the main objective of agricultural production is to optimize the use of resources and patterns to reduce risks while pursuing better production in terms of volume as well as better terms when bargaining with insurance companies. For all the retainers/ agricultural companies involved in the cultivation of crops, insurance is an important component of their risk management, as the vast majority of activities of these companies is greatly influenced by many indeterminate factors impossible to avoid or to modify. First of all, the most important factor is weather and agro-climatic conditions. One must not omit the fact that the extreme weather conditions especially due to climate change will affect most European territories, and thus, agriculture is located in the high risky jobs, which greatly increases the probability of future crop loss.

Consequently, forecasting accurately the future scenarios will ensure that farmers can deal with these changes more effectively. In 1985 the volume of production of crop cultivation in Aquitaine was 4 tones per year, while it is projected to drop in 3,5 tones. This is estimated to a 13% decrease, excluding the typically high insurance cost, which makes of the total loss even bigger. With the increased of risk degree, an insurance company can respond with the revision of conditions by raising tariffs (change of percentage in trigger line), refusing to insure high risks crops, limiting coverage in different regions or even transmitting risks of to the Government and the European Union. Consequently, a key task is to find the optimal insurance rates that can satisfy both insurance companies and retainers/ farmers, as well as to outline the best security procedure that would be able to increase the efficiency of farmers.

Security strategy should imply the development of different innovative products and systems that introducing new insurance technologies that will reduce vulnerability and forecast the crop productions in the future which was the initial aim of this thesis. The method developed could be also used by the agricultural producers in the face of natural factors that will provide support for right decision making and lead to a more sustainable and eco-friendly agriculture. Lastly using this model, agricultural businesses could be benefited not only in financial terms with high crop yields, but also with the creation of new favorable, stable and long-term conditions for crop raising, within the context of the whole industry and in the field of risk-insurance. In order to improve the efficiency of agricultural development in the future, it is very important to develop and implement targeted programmes of agricultural insurance across Europe, based on the use of the optimum insurance rates that are generated with the aid of accurate forecasting models.

Appendix

Some functions of CLIMADA that are taken into consideration are the below ones:

Import Hazard: Hazard is about the intensity and the frequency of the weather and the climate events. Here, the hazard is represented by normalized crop yield. Normalized crop yield is the relative deviation of the simulated crop yield per grid cell from a historical mean value.

Import Exposure: Exposure describes people, ecosystems & assets that can be affected by the hazard. Here, exposure is represented by the baseline crop production gridded historical mean crop production per crop type.

Import ImpactFuncSet: Impact function is the vulnerability term in the risk calculation formula. It relates hazards to the degrees of damage. In other words, impact describes the percentage of damage in the exposure to the hazard intensity.

Import Impact: Impact from climada_engine is the final function that, given the exposure, the hazard, and the impact function that relates them, calculates the risk.

GetPlots Method

The getPlots code was created by the writer in order to pull the extracted data of the CSV files and make them graphs (the well-known time series).

Get Time Series

This is a class with two internal functions. A class is essentially an object in python, grouping functions that perform a purpose (not to mention many are complex). This class contains the above two functions (codes calc_admin & getPlots). The class is called by the main program call_get_time_series. The main program is made so that the user gets the results by changing only the variable crop_type.

For each crop type it repeatedly calls the functions of the class for all scenarios (historical scenario & two future scenarios). Obviously, if you want to run for a specific region, different from the default, you make the necessary changes. Here, France is the country that is analyzed only, but different regions-departments per crop type.

Graphs, generally, can go from the temporal analysis of the phenomenon to the temperature. Specifically, they collect all the data from all the climate models-scenarios and are grouped by the increase in the global mean temperature.

References

Aggarwal, P., Vyas, S., Thornton, P., Campbell, B. M., & Kropff, M. (2019). Importance of considering technology growth in impact assessments of climate change on agriculture. *Global Food Security*, *23*, 41–48. https://doi.org/10.1016/j.gfs.2019.04.002

Ahmed, M., Stöckle, C. O., Nelson, R., & Higgins, S. (2017). Assessment of Climate Change and Atmospheric CO2 Impact on Winter Wheat in the Pacific Northwest Using a Multimodel Ensemble. *Frontiers in Ecology and Evolution*, *5*, 51. https://doi.org/10.3389/fevo.2017.00051

Ainsworth, E. A., & Long, S. P. (2021). 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology*, *27*(1), 27–49. https://doi.org/10.1111/gcb.15375

Ainsworth, E. A., & Long, S. P. (February). What have we learned from 15 years of free-air CO2 enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising CO2. *New Phytologist*, *165*(2), 351–372. https://doi.org/10.1111/j.1469-8137.2004.01224.x

Akinseye, F. M., Adam, M., Agele, S. O., Hoffmann, M. P., Traore, P. C. S., & Whitbread, A. M. (2017). Assessing crop model improvements through comparison of sorghum (sorghum bicolor L. moench) simulation models: A case study of West African varieties. *Field Crops Research*, *201*, 19–31. https://doi.org/10.1016/j.fcr.2016.10.015

AON. (2018). *Weather, Climate & Catastrophe Insight: 2018 Annual Report*. London, UK: AON.

Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., … Zhu, Y. (2015). Rising temperatures reduce global wheat production. *Nature Climate Change*, *5*(2), 143–147. https://doi.org/10.1038/nclimate2470

Aznar-Siguan, G., & Bresch, D. N. (2019). CLIMADA v1: A global weather and climate risk assessment platform. *Geoscientific Model Development*, *12*(7), 3085–3097. https://doi.org/10.5194/gmd-12-3085-2019

Balkovič, J., van der Velde, M., Schmid, E., Skalský, R., Khabarov, N., Obersteiner, M., … Xiong, W. (2013). Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation. *Agricultural Systems*, *120*, 61–75. https://doi.org/10.1016/j.agsy.2013.05.008

Barriopedro, D., Fischer, E. M., Luterbacher, J., Trigo, R. M., & García-Herrera, R. (2011). The hot summer of 2010: Redrawing the temperature record map of Europe. *Science*, *332*(6026), 220–224. https://doi.org/10.1126/science.1201224

Basso, B., & Liu, L. (2019). Seasonal crop yield forecast: Methods, applications, and accuracies (Chapter Four). In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 154, pp. 201–255). Academic Press. https://doi.org/10.1016/bs.agron.2018.11.002

Battisti, R., Sentelhas, P. C., & Boote, K. J. (2017). Inter-comparison of performance of soybean crop simulation models and their ensemble in southern Brazil. *Field Crops Research*, *200*, 28–37. https://doi.org/10.1016/j.fcr.2016.10.004

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., Van der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. *Nature Communications*, *9*, 1627. https://doi.org/10.1038/s41467-018-04087-x

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine Learning in Agriculture: A Comprehensive Updated Review. *Sensors*, *21*(11), 3758. https://doi.org/10.3390/s21113758

Bert, F., de Estrada, M., Naumann, G., Negri, R., Podestá, G., Milagros Skansi6, M. de los, … Quesada, M. (2021). *The 2017-18 drought in the Argentine Pampas – Impacts on Agriculture* [GAR Special Report on Drought 2021 - Case studies]. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction.

Boote, K. J., Jones, J. W., White, J. W., Asseng, S., & Lizaso, J. I. (2013). Putting mechanisms into crop production models. *Plant, Cell & Environment*, *36*(9), 1658–1672. https://doi.org/10.1111/pce.12119

Bresch, D. N., & Aznar-Siguan, G. (2021). CLIMADA v1.4.1: Towards a globally consistent adaptation options appraisal tool. *Geoscientific Model Development*, *14*(1), 351–363. https://doi.org/10.5194/gmd-14-351-2021

Brisson, N., Gate, P., Gouache, D., Charmet, G., Oury, F.-X., & Huard, F. (2010). Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. *Field Crops Research*, *119*(1), 201–212. https://doi.org/10.1016/j.fcr.2010.07.012

Camargo, G. G. T., & Kemanian, A. R. (2016). Six crop models differ in their simulation of water uptake. *Agricultural and Forest Meteorology*, *220*, 116–129. https://doi.org/10.1016/j.agrformet.2016.01.013

Cardona, O.-D., van Aalst, M. K., Birkmann, J., Fordham, M., McGregor, G., Perez, R., … Sinh, B. T. (2012). Determinants of Risk: Exposure and Vulnerability (Chapter Two). In C. B. Field, V. Barros, T. F. Stocker, Q. Dahe, D. J. Dokken, K. L. Ebi, … P. M. Midgley (Eds.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (pp. 65–108). Cambridge, UK, and New York, NY: Cambridge University Press

Challinor, Andy. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(4), 287–291. https://doi.org/10.1038/nclimate2153

Ciscar, J.-C., Fisher-Vanden, K., & Lobell, D. B. (2018). Synthesis and Review: An inter-method comparison of climate change impacts on agriculture. *Environmental Research Letters*, *13*(7), 070401. https://doi.org/10.1088/1748-9326/aac7cb

Crane-Droesch, A. (2018). Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. *Environmental Research Letters*, *13*(11), 114003. https://doi.org/10.1088/1748-9326/aae159

d'Amour, C. B., Wenz, L., Kalkuhl, M., Steckel, J. C., & Creutzig, F. (2016). Teleconnected food supply shocks. *Environmental Research Letters*, *11*(3), 035007. https://doi.org/10.1088/1748-9326/11/3/035007

De Graaff, M.-A., Van Groenigen, K.-J., Six, J., Hungate, B., & Van Kessel, C. (2006). Interactions between plant growth and soil nutrient cycling under elevated CO2: A meta-analysis. *Global Change Biology*, *12*(11), 2077–2091. https://doi.org/10.1111/j.1365-2486.2006.01240.x

de Janvry, A., & Sadoulet, E. (2010). Agricultural Growth and Poverty Reduction. *World Bank Research Observer*, *25*(1), 1–20. https://doi.org/10.1093/wbro/lkp015

Duncan, J., & Myers, R. J. (2000). Crop Insurance under Catastrophic Risk. *American Journal of Agricultural Economics*, *82*(4), 842–855. https://doi.org/10.1111/0002-9092.00085

Elliott, J., Müller, C., Deryng, D., Chryssanthacopoulos, J., Boote, K. J., Büchner, M., … Sheffield, J. (2015). The Global Gridded Crop Model Intercomparison: Data and modeling protocols for Phase 1 (v1.0). *Geoscientific Model Development*, *8*(2), 261–277. https://doi.org/10.5194/gmd-8-261-2015

Elliott, Joshua, Kelly, D., Chryssanthacopoulos, J., Glotter, M., Jhunjhnuwala, K., Best, N., … Foster, I. (2014). The parallel system for integrating impact models and sectors (pSIMS). *Environmental Modelling & Software*, *62*, 509–516. https://doi.org/10.1016/j.envsoft.2014.04.008

Ettinger, A. K., Chuine, I., Cook, B. I., Dukes, J. S., Ellison, A. M., Johnston, M. R., … Wolkovich, E. M. (2019). How do climate change experiments alter plot-scale climate? *Ecology Letters*, *22*(4), 748–763. https://doi.org/10.1111/ele.13223

Evenson, R. E., & Gollin, D. (2003). Assessing the impact of the green revolution, 1960 to 2000. *Science*, *300*(5620), 758–762. https://doi.org/10.1126/science.1078710

Ewert, F., van Bussel, L. G. J., Zhao, G., Hoffmann, H., Thomas Gaiser, Specka, X., … Moriondo, M. (2014). Uncertainties in Scaling-Up Crop Models for Large-Area Climate Change Impact Assessments. In D. Hillel & C. Rosenzweig (Eds.), *Handbook of Climate Change and Agroecosystems: The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments—Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America (In 2 Parts)*:

Vol. Volume 3 (pp. 261–277). London, UK: Imperial College Press. https://doi.org/10.1142/9781783265640_0010

Eyshi Rezaei, E., Siebert, S., & Ewert, F. (2017). Climate and management interaction cause diverse crop phenology trends. *Agricultural and Forest Meteorology*, *233*, 55–70. https://doi.org/10.1016/j.agrformet.2016.11.003

Fischer, E. M., Sippel, S., & Knutti, R. (2021). Increasing probability of record-shattering climate extremes. *Nature Climate Change*, *11*(8), 689–695. https://doi.org/10.1038/s41558-021-01092-9

Folberth, C., Elliott, J., Müller, C., Balkovič, J., Chryssanthacopoulos, J., Izaurralde, R. C., … Wang, X. (2019). Parameterization-induced uncertainties and impacts of crop management harmonization in a global gridded crop model ensemble. *PLoS ONE*, *14*(9), e0221862. https://doi.org/10.1371/journal.pone.0221862

Frei, E. R., Schnell, L., Vitasse, Y., Wohlgemuth, T., & Moser, B. (2020). Assessing the Effectiveness of in-situ Active Warming Combined With Open Top Chambers to Study Plant Responses to Climate Change. *Frontiers in Plant Science*, *11*, 539584. https://doi.org/10.3389/fpls.2020.539584

Fuglie, K. O. (2018). Is agricultural productivity slowing? *Global Food Security*, *17*, 73–83. https://doi.org/10.1016/j.gfs.2018.05.001

Galarnyk, M. (2018, September 12). Understanding Boxplots [Online article]. Retrieved February 22, 2022, from Medium website: https://towardsdatascience.com/understanding-boxplots-5e2df7bcbd51

Gaupp, F., Hall, J., Hochrainer-Stigler, S., & Dadson, S. (2020). Changing risks of simultaneous global breadbasket failure. *Nature Climate Change*, *10*(1), 54–57. https://doi.org/10.1038/s41558-019-0600-z

Gonzalez-Sanchez, A., Frausto-Solis, J., & Ojeda-Bustamante, W. (2014). Predictive ability of machine learning methods for massive crop yield prediction. *Spanish Journal of Agricultural Research*, *12*(2), 313–328. https://doi.org/10.5424/sjar/2014122-4439

Goswami, A., Borasi, P., & Kumar, V. (n.d.). Crop Insurance Market Size, Share | Industry Analysis & Growth by 2027 [Online]. Retrieved November 26, 2021, from Allied Market Research website: https://www.alliedmarketresearch.com/crop-insurance-market-A06791

Hoffman, A. L., Kemanian, A. R., & Forest, C. E. (2017). Analysis of climate signals in the crop yield record of sub-Saharan Africa. *Global Change Biology*, *24*(1), 143–157. https://doi.org/10.1111/gcb.13901

Hohl, R. M. (2019). *Agricultural Risk Transfer: From Insurance to Reinsurance to Capital Markets* (1st edition). Chichester, West Sussex, United Kingdom: Wiley.

Holzworth, D. P., Snow, V., Janssen, S., Athanasiadis, I. N., Donatelli, M., Hoogenboom, G., … Thorburn, P. (2015). Agricultural production systems modelling and software: Current status and future prospects. *Environmental Modelling & Software*, *72*, 276–286. https://doi.org/10.1016/j.envsoft.2014.12.013

Iizumi, T., & Ramankutty, N. (2016). Changes in yield variability of major crops for 1981–2010 explained by climate change. *Environmental Research Letters*, *11*(3), 034003. https://doi.org/10.1088/1748-9326/11/3/034003

Iturrioz, R. (2009). *Agricultural insurance* (No. Working Paper No. E20-77). Washington, D.C.: The World Bank.

Jeong, J. H., Resop, J. P., Mueller, N. D., Fleisher, D. H., Yun, K., Butler, E. E., … Kim, S.-H. (2016). Random Forests for Global and Regional Crop Yield Predictions. *PLoS ONE*, *11*(6), e0156571. https://doi.org/10.1371/journal.pone.0156571

Johnston, B. F., & Mellor, J. W. (1961). The Role of Agriculture in Economic Development. *The American Economic Review*, *51*(4), 566–593.

Jones, J. W, Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., … Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, *18*(3), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jones, James W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., … Wheeler, T. R. (2017a). Brief history of agricultural systems modeling. *Agricultural Systems*, *155*, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014

Jones, James W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., … Wheeler, T. R. (2017b). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems*, *155*, 269–288. https://doi.org/10.1016/j.agsy.2016.09.021

Lamichhane, J. R. (2021). Rising risks of late-spring frosts in a changing climate. *Nature Climate Change*, *11*(7), 554–555. https://doi.org/10.1038/s41558-021-01090-x

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. https://doi.org/10.1038/nature16467

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine Learning in Agriculture: A Review. *Sensors*, *18*(8), 2674. https://doi.org/10.3390/s18082674

Lobell, D. B., & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, *12*(1), 015001. https://doi.org/10.1088/1748-9326/aa518a

Lobell, D. B., & Burke, M. B. (2010a). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology*, *150*(11), 1443–1452. https://doi.org/10.1016/j.agrformet.2010.07.008

Lobell, D. B., & Burke, M. B. (2010b). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology*, *150*(11), 1443–1452. https://doi.org/10.1016/j.agrformet.2010.07.008

Lobell, D. B., & Field, C. B. (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, *2*, 014002. https://doi.org/10.1088/1748-9326/2/1/014002

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, *3*(5), 497–501. https://doi.org/10.1038/nclimate1832

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. *Science*, *333*(6042), 616–620. https://doi.org/10.1126/science.1204531

Long, S. P., Ainsworth, E. A., Rogers, A., & Ort, D. R. (2004). Rising atmospheric carbon dioxide: Plants FACE the future. *Annual Review of Plant Biology*, *55*, 591–628. https://doi.org/10.1146/annurev.arplant.55.031903.141610

Manderscheid, R., Erbs, M., & Weigel, H.-J. (2014). Interactive effects of free-air CO2 enrichment and drought stress on maize growth. *European Journal of Agronomy*, *52*(Part A), 11–21. https://doi.org/10.1016/j.eja.2011.12.007

Mcgill, R., Tukey, J. W., & Larsen, W. A. (1978). Variations of Box Plots. *The American Statistician*, *32*(1), 12–16. https://doi.org/10.1080/00031305.1978.10479236

Meijerink, G. W., & Roza, P. (2007). *The role of agriculture in economic development* (pp. 1–38) [Research report]. Wageningen, The Netherlands: Stichting DLO / Wageningen UR.
Nicholls, N. (1997). Increased Australian wheat yield due to recent climate trends. *Nature*, *387*(6632), 484–485. https://doi.org/10.1038/387484a0

Palosuo, T., Kersebaum, K. C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J. E., … Rötter, R. (2011). Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models. *European Journal of Agronomy*, *35*(3), 103–114. https://doi.org/10.1016/j.eja.2011.05.001

Pawlak, K., & Kołodziejczak, M. (2020). The Role of Agriculture in Ensuring Food Security in Developing Countries: Considerations in the Context of the Problem of Sustainable Food Production. *Sustainability*, *12*(13), 5488. https://doi.org/10.3390/su12135488

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., … Travasso, M. I. (2014). Food Security and Food Production Systems (Chapter Seven). In C. B. Field, V. R.

Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, … L. L. White (Eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.* (pp. 485–533). Cambridge, UK and New York, N.Y.: Cambridge University Press.
Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., & Foley, J. A. (2012). Recent patterns of crop yield growth and stagnation. *Nature Communications*, *3*(1), 1293. https://doi.org/10.1038/ncomms2296

Rippey, B. R. (2015). The U.S. drought of 2012. *Weather and Climate Extremes*, *10*(Part A), 57–64. https://doi.org/10.1016/j.wace.2015.10.004

Roberts, M. J., Braun, N. O., Sinclair, T. R., Lobell, D. B., & Schlenker, W. (2017). Comparing and combining process-based crop models and statistical models with some implications for climate change. *Environmental Research Letters*, *12*(9), 095010. https://doi.org/10.1088/1748-9326/aa7f33

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., … Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences*, *111*(9), 3268–3273. https://doi.org/10.1073/pnas.1222463110

Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*(3), 197–202. https://doi.org/10.1016/S0959-3780(02)00008-0

Rötter, R. P., Palosuo, T., Kersebaum, K. C., Angulo, C., Bindi, M., Ewert, F., … Trnka, M. (2012). Simulation of spring barley yield in different climatic zones of Northern and Central Europe: A comparison of nine crop models. *Field Crops Research*, *133*, 23–36. https://doi.org/10.1016/j.fcr.2012.03.016

Saini, G. R. (1976). Green Revolution and the Distribution of Farm Incomes. *Economic and Political Weekly*, *11*(13), A17–A22.
Sakurai, G., Iizumi, T., Nishimori, M., & Yokozawa, M. (2014). How much has the increase in atmospheric CO2 directly affected past soybean production? *Scientific Reports*, *4*(1), 4978. https://doi.org/10.1038/srep04978

Schauberger, B., Ben-Ari, T., Makowski, D., Kato, T., Kato, H., & Ciais, P. (2018). Yield trends, variability and stagnation analysis of major crops in France over more than a century. *Scientific Reports*, *8*, 16865. https://doi.org/10.1038/s41598-018-35351-1

Seneviratne, S. I., Nicholls, N., Easterling, D., Goodess, C. M., Kanae, S., Kossin, J., … Zhang, X. (2012). Changes in climate extremes and their impacts on the natural physical environment (Chapter Three). In C. B. Field, V. Barros, T. F. Stocker, Q. Dahe, D. J. Dokken, K. L. Ebi, … P. M. Midgley (Eds.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (pp. 109–230). s, Cambridge, UK, and New York, NY: Cambridge University Press.

Shelia, V., Hansen, J., Sharda, V., Porter, C., Aggarwal, P., Wilerson, C. J., & Hoogenboom, G. (2019). A multi-scale and multi-model gridded framework for forecasting crop production, risk analysis, and climate change impact studies. *Environmental Modelling & Software*, *115*, 144–154. https://doi.org/10.1016/j.envsoft.2019.02.006

Shields, D. A. (2015). *Federal Crop Insurance: Background* (No. R40532 (7-5700)). Washington, D.C: Congressional Research Service.

Soltani, A., & Sinclair, T. R. (2015). A comparison of four wheat models with respect to robustness and transparency: Simulation in a temperate, sub-humid environment. *Field Crops Research*, *175*, 37–46. https://doi.org/10.1016/j.fcr.2014.10.019

Stöckle, C. O., Donatelli, M., & Nelson, R. (2003). CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, *18*(3), 289–307. https://doi.org/10.1016/S1161-0301(02)00109-0

Sudhakar, P., Latha, P., & Reddy, P. V. (Eds.). (2016). *Phenotyping Crop Plants for Physiological and Biochemical Traits*. Boston, MA: Academic Press.

Swiss Re. (2013). *Partnering for food security in emerging markets* (No. Sigma No 1/2013). Zurich, Switzerland: Swiss Reinsurance Company Ltd.

Tao, F., Rötter, R. P., Palosuo, T., Gregorio Hernández Díaz-Ambrona, C., Mínguez, M. I., Semenov, M. A., … Schulman, A. H. (2018). Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. *Global Change Biology*, *24*(3), 1291–1307. https://doi.org/10.1111/gcb.14019

Tao, F., Xiao, D., Zhang, S., Zhang, Z., & Rötter, R. P. (2017). Wheat yield benefited from increases in minimum temperature in the Huang-Huai-Hai Plain of China in the past three decades. *Agricultural and Forest Meteorology*, *239*, 1–14. https://doi.org/10.1016/j.agrformet.2017.02.033

Tester, M., & Langridge, P. (2010). Breeding technologies to increase crop production in a changing world. *Science*, *327*(5967), 818–822. https://doi.org/10.1126/science.1183700

Thompson, D. W. J., Barnes, E. A., Deser, C., Foust, W. E., & Phillips, A. S. (2015). Quantifying the Role of Internal Climate Variability in Future Climate Trends. *Journal of Climate*, *28*(16), 6443–6456. https://doi.org/10.1175/JCLI-D-14-00830.1

Trnka, M., Rötter, R. P., Ruiz-Ramos, M., Kersebaum, K. C., Olesen, J. E., Žalud, Z., & Semenov, M. A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change*, *4*(7), 637–643. https://doi.org/10.1038/nclimate2242

Unterberger, C., Brunner, L., Nabernegg, S., Steininger, K. W., Steiner, A. K., Stabentheiner, E., … Truhetz, H. (2018). Spring frost risk for regional apple production under a warmer climate. *PLoS ONE*, *13*(7), e0200201. https://doi.org/10.1371/journal.pone.0200201

Urban, D., Roberts, M. J., Schlenker, W., & Lobell, D. B. (2012). Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields. *Climatic Change*, *112*(2), 525–533. https://doi.org/10.1007/s10584-012-0428-2

van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, *177*, 105709. https://doi.org/10.1016/j.compag.2020.105709

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., & Schewe, J. (2014). The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP): Project framework. *Proceedings of the National Academy of Sciences*, *111*(9), 3228–3232. https://doi.org/10.1073/pnas.1312330110

Webber, H., Lischeid, G., Sommer, M., Finger, R., Nendel, C., Gaiser, T., & Ewert, F. (2020). No perfect storm for crop yield failure in Germany. *Environmental Research Letters*, *15*(10), 104012. https://doi.org/10.1088/1748-9326/aba2a4

Wolanin, A., Mateo-García, G., Camps-Valls, G., Gómez-Chova, L., Meroni, M., Duveiller, G., … Guanter, L. (2020). Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt. *Environmental Research Letters*, *15*(2), 024019. https://doi.org/10.1088/1748-9326/ab68ac

Yang, X., Chen, F., Lin, X., Liu, Z., Zhang, H., Zhao, J., … Tang, H. (2015). Potential benefits of climate change for crop productivity in China. *Agricultural and Forest Meteorology*, *208*, 76–84. https://doi.org/10.1016/j.agrformet.2015.04.024

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., … Asseng, S. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences*, *114*(35), 9326–9331. https://doi.org/10.1073/pnas.1701762114

Zhao, C., Piao, S., Huang, Y., Wang, X., Ciais, P., Huang, M., … Peng, S. (2016). Field warming experiments shed light on the wheat yield response to temperature in China. *Nature Communications*, *7*(1), 13530. https://doi.org/10.1038/ncomms13530

Zheng, B., Chapman, S. C., Christopher, J. T., Frederiks, T. M., & Chenu, K. (2015). Frost trends and their estimated impact on yield in the Australian wheatbelt. *Journal of Experimental Botany*, *66*(12), 3611–3623. https://doi.org/10.1093/jxb/erv163

Zipper, S. C., Qiu, J., & Kucharik, C. J. (2016). Drought effects on US maize and soybean production: Spatiotemporal patterns and historical changes. *Environmental Research Letters*, *11*(9), 094021. https://doi.org/10.1088/1748-9326/11/9/094021

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., … Zhang, X. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3