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INSTITUTE OF LIFE SCIENCE AND FACILITY MANAGEMENT
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How Climate Change Influences Grain Maize Yield: A Case Study for the Canton of Berne

Bachelor Thesis

Natural Resource Sciences

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Abstract

Since agricultural productivity is strongly dependent on climate, farmers need reliable crop yield forecasts to help them adapting to climate change. This Bachelor's Thesis aims at identifying the effects of climate on grain maize yields in the canton of Berne (Switzerland) by assessing relevant agroclimatic indicators for the period 1990 to 2018 by means of regression analysis. In addition, the regressions performed are used to investigate the suitability of the canton of Berne for grain maize cultivation. A total of four regression models are proposed, using an Ordinary Least Squares framework to estimate the model coefficients. To consider the changing influence of climate on maize yield in different growth stages, agroclimatic indicators are calculated specifically for the vegetative and reproductive period in addition to the total growing season. It appears that basic climate indicators such as mean temperature and precipitation totals are often better at explaining yield variability than complex indicators such as Vapor Pressure Deficit or Growing Degree Days. Furthermore, it is found that a uniform increase of mean temperature of about 1.5°C during the growing season is positive for yield. But increasing mean temperature only during the vegetative period or additional heat days from July to August have a negative effect on yield. In the reproductive phase from August onwards, there is still potential for yield gains through moderate mean temperature increases. For precipitation over the entire growing season, the model estimates indicate a positive effect of moderate precipitation and a negative effect of heavy precipitation on yield. The adverse effect of heavy precipitation is more pronounced for the vegetative period than for the reproductive period.

Zusammenfassung

Da die landwirtschaftliche Produktivität stark vom Klima abhängt, benötigen Landwirte zuverlässige Ertragsvorhersagen, um sich an den Klimawandel anpassen zu können. Ziel dieser Bachelorarbeit ist es, die Auswirkungen des Klimas auf die Körnermaiserträge im Kanton Bern (Schweiz) zu identifizieren, indem relevante agroklimatische Indikatoren für den Zeitraum 1990 bis 2018 mittels Regressionsanalyse ausgewertet werden. Zudem soll mit den durchgeführten Regressionen die Eignung des Kanton Berns für den Körnermaisanbau untersucht werden. Es werden insgesamt vier Regressionsmodelle vorgeschlagen, wobei zur Schätzung der Modellkoeffizienten die Methode der kleinsten Quadrate verwendet wird. Um den wechselnden Einfluss des Klimas auf den Maisertrag in verschiedenen Wachstumsstadien zu berücksichtigen, werden agroklimatische Indikatoren zusätzlich zur gesamten Vegetationszeit speziell für die vegetative und reproduktive Periode berechnet. Die Modellparameter deuten darauf hin, dass elementare Klimaindikatoren wie die mittlere Temperatur und Niederschlagssummen oft besser geeignet sind, die Ertragsvariabilität zu erklären, als komplexe Indikatoren wie Dampfdruckdefizit (VPD) oder Wachstumsgradtage (GDD). Es zeigt sich weiter, dass ein gleichmässiger Anstieg der Durchschnittstemperatur um etwa 1,5°C über die gesamte Saison positiv für den Ertrag ist. Doch eine Erhöhung der mittleren Temperatur nur während der Vegetationsperiode oder zusätzliche Hitzetage von Juli bis August haben einen negativen Effekt auf den Ertrag. In der reproduktiven Phase gibt es noch Potenzial für Ertragssteigerungen durch eine moderate Erhöhung der Durchschnittstemperatur. Für Niederschlag über die gesamte Saison zeigen die Modellschätzungen einen positiven Effekt von mässigem Niederschlag und einen negativen Effekt von Starkniederschlag auf den Ertrag. Der negative Effekt von Starkniederschlägen ist für die Vegetationsperiode stärker ausgeprägt als für die Reproduktionsperiode.

Contents

1 Introduction

Climate change is altering mean temperature and precipitation patterns on a global scale (IPCC, 2018a). Since agricultural productivity is strongly dependent on the climate (Belyaeva & Bokusheva, 2018; Schlenker & Roberts, 2009), farmers need reliable crop yield forecasts to help them adapting to climate change (Finger, 2009).

It is also expected of climate change to increase the occurrence of extreme weather events (Calanca, 2007). This can also be problematic for agriculture, as shown by the yield losses during the 2003 heatsummer in Switzerland (Finger, 2009).

In agricultural science, there are two approaches to study the consequences of climate change on crop yields (Roberts et al., 2013). Process-based crop simulation models are built upon the results of field experiments and known physiological plant characteristics. A key advantage of process-based models lies in the ability to incorporate different agronomic practices and technological measures (Belyaeva & Bokusheva, 2018). However, the high complexity of these models is also a disadvantage, because it leads to considerable model prediction uncertainties and impairs their application on larger spatial scales (Belyaeva & Bokusheva, 2018; Schlenker & Roberts, 2009).

The second approach is based on statistical models. To estimate the impact of climate change on yield using this method, the projected changes in selected weather variables are multiplied by corresponding model coefficients derived from historical data (Belyaeva & Bokusheva, 2018). Investigating yield with statistical models, given sufficient data availability, is generally more straightforward than with crop simulation models (Finger, 2009). In addition, when using historical data, adaptation strategies by farmers to past climate change are already included in the model (Finger, 2009). A disadvantage of the statistical approach is that future technological or agronomic improvements cannot be included in the analysis because the statistical estimates are based only on observations of the past (Belyaeva & Bokusheva, 2018).

There have also been efforts to combine the respective strengths of both of the approaches described. For example, Roberts et al. (2013) have integrated individual concepts of biophysical plant models, such as improved agroclimatic indicators, into their statistical analysis.

This bachelor thesis is based on the statistical approach and aims to find relevant agroclimatic indicators of grain maize yield for the canton of Berne (Switzerland) by means of regression analysis. In addition, the regressions performed are used to investigate the suitability of the canton of Berne for grain maize cultivation. The period studied extends from 1990 to 2018. This work is guided by regression studies that have already been carried out for similiar research questions and various crops, e.g. Belyaeva & Bokusheva (2018), Lobell & Field (2007), Lobell & Burke (2010), Roberts et al. (2013). Furthermore, this thesis draws on findings of the studies on climatic yield potential of grain maize in Switzerland by Holzkämper et al. (2011, 2013, 2015).

This work is structured as follows: First, the theoretical basics of climate change, extreme weather events, climate indicators, agriculture, and the impact of climate change on crop yields are presented. Some of the theoretical background is written in a global and European context, but the main focus is on Switzerland. The Theoretical Framework is followed by the practical part of the thesis which is presented in form of a case study for the canton of Berne.

In this Bachelor Thesis, the following research questions are being addressed:

- How is climate change expected to interfere with crop production in Switzerland?
- What influence does the timing of climate and extreme weather events have on grain maize yield in Switzerland?
- Which are suitable agroclimatic indicators for explaining grain maize yields in the canton of Berne?
- What is the influence of mean temperature and precipitation on grain maize yields in the canton of Berne?
- How do extreme weather events like heat days or heavy precipitation influence grain maize yields in the canton of Berne?
- How well is the canton of Bern climatically suited for the production of grain maize?

2 Theoretical Framework

2.1 Climate Change

2.1.1 Introduction

The following subchapter offers an overview of relevant processes related to climate change. Given such a complex and widely studied topic, however, simplifications must inevitably be made. This subchapter is intended to provide the necessary background for interpreting later discussion points regarding climate extremes and agriculture.

Among the topics presented are past climate, the causes of climate change, climate variability, models, and projections of future climate. Changes in physical processes such as temperature and precipitation are also discussed. Finally, some of the consequences of climate change are presented. Although the subchapter describes climate change from a rather global perspective, concrete examples from Europe, the Alpine region and Switzerland are included.

The main sources for the information presented are the reports of the Intergovernmental Penal on Climate Change (IPCC) – mainly from the fifth assessment cycle. Another widely used source is the report *Brennpunkt Klima Schweiz*, published by the Swiss Academy of Sciences (SCNAT). Further information comes from scientific articles.

2.1.2 Definition

Climate change is defined by the IPCC as “a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and the variability of its properties, and that persists for an extended period, typically decades or longer” (Cubasch et al., 2013, p. 126). Climate change is caused by either internal natural processes or *external forcings*. Such forces are for example modulations of the solar cycles, volcanic activities or anthropogenic changes in the composition of the atmosphere.

The *Framework Convention on Climate Change* defines climate change as “a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods” (United Nations, 1992, p. 7). Unlike the above definition by the IPCC, this definition by the UNFCC distinguishes between climate change from anthropogenic influence and climate variability attributable to natural causes (IPCC, 2013a).

2.1.3 Past Climate

Bradley (2015) describes *paleoclimatology* as the study of climate prior to the period of instrumental measurements. Climate records gathered through instrumental measurements only cover a tiny fraction of the Earth’s climatic history and therefore provide an inadequate perspective.

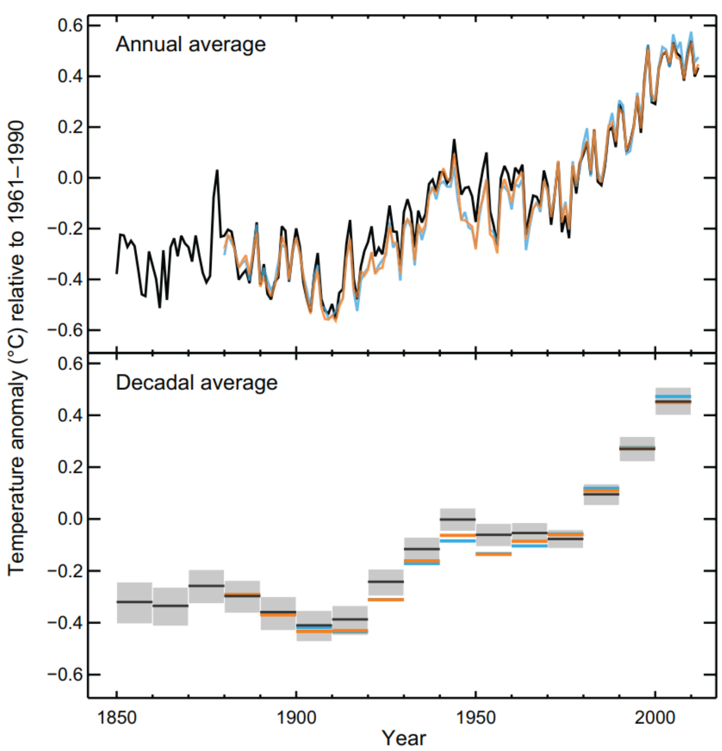
The climate system has always responded to solar, volcanic and orbital forces as well as to changes in atmospheric composition and will keep doing so. Paleoclimate datasets provide quantitative information on the reaction of the climate system to these forces (Masson-Delmotte et al., 2013). A measure of this reaction can be obtained through the analysis of climate dependent natural phenomena, that incorporate into their structure a measure of this dependency (Bradley, 2015). Such natural phenomena for example can be studied based on ice cores, lake sediments, tree rings or historical documents (SCNAT, 2016).

Global Perspective

It is estimated that due to human activities, the earth has warmed approximately 1.0°C (with a likely range of 0.8°C to 1.2°C) compared to pre-industrial levels (IPCC, 2018b). Figure 1 illustrates this by showing the observed globally averaged combined land and ocean surface temperature anomaly for the period 1850–2012 (IPCC, 2013b).

Concentrations of the greenhouse gases carbon dioxide, methane and nitrous oxide are higher today than at any time in the last 800,000 years (IPCC, 2013b; SCNAT, 2016). The comparison of today's measured temperatures with climate reconstructions shows that the annual mean temperature of the northern hemisphere of the period 1983-2012 was very likely higher than during any other thirty-year period of the last 800,000 years (IPCC, 2013b). On the continental scale, however, there were probably decades of phases in the Middle Ages that were as warm as certain phases in the second half of the 20th century (SCNAT, 2016).

Since the middle of the 19th century, sea levels have risen faster than the average for the last 2,000 years (IPCC, 2013c; SCNAT, 2016). In the case of droughts and floods, where non-climatic factors also play a role, the situation is less clear: In the last thousand years droughts have occurred that were more severe and lasted longer than those observed since 1900. In the context of the last 1,000 years, the current flood magnitudes in Europe are not unusual (Masson-Delmotte et al., 2013; SCNAT, 2016).



Source: IPPC (2013b)

Figure 1: Observed Global Mean Combined Land and Ocean Surface Temperature Anomalies

Note: For the period from 1850-2012 and relative to the mean of 1961-1990. Data from three data sets from the IPCC (each color represents a data set). The top panel shows the annual mean values. The bottom panel shows the decadal mean values, including the estimate of uncertainty for the black colored dataset.

Alpine Region

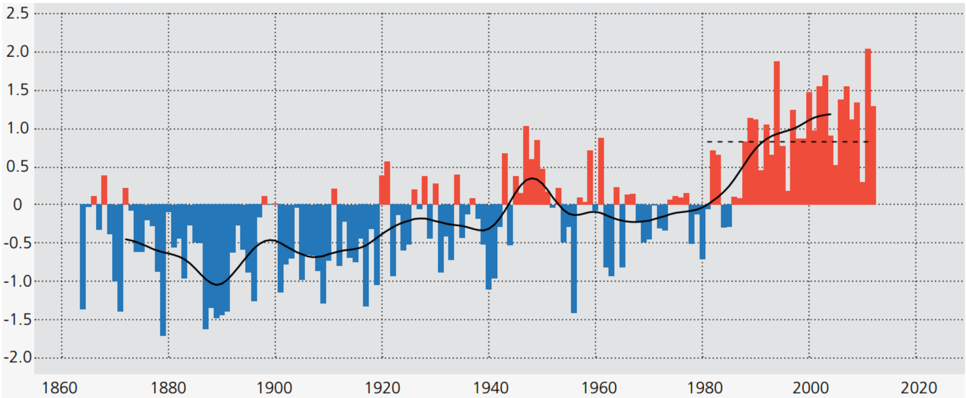
Summer temperatures in the European Alps in the years 755-2004 were reconstructed by Büntgen et al. (2006) on the basis of historic larch density series. In a comparable study, Trachsel et al. (2012) reconstructed the summer temperatures of the last millennium for the Alpine region using a multi-archive approach. The results are comparable with those of Büntgen et al. and other studies for the Alpine region (SCNAT, 2016). The investigated records can show the complete range of European temperature variability – including the extreme years 1816 and 2003 (Büntgen et al., 2006).

In the 10th and 13th centuries there was a warmer phase, with temperatures similar to those of today (Büntgen et al., 2006). Also according to Trachsel et al. (2012) the summers between 1050 and 1200 were the warmest (0.3°C warmer than the average in the 20th century). However, the last decade of the 20th century was even warmer according to Trachsel et al. (2012). Maximum amplitude of mean temperature over the past 1250 years is estimated to be 3.1°C (Büntgen et al., 2006).

From 1350 to 1700 there was a cooler period (Büntgen et al., 2006). The lowest temperatures were in the 16th and 17th century (Trachsel et al., 2012). They were about 1°C colder than the average of the 20th century. Since this "little ice age" in the late 17th century, summer temperatures have risen by more than two degrees Celsius, with most of the increase occurring after 1975 (SCNAT, 2016). Figure 2 shows this warming trend.

In the early 19th century – partly as a result of two volcanic eruptions – the temperature was well below the fluctuation range of the last 330 years. In the last 25 years, especially in the summers of 2003 and 2015, the temperature was well above the previous range (SCNAT, 2016).

The complete absence of cold summers since 1980 is also striking to SCNAT (2016). Summer precipitation shows considerable fluctuations from year to year, sometimes even fluctuations over several years. However, they do not show any long-term changes (SCNAT, 2016).



Source: Croci-Maspoli et al. (2014)

Figure 2: Long-term Trend of Swiss Annual Mean Temperature Since 1864

Note: This figure shows the long-term trend of the Swiss annual mean temperature since 1864: Red and blue shows the annual deviation of the temperature from the reference period 1961 to 1990, and the black curve shows a smoothed trend. The dashed line describes the level of the mean 1981 to 2010.

2.1.4 Causes of Climate Change

Climate change is driven by substances and processes that alter the Earth's energy budget. Those substances can be of natural or anthropogenic nature (IPCC, 2014). Greenhouse gases and aerosols alter the incoming solar- and outgoing infrared radiation. A change in the abundance of these gases and particles can result in a warming or cooling of the climate system (Ramachandran, 2018).

Radiative forcing quantifies the perturbation of energy into the Earth system caused by these natural and anthropogenic drivers. Radiative forcings larger than zero lead to a near-surface warming, and radiative forcings smaller than zero lead to a cooling (Stocker et al., 2013). Increase of RF is nearly continuous since 1750 and especially since about 1860. However, the total anthropogenic RF increase rate is much greater now (since 1960) than during earlier Industrial Era periods (Stocker et al., 2013).

According to the IPCC (IPCC, 2014), human influence has been detected in warming of the atmosphere and the ocean as well as in changes in the global water cycle: Economic and population growth since the pre-industrial era are the major drivers of increased anthropogenic greenhouse gas emissions, which are now higher than ever (Figure 3). It is extremely likely that the effects these greenhouse gases have on the irradiation balance of the Earth are the dominant causes of the observed warming since the mid-20^{th} century (IPCC, 2014).

Natural changes in solar irradiance and volcanic aerosols are causing natural radiative forcing. Stratospheric volcanic aerosols for example can strongly cool the climate system. However, the proportion of those natural radiative forcings today is very small compared to the total amount (IPCC, 2014).

2.1.5 Climate Projections and Models

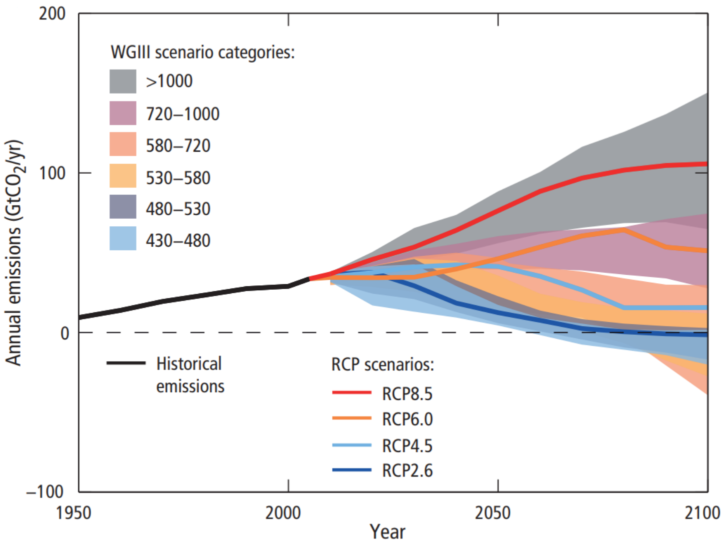
A *climate model* is a mathematical representation of the Earth's climate system. The models considered for analysis in the 5^{th} IPCC assessment report have a wide range of complexity (IPCC, 2014).

General Circulation Models (GCMs) incorporate the oceans and atmosphere as three-dimensional structures and they can replicate the pattern of the atmosphere, oceans, land surface and snow-covered areas over the globe (Jalota et al., 2018). GCM models used in the 5^{th} IPCC assessment cycle have been extensively tested against historical observations (IPCC, 2014).

The *Representative Concentration Pathways* (RCPs) describe four different paths for greenhouse gas emissions in the 21^{st}-century. They describe emissions and atmospheric concentrations, air pollutant emissions as well as land use (IPCC, 2014). The RCPs form a comprehensive data set with high spatial and sectoral resolution for a period up to the year 2100 (Vuuren et al., 2011) and are being used for impact and adaptation assessment (IPCC, 2014).

The different RCPs are described in the *IPCC Synthesis Report* (IPCC, 2014) as follows: RCP2.6 is a strict mitigation scenario. RCP4.5 and 6.0 are intermediate scenarios and RCP8.5 is a scenario with very high GHG emissions. Figure 3 shows a projected time series for the different RCPs (IPCC, 2014).

Scenarios where no more efforts to constrain emissions are being taken are called *baseline scenarios*. They lead to pathways between RCP6.0 and RCP8.5 (IPCC, 2014). RCP2.6 represents a scenario aiming to keep global warming below 2°C above pre-industrial temperatures (IPCC, 2014).



Source: IPCC (2014)

Figure 3: Past and Projected Carbon Dioxide Emissions for Different RCPs

Note: Black line in this figure represents historical emissions of carbon dioxide ($GtCO_2/yr$), the colored lines show the projected time series for emissions from carbon dioxide of different RCPs. Each coloured line represents estimates of a specific RCP. The coloured areas represent the range of emission scenarios estimated in the scientific literature assessed by the working by group III from the 5th IPCC assessment cycle.

2.1.6 Climate Variability

Climate variability describes variations in the climate. These variations refer to the mean state of the climate or other statistical features, such as standard deviation or the number of extreme weather events (IPCC, 2014). Processes that influence the climate are subject to this natural variability – even in the absence of external forcing (Cubasch et al., 2013).

This paragraph contains information on climate variability as described by SCNAT (2016): Changes in climate occur over a very long timeline. Trends like human-induced climate change are masked by short-term variability, which cannot be predicted for the coming years and decades. However, the proportion of short-term climate variability is very small in the long term and on a large spatial scale. But short-term variability is a major uncertainty factor in forecasts for small geographical areas or short time spans. Extreme weather events are also affected by short-term climate variability and are therefore difficult to predict.

2.1.7 Consequences of Climate Change

The following section aims to take a broad view of the possible consequences of climate change from a global, European and Swiss perspective and across several sectors. It is by no means the aim of this section to show all the consequences, because that would go beyond the scope of this work. Also, the concrete consequences of climate change for agriculture and crop production in Switzerland will be discussed in more detail in subchapter 2.5. Extreme events are further outlined in subchapter 2.2.

Global Perspective

"In recent decades, changes in climate have caused impacts on natural and human systems on all continents and across the oceans." (IPCC, 2014, p. 6). Climate change impacts such as heat waves, droughts, floods, cyclones, or forest fires show how vulnerable ecosystems and certain human sectors are to global warming. In the IPCC report on *Impacts, Adaptation, and Vulnerability*, Field et al. (Field et al., 2014) examine these consequences and the risks they entail.

Field et al. (Field et al., 2014) states that the effects of climate change are most strongly seen in natural systems. The observed effects of climate change threaten ecosystems and biodiversity (EEA, 2017; Field et al., 2014). Many land-based animal and plant species are changing their life cycle and migrating to northern or upland areas. The immigration of invasive species is also favored by climate change (Field et al., 2014).

Global changes in the cryosphere affect physical, biological and human systems in the mountains and surrounding lowlands as well as the oceans. Observations collected by the IPCC (2019) show that snow cover in lower altitudes, glacial areas, and permafrost layers is decreasing due to climate change. As a result of this instability, more people in mountain regions are now affected by natural hazards (more on this in section 2.2.3) (IPCC, 2019). The changes in glacial landscapes also lead to new types of discharge regimes of glacier-fed watercourses. Another decisive consequence of these complex changes in the hydrological cycle is the rise in sea level (IPCC, 2019).

However, the effects of climate change are also detectable in human systems (Field et al., 2014). *Impacts* and *risks* of climate change for humans depend on the region, population, spatiotemporal factors and on the extent of adaptation and mitigation measures (Field et al., 2014). So, most of the differences in *vulnerability* and *exposure* stem from non-climatic factors and from multidimensional inequalities and are often caused by unequal development processes (Field et al., 2014).

Possible global consequences of climate change impacts include the disruption of food production, impaired water supplies, damage to infrastructure and settlements, morbidity and mortality, and consequences for mental health and well-being (Field et al., 2014).

European Perspective

In the context of the research questions in my thesis, it makes sense to shift away from a global perspective and take a closer look at the consequences of climate change for Europe. The information in this section is mainly taken from the report *Climate Change, Impacts and Vulnerability in Europe 2016* of the European Environment Agency (EEA). Even though extreme events are broadly mentionned in the following paragraphs, they will be described in more detail in section 2.2.3.

Between 2006 and 2015, land temperatures in Europe were about 1.5° C warmer than before the industrial era (EEA, 2017). In the future, temperatures are expected to continue to rise at an above-average rate compared to the temperature increase in the rest of the world (EEA, 2017).

Since 2003, Europe has been hit by several extreme summer heat waves. Some have resulted in high mortality rates and economic losses (EEA, 2017). According to forecasts, such extreme heat events are expected to occur every second year in the future (in the second half of the 21st century and under a high emission scenario) (EEA, 2017; Field et al., 2014). Southern Europe will be most affected by such heat waves (EEA, 2017).

According to the EEA (2017), precipitation has increased in most areas of northern Europe, especially in winter. In summer, rainfall has decreased in most areas of southern Europe, with the summer months being particularly critical – this pattern should continue to develop in the future (EEA, 2017). Heavy rainfall events have also increased in several regions in recent decades, mainly in northern and northeastern Europe (EEA, 2017). According to studies, they are expected to occur in the future with increased frequency throughout Europe, particularly in winter (EEA, 2017).

The EEA (2017) further looked at the occurrence of windstorms. They found that these events are subject to considerable spatial and temporal variability. Nevertheless, most studies agree that the risk of severe storms in winter and possibly also in autumn will increase in the future (northern, north-western, and central Europe) (EEA, 2017). The EEA (2017) cannot provide information on the trend in hail events, as such projections are still very uncertain.

The negative consequences of climate change for human systems in Europe include increased injuries and deaths due to heat waves, increased risk of damage and death due to flooding and gravitational natural hazards, infrastructural damage, economic losses and energy shortage (EEA, 2017; Field et al., 2014). In addition, forestry and agriculture are particularly vulnerable (Field et al., 2014). The interaction between climate change and the latter is discussed in subchapter 2.5.

Swiss Perspective

The previous part of this subchapter has provided a general overview of global and European climate change. Switzerland shares many facets of climate change with its Western European neighbors. But the Alps make Switzerland more vulnerable to climate change due to the importance of sectors such as alpine tourism or hydropower. It is therefore not surprising that the Alpine region is a central area for Swiss climate research (Brönnimann et al., 2014).

The retreat of the alpine glaciers will continue according to the EEA (2017): Since 1900 the Alps have lost about half of their glacier volume. Since the 1980s this process has also clearly accelerated. The retreat of the glaciers changes the discharge regimes and thus indirectly affects drinking water supply, power generation and also agriculture (irrigation) (EEA, 2017; IPCC, 2019). Since the 1920s, the snow cover has also decreased, and here, too, an acceleration of the decrease has been visible since 1980 (IPCC, 2019).

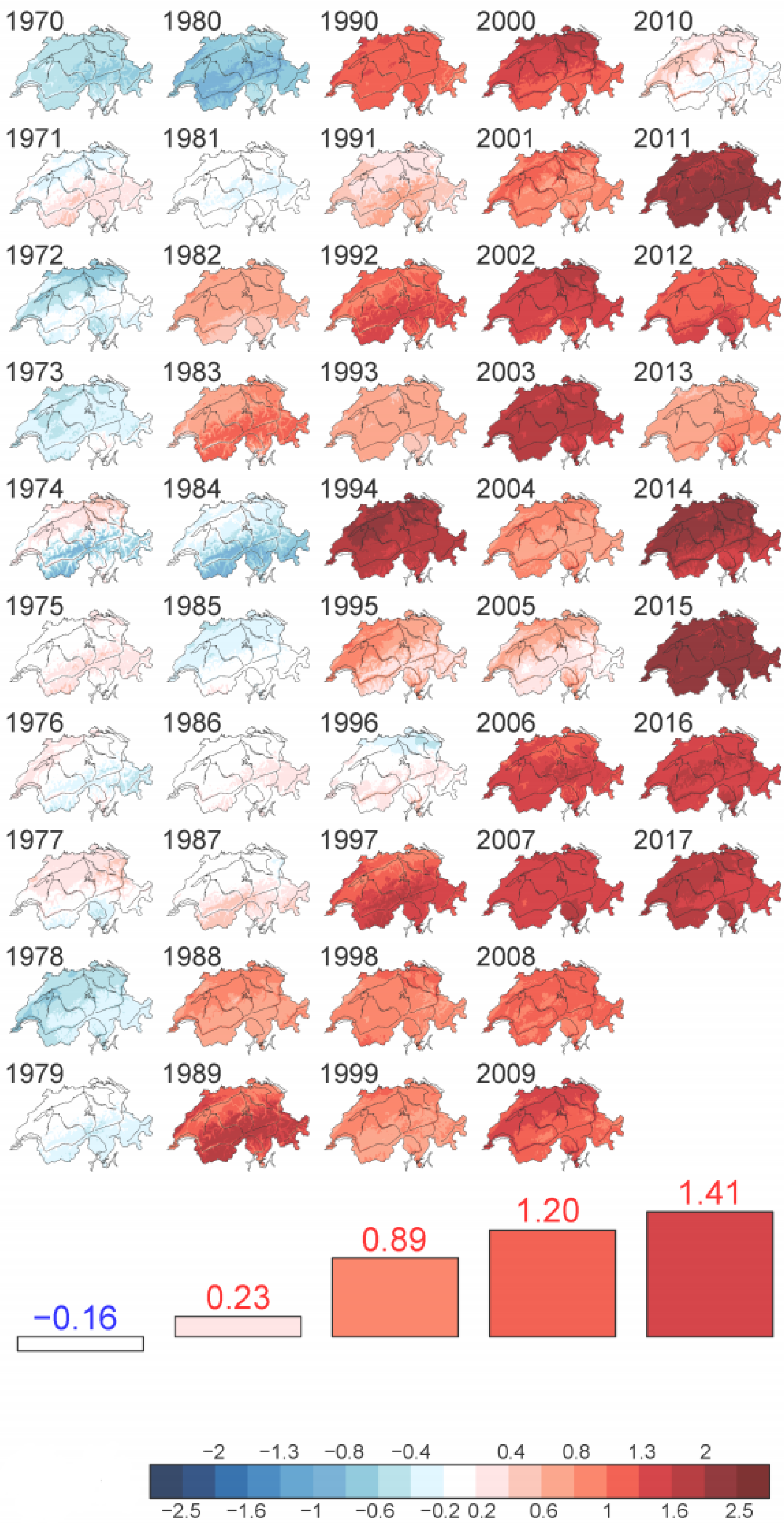
According to SCNAT (2016), the greatest challenges of climate change for Switzerland are extremes such as heat waves, droughts or heavy precipitation and other related natural hazards. On the other hand, they highlight subtle changes in landscapes and ecosystems such as glacier retreat or changes in biodiversity, water quality and the effects of pests and diseases (SCNAT, 2016).

Climate change in Switzerland has a direct impact on society (e.g. health) and the economy (e.g. agriculture, tourism) and already causes costs (SCNAT, 2016). The financial effort required to prevent and minimize damage and the risks will continue to increase because of the ongoing changes with increasing climate change (SCNAT, 2016).

Near-surface air temperatures in Switzerland are subject to strong interannual fluctuations (NCCS, 2018). Nevertheless, a pronounced long-term trend can be recognized: Since the beginning of systematic measurements (1864) the average temperature in Switzerland has increased by about 1.8°C (SCNAT, 2016). This is about ~1.3°C warming per one hundred years (NCCS, 2018). The strongest temperature increase is visible since the late 1980s (Appenzeller et al., 2008; Begert et al., 2005; Ceppi et al., 2012; NCCS, 2018). This trend is visible in figure 4. The rate of temperature increase in Switzerland is more than twice as high as the global average and is also higher compared to the land mass of the northern hemisphere (NCCS, 2018). There has not been a year in the last 30 years in Switzerland where temperatures have been below the 1961-1990 mean, and nine of the ten warmest years since measurements began have been measured in the 21st century (NCCS, 2018).

Figure 7 shows the calculated temperature changes for the northern and southern sides of the Alps for the years 2030, 2050 and 2070 (Frei et al., 2007). According to them, Switzerland will increasingly be exposed to faster and stronger climatic changes (Frei et al., 2007).

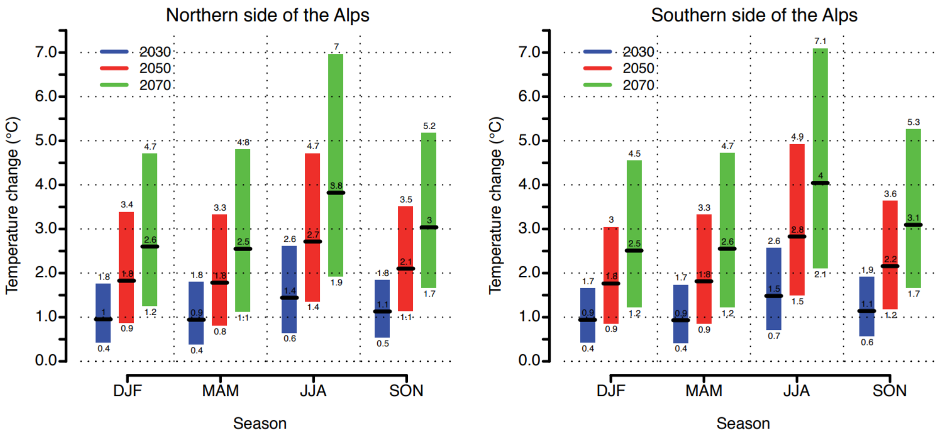
Frei et al. (2007) expect the temperature in northern Switzerland to increase by 1.8°C in winter and 2.7°C in summer (all estimates are calculated for the year 2050). In southern Switzerland, the same study predicts an increase in temperature of 1.8°C in winter and 2.8°C in summer. In spring, Frei et al. (2007) estimate temperatures in the northern part to rise by 1.8°C and by 2.1°C in the southern part. For autumn, they expect a temperature increase of 2.1°C in the north and 2.2°C in the south (Frei et al., 2007).



Source: Modified from NCCS (2018)

Figure 4: Swiss Mean Temperature Deviation from 1961-1990

Note: Average temperature deviation (in °C) from the mean of the period 1961-1990. Each map represents one year from 1970 to 2017. The bars and numbers in the lower part represent decadal means for Switzerland. Red represents values above the mean and blue represents values below the mean. Scale: -2.5°C to 2.5°C.



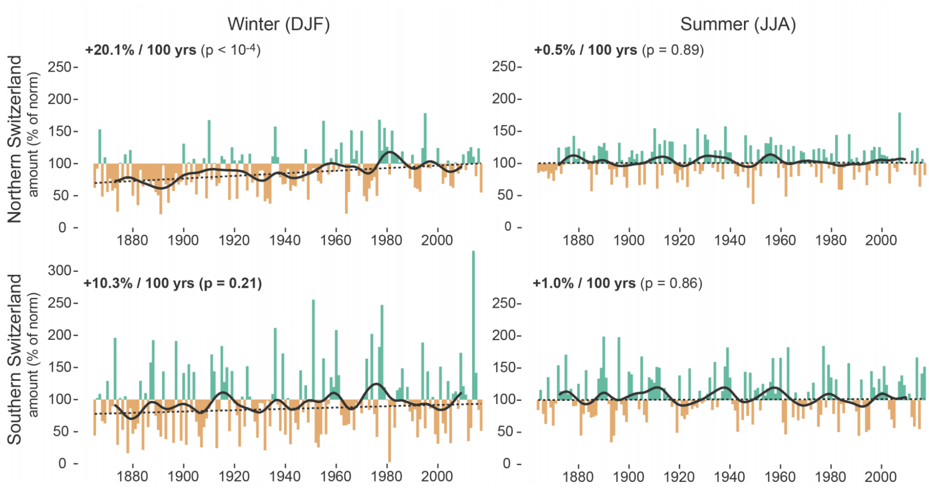
Source: Frei et al. (2007)

Figure 5: Projected Change of Mean Temperature North and South of Swiss Alps

Note: This figure shows the projected change in the Swiss mean temperature for winter (DJF, December to February), spring (MAM, March to May), summer (JJA, June to August) and autumn (SON, September to November) in the northern and southern sides of the Alps of the years 2030, 2050 and 2070 compared to 1990. The horizontal lines represent the medians. The colored bars show the 95% confidence interval.

Winter precipitation has since 1864 gone up by about 20% to 30% - however, part of this apparent change may be due to natural variability (NCCS, 2018). Precipitation over time is depicted in figure 6. Looking at the changes for heavy precipitation since the beginning of the 20th century, there are robust signals indicating that it has become more frequent (+30%) and more intense (+12%) (NCCS, 2018).

No robust signals on long-term trends in the observational record are found for summer precipitation (NCCS, 2018). Either is it unclear at this point how they are affected by climate change, or the expected anthropogenic influence has not yet signaled within the observed large natural variability (NCCS, 2018).

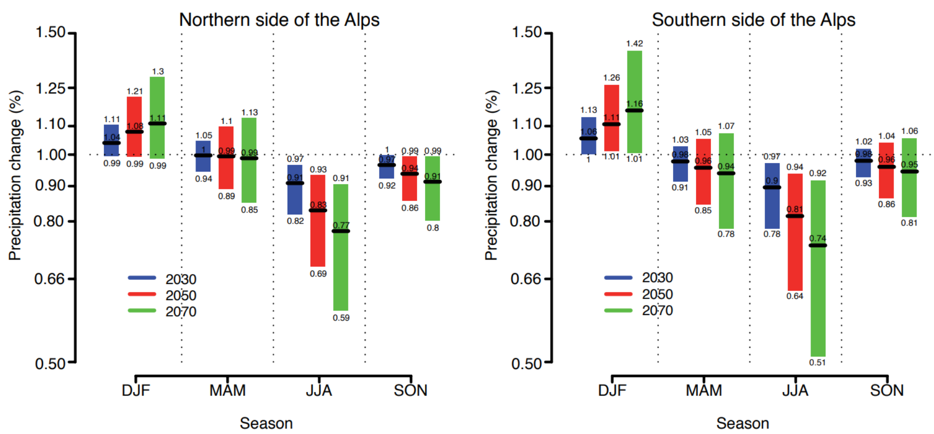


Source: NCCS (2018)

Figure 6: Precipitation in Switzerland From 1864 to 2017

Note: Precipitation from 1864 to 2017 is depicted for northern (top row: mean of Bern, Genève, Basel, and Zürich) and southern (bottom row: Lugano) Switzerland. Precipitation is shown as seasonal amounts for winter (left: DJF) and summer (right: JJA) in percent of the 1961-1990 mean. The solid line represents a smooth trend (Gaussian) and the dashed line represents a linear trend.

Precipitation estimates for the year 2050 by Frei et al. (2007) for the northern and southern part of Switzerland differ only slightly (7). Rainfall is expected to increase by 8% in winter in the northern part (11% on the southern side) and to decrease by 17% in summer (19% on the southern side) until 2050. For spring and autumn, the expected changes are not that clear. Also, in summer, there is a large amount of uncertainty (Frei et al., 2007).



Source: Frei et al. (2007)

Figure 7: Projected Changes in Precipitation North and South of Swiss Alps

Note: This figure shows the projected change in Swiss precipitation for winter (DJF, December to February), spring (MAM, March to May), summer (JJA, June to August) and autumn (SON, September to November) in the northern and southern sides of the Alps of the years 2030, 2050 and 2070 compared to 1990 (on a log scale: A value of 0.50 indicates a decrease by 50%, a value of 1.25 an increase by 25%). The horizontal lines represent the medians. The colored bars show the 95% confidence interval.

2.2 Extreme Weather Events

In the previous subchapter 2.1, climate extremes have already been mentioned briefly since they are an integral part of climate change. However, in this subchapter extreme events are described in more detail: First, climate extremes are presented from a general perspective, then the focus shifts towards Switzerland.

2.2.1 Defining Climate Extremes

The IPCC defines an *extreme weather or climate event* or *climate extreme* as “the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable” (Seneviratne et al., 2012, p. 116).

A absolute threshold may also be chosen to define an extreme event, but it’s important to note that which meteorological event is considered a climate extreme varies from place to place and over time, assuming a society can partially adapt to extreme conditions (Seneviratne et al., 2012).

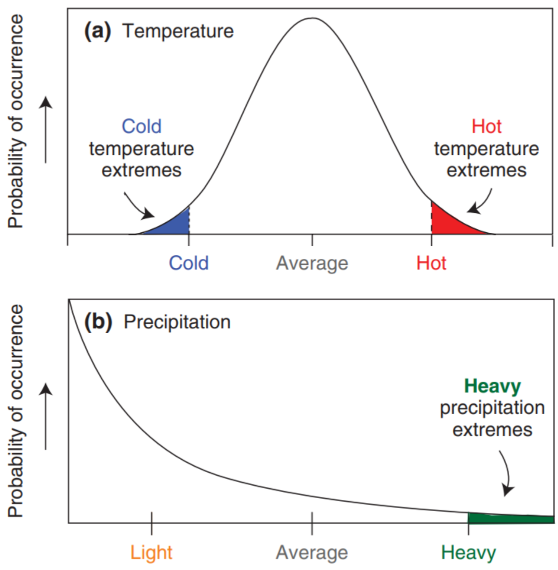
According to Seneviratne (2012), it is possible that several moderate weather events that occur simultaneously present an extreme event. In this case the accumulation itself is extreme. If several parameters deviate extremely from the average at the same time, one also speaks of *compound extremes* (Martius et al., 2016).

Extreme events can generally be specified for any meteorological variable or combination of variables (NCCS, 2018). However, usually the most relevant are temperature extremes, heat stress (combining aspects of temperature and humidity) and precipitation extremes (NCCS, 2018).

2.2.2 Probability and Indication

Figure 8 shows a visualization of climate extremes according to the definition by IPCC (Seneviratne et al., 2012). It is apparent that the occurrence of extremes is linked to the center as well as the width of the distribution. Various indices of extremes may differ in the way their distribution is defined, and where in the tails of the distribution the threshold is located (Zhang et al., 2011). Generally, it can be stated, that the further to the end of the tail a threshold is set, the more uncertain it’s analysis becomes, which is due to a limited data availability (Zhang et al., 2011).

The measurement of climate extremes of various kinds is usually done by the use of *climate indicators*. They are discussed in the next subchapter (2.3).



Source: Zhang et al. (2011)

Figure 8: Probability Distributions of Temperature and Precipitation

2.2.3 Global Observations and Projections

Extreme floods, storms, droughts, and temperature have always been part of the climate. There are numerous records of extreme events of the last centuries and millennia and their effects (SCNAT, 2016). However, from a global perspective, significant changes in certain extremes have become apparent over the last decades:

Temperature

Since 1950 there has been a significant worldwide trend towards more very warm and less cold days and nights (Alexander et al., 2006; Donat et al., 2013; Seneviratne et al., 2012). Also, the intensity, frequency, and duration of heatwaves have increased at global scale (Fischer & Knutti, 2014; Perkins et al., 2012; Rahmstorf & Coumou, 2011). This trend is likely to be influenced by humans (Seneviratne et al., 2012).

In the 21st century, the number and magnitude of unusually cold days will probably increase (Seneviratne et al., 2012). It is also very likely that the length, frequency, and intensity of heat events will increase over most land areas (Seneviratne et al., 2012). Fischer et al. (2013) also suggest that about half of the land fraction will see significantly more intense hot extremes within three decades.

Precipitation

For precipitation, widespread and significant trends are recognizable. However, their spatial distribution is much less homogeneous than that of the temperature values (Donat et al., 2013). Large-scale observations have shown an increase in mean precipitation in certain areas of the globe (Alexander et al., 2006). In certain regions mean precipitation has decreased, but the intensity of precipitation events has gone up (Alexander et al., 2006; Rajczak et al., 2013).

Allen & Soden (2008) have observed a distinct link between precipitation extremes and temperature in the tropics: During warm periods, heavy rain events tend to increase while during cold periods they rather decrease (Allan & Soden, 2008).

To Fischer et al. (2013), a further increase in the frequency of heavy rain events in the 21st century is likely. This applies to large parts of the earth but especially to high altitudes, the tropics and in winter to the northern mid-latitudes (Seneviratne et al., 2012). Allen & Soden (2008) has found the observed amplification of rainfall extremes to be larger than predicted by models. This implies that projections of future changes in precipitation extremes in response to anthropogenic global warming may be underestimated (Allan & Soden, 2008; Fischer et al., 2013).

Drought events have, with medium probability, increased in frequency and duration in certain parts of the world - mainly in southern Europe and West Africa (Seneviratne et al., 2012). However, there are also opposing trends (Seneviratne et al., 2012). And since the indications of change are partly dependent on local definitions of drought and therefore vary regionally, statements on global change in droughts remain uncertain (Sheffield et al., 2012; Trenberth et al., 2014).

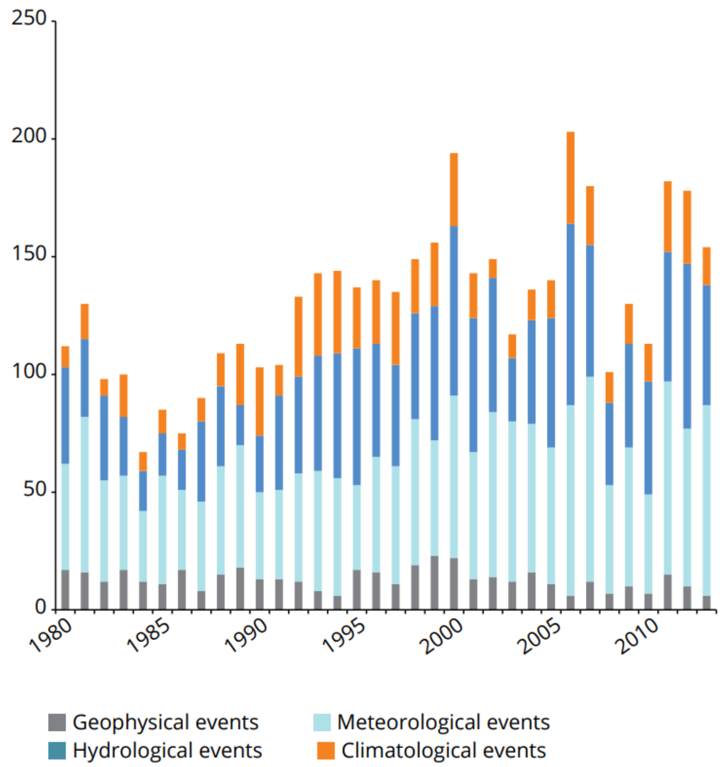
According to Seneviratne et al. (2012) it can be assumed with medium confidence that drought events will continue to increase in the 21st century in southern Europe, the Mediterranean region, central Europe, central North America, Central America, southern Africa and northeastern Brazil.

2.2.4 European Perspective

In recent decades, the number of extreme weather events and the socio-economic damage they cause has increased in Europe (EEA, 2017; Kron et al., 2019). Figure 9 seems to depict this trend. In addition to Asia and Australia, Europe is particularly impacted by heat waves in summer and exceptionally warm periods in other seasons (SCNAT, 2016). According to climate projections, the risk of drought is increasing in central Europe and the Mediterranean region (SCNAT, 2016).

A clear imbalance has become apparent in Europe since the middle of the 20th century: More heat records have been recorded, but significantly fewer cold records than theoretically expected without climate warming (SCNAT, 2016).

Although changes in heavy precipitation are more difficult to detect than changes in temperature (because precipitation intensities vary greatly over short distances), an increase is reliably detectable in Europe in certain regions and seasons (SCNAT, 2016). Especially in southern Europe, but also in central Europe in summer, climate change leads to a decrease in precipitation totals and to increased evaporation (Orlowsky & Seneviratne, 2013).



Source: EEA (2017)

Figure 9: Number of Extreme Events According to Hazard Category in Europe

Note: This figure shows the number of extreme events with recorded impacts according to hazard category in Europe. Events affecting several countries are counted only once. Hazard categories: geophysical events (earthquakes, tsunamis, volcanic eruptions); meteorological events (storms); hydrological events (floods, mass movements); climatological events (heat waves, cold waves, droughts, forest fires).

2.2.5 Swiss Perspective

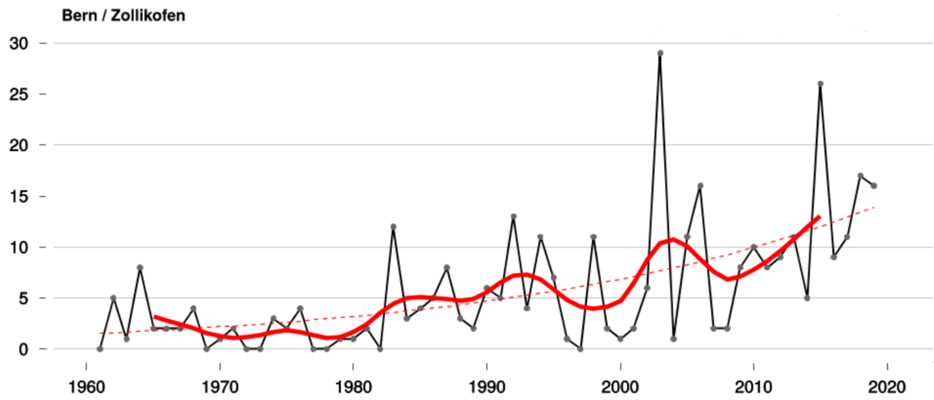
Extreme events are likely becoming more frequent in Switzerland as well (Brönnimann et al., 2014). Figures 10, 11 and 12 show the time trends of indicators representing climate extremes from 1960-2019[1].

In Berne, the number of *heat days* per year has been going up since the year 1960. 2003, 2006, 2015 and 2018 were the most extreme years in Berne according to the head days index (figure 10).

For precipitation extremes – measured as maximal precipitation within 5 days per year – it is difficult to detect a trend by eye within Figure 11. This is consistent with the finding that precipitation trends are harder to recognize than temperature (Frei et al., 2007; SCNAT, 2016). The years with the highest amounts of 5-day-precipitation according to Figure 11 for the period 1961-2019 were: 1974, 1978 and 2006.

Figure 12 shows the maximum number of *consecutive dry days* (CDD, where precipitation <1 mm) per year also for the same meteorological station in Berne/Zollikhofen. Again, it is hard to detect a trend within the given illustration by eye. Years with the longest CDD period were 1963, 1972, 1983 and 2016.

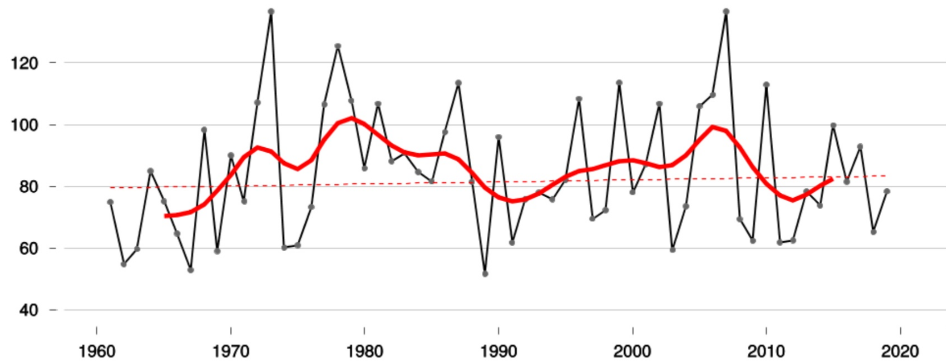
[1] For this representation, the meteorological station Bern/Zollikhofen was chosen as an example because of it's relevance to the case study in the second part of this paper.



Source: MeteoSwiss (2020)

Figure 10: Number of Heat Days per Year at Bern/Zollikhofen

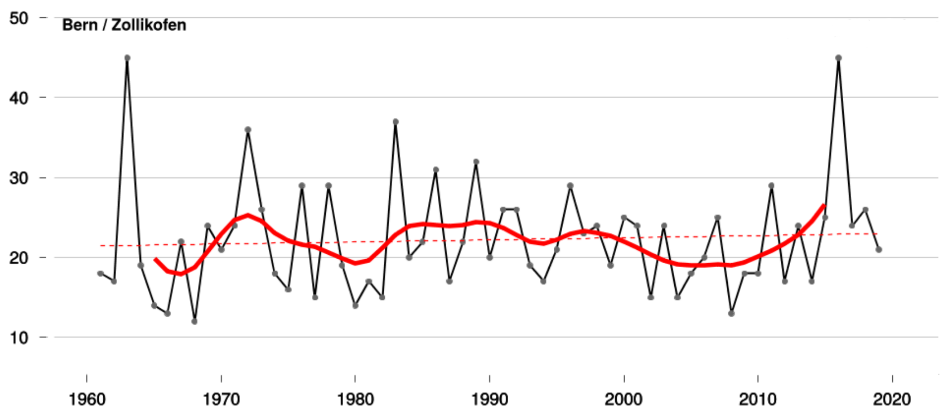
Note: The black line connects the number of days with temperatures above 30°C (heat days) per year (Jan-Dec) for the meteorological station Bern/Zollikhofen. The bold red line represents the 10 year rolling average, the dashed red line represents a logistic trend.



Source: MeteoSwiss (2020)

Figure 11: Maximal 5-Day Precipitation per Year at Bern/Zollikhofen

Note: The black line connects the amounts of maximal precipitation within 5 days (in mm) per year (Jan-Dec) at the meteorological station Bern/Zollikhofen. The bold red line represents the 10 year rolling average, the dashed red line represents a logistic trend.



Source: MeteoSwiss (2020)

Figure 12: Maximum Number of Consecutive Dry Days pre Year at Bern/Zollikhofen

Note: The black line shows the maximum number of consecutive dry days (CDD, where precipitation <1 mm) per year (Jan-Dec) for the meteorological station Bern/Zollikhofen. The bold red line represents the 10 year rolling average, the dashed red line represents a logistic trend.

Temperatures and drought in summer will tend to be longer and more extreme and there will be more heat days (Brönnimann et al., 2014; NCCS, 2018). Nights will also warm up and in summer there will be more *tropical nights* (i.e. nights where temperature will not drop below 20°C) (NCCS, 2018). The fact that these temperature-related changes are most strongly expected in the Central Plateau, where most people live, leads to an even higher risk for human systems (NCCS, 2018). The number of extreme heat days increases exponentially with warming: this means that RCP8.5 is expected to have 3 to 5 times more heat days than an RCP2.6 scenario (NCCS, 2018).

There is a high probability that the frequency of extreme precipitation will also increase (Brönnimann et al., 2014; NCCS, 2018). According to the NCCS (2018), heavy rainfall will increase in all seasons, but especially in the winter months. The intensity of extreme events will increase more than the mean value and may even go up as the mean rainfall decreases (NCCS, 2018).

2.3 Climate Indicators

"According to an old saying, a person standing with one foot on a hot stove and the other on a block of ice is comfortable on average" (Zhang et al., 2011, p. 1). This metaphor illustrates in a nice way that it is not enough to only describe the climate through mean values, since the mean is not suitable to explain extreme events (located at the edges of the distribution curve, as described in 2.2) (Zhang et al., 2011).

To measure mean and extreme climate, *climate indicators* are used. They make it possible to quantify climate change and climate extremes for specific systems within ecology, economy or society (Seneviratne et al., 2012; Walsh et al., 2020; Zubler et al., 2014; Zubler & Scherrer, 2014). Climate indicators are derived from meteorological data and usually focus on a specific aspect of climate (Svoboda & Fuchs, 2016). To do this there are different ways: Basic indicators, such as temperature or rainfall, are measured directly. But there are also indicators that are mathematically derived or combined from several measurements or indicators, for example *growing degree days* (Walsh et al., 2020).

2.3.1 Agroclimatic Indicators

Climate Indicators that are used in an agricultural context are called *agroclimatic indicators*. They provide a signal of the impact of climate change on a system such as crop production and therefore lay the foundation for quantitative analysis of climate events (Hatfield et al., 2018). Also, they allow for the comparison of climate trends between regions and are useful for decision-making (Walsh et al., 2020).

In a 2016 study, Ben-Ari et al. (Ben-Ari et al., 2016) analyzed multiple agroclimatic indicators for their usefulness in identifying crop yield loss in Europe. Key take-aways from their work regarding agroclimatic indcators were that indicators are crop and country specific and that more complex indicators (i.e., that consider plant physiology and/or phenology) do not necessarily predict yield loss better than simpler indicators (Ben-Ari et al., 2016).

2.3.2 Important Agroclimatic Indicators for Switzerland

During literature research, a list of over 70 climate indicators was compiled from scientific literature (for complete list see supplementary material). A requirement for being included in the list was that the indicators were previously applied in an agroclimatic context or have potential for doing so.

From this list, a selection of agroclimatic indicators specifically relevant to Switzerland and grain maize was made in collaboration with an external expert [2]. In the following, these indicators are summarized (in alphabetical order). Please note that indicator selection specifically for the case study later in this thesis is covered in the Methods chapter 4.1.

[2]Meeting and discussion with Pierluigi Calanca from Agroscope's Climate and Agriculture Research Group and Raushan Bokusheva, Head of Agricultural and Resource Economics Group at the Zurich University of Applied Sciences. It was held on 30.09.2020 at the Agroscope site in Zürich Reckenholz.

Evapotranspiration and Reference Evapotranspiration

"The combination of two separate processes whereby water is lost on the one hand from the soil surface by evaporation and on the other hand from the crop by transpiration is referred to as *evapotranspiration* (ET)" (Allen et al., 1998, p. 1). The rate of evapotranspiration is normally expressed in millimetres (mm) per unit time.

Reference evapotranspiration (ETo), a concept introduced by the *Food and Agriculture Organization* (FAO) in the 1990s, defines the evapotranspiration potential of an abundantly watered standard vegetation (Calanca et al., 2011). The concept was introduced to study the evaporative demand of the atmosphere independently of crop type, development stages and agricultural practices (Allen et al., 1998). Because the ETo is a standardized value that depends exclusively on climate factors (radiation, temperature, wind speed and humidity), it can be compared between different regions or seasons (Allen et al., 1998).

Evapotransiration has been applied to measure the impacts of climate on grain maize by Ben-Ari et al. (2016) among others. In a Swiss agroclimatic context, Calanca (2011) has written about it.

Frost Days

The *frost days* indicator is determined by a threshold value in °C. Its boundary value is usually 0°C (NCCS, 2018; Zubler et al., 2014). If the minimum temperature falls below the threshold on a day, this day is considered a frost day (Calanca, 2020).

In a Swiss context, frost days have been applied by Zubler at al. (2014) and described by NCCS (NCCS, 2018).

Growing Degree Days

Growing degree days (GDD) are calculated as follows:

$$GDD = max\{\tfrac{T_n + min\{T_x, T_m\}}{2} - T_b,\ 0\} \tag{1}$$

$$\longrightarrow \textit{summed over all days in the growing season}$$

Where T_n is the daily minimum temperature in °C, T_x is the daily maximum temperature in °C, T_m a given upper bound and T_b is a lower bound. Possible bounds for grain maize are 30°C as upper bound T_m and 0°C as lower bound T_b, as defined by Calanca (2020).

A GDD represents a relationship between heat and biological development (Snyder, 1985). Its accumulation can be used by farmers and researchers to monitor the biological processes and to approximate stages of plant growth (Roberts et al., 2013). Degree days have also shown to be useful in pest management (Snyder, 1985).

Growing degree days have been studied for a long time and found application in many agroclimatic studies including Switzerland and grain maize (Belyaeva & Bokusheva, 2018; Ben-Ari et al., 2016; Felber et al., 2018; Grigorieva, 2020; Holzkämper et al., 2015; Kukal & Irmak, 2018; Roberts et al., 2013).

Heat Days

Heat days work in the same way as frost days, except that here in most studies the temperature threshold is set to 30°C (Ben-Ari et al., 2016; Holzkämper et al., 2013, 2015; Klein et al., 2017; Pagani et al., 2017; Zhang et al., 2011) and days are counted when the maximum temperature exceeds this value. But depending on the crop and region, temperature thresholds may change. A heat day boundary of 30°C is also assumed for this study (Calanca, 2020).

In Switzerland, heat days have been applied in an agricultural context for grain maize by Holzkämper et al. (2015), where an upper limit of 35°C was chosen.

Precipitation

Precipitation is a basic climate indicator. It is usually measured in millimeters as the accumulated total over the growing season (Belyaeva & Bokusheva, 2018; Ben-Ari et al., 2016; Holzkämper et al., 2015; Roberts et al., 2013; Zhang et al., 2011).

For crop cultivation, the timing of rain events often plays a major role. Heavy rainfall events or their absence have a different effect depending on the growth stage of the plants. Therefore, the sum of rainfall is often calculated for several sub-periods of the season (Belyaeva & Bokusheva, 2018). The complex interplay of precipitation, temperature and humidity and its effects on plant production is further discussed in chapter 2.5.

There are also alternative indicators that can be derived from basic precipitation. For example, one often counts the days on which the precipitation exceeds a threshold value. Again here, the limit can be given in absolute figures (for example “very wet days”, when the daily rain sum exceeds 20 millimeters) or as a percentile. The latter case, which measures the tails of the distribution, is often used to indicate for extreme events (NCCS, 2018).

The absence of rain can also be used as an indicator of drought. A widely used indicator for this is *consecutive dry days*, where the maximum number of consecutive days without precipitation per season is measured (Alidoost et al., 2019; Orlowsky & Seneviratne, 2012; Zhang et al., 2011).

Solar Irradiance

A measure for the mean solar radiation in $W\,m^{-2}$ (Calanca, 2020). More solar radiation increases photosynthesis and thus leads to higher plant yields (Holzkämper et al., 2015). However, increased temperature values at the same time can have negative effects on agricultural yields, since the spike growth is shortened (Nalley et al., 2009).

Solar radiation is a widely used indicator in crop science. In Switzerland, it was used by Holzkämper et al. (2011, 2013).

Temperature

The measurement of mean temperatures in °C is one of the most straightforward climate indicators, along with precipitation.

To use temperature as a climate indicator, one can specify the indicator directly in degrees Celcius (°C) and look at minimum, mean or maximum values over a specific period. This is most commonly done in agroclimatic studies.

It is also possible to define a threshold value (°C) and count on how many days per season or year the temperature is below or above this value (NCCS, 2018; Zhang et al., 2011). This allows for the choice between an absolute threshold value in °C or a relative one that is quantile based. Quantile based thresholds have the advantage that they can be better compared over large spatial distances, where absolute values cannot be compared (Zhang et al., 2011).

Temperature is used in many studies as a basic indicator of climate effects in crop cultivation (Ben-Ari et al., 2016; Holzkämper et al., 2013; Pavlova et al., 2014). There are also many indicators derived from temperature values, such as the number of heat days (Alidoost et al., 2019; NCCS, 2018; Zhang et al., 2011; Zubler et al., 2014).

Vapor Pressure Deficit

Vapor pressure deficit (VPD) can be approximated as follows, where T_a is the daily average temperature in °C and a_d is the mean daily vapor pressure in hPa (Calanca, 2020).

$$VPD_d = 6.108\, e^{\left(\frac{17.27 T_a}{237.3 + T_a}\right)} - a_d \tag{2}$$

$\longrightarrow$ *summed over all days in the growing season*

VPD is the difference (deficit) between the amount of moisture in the air and how much moisture the air can hold when it is saturated (Roberts et al., 2013). The amount of water it is currently holding is given by the dew point – and if it is often measured in pounds per square inch (psi) or kilopascal (kPa).

If VPD is high (>1 kPa) the air can still hold a large amount of water (Wollaeger & Runkle, 2016). A low VPD shows that the air is near saturation. Finally, a VPD of zero means the air is fully saturated and thus plants cannot transpire effectively (Wollaeger & Runkle, 2016).

In agroclimatic context, VPD has been applied by Roberts et al. (2013) and Ben-Ari et al. (2016) for grain maize, and Pavlova et al (2014) for spring and winter wheat, among others.

Water Balance

The *water balance* is a measure of drought. It is the difference between precipitation and ETo (Calanca, 2020). If the values of the water balance are positive, more water enters the soil through precipitation than evaporates from it. If the values are negative, the soil dries out because more water evaporates than is supplied to the soil (BAFU, 2019).

Water balance was used in a Swiss agroclimatic context by Holzkämper et al. (2011, 2013, 2015).

Wet Days and Dry Days

As already mentioned above, the number of *wet days* is derived from precipitation measurements. It usually counts days where the daily precipitation sum is greater than 1 mm (Calanca, 2020). From wet days, indicators such as wet days intensity (average precipitation amount on wet days for each year or season) or the maximum number of consecutive wet days can further be derived (Orlowsky & Seneviratne, 2012; Zhang et al., 2011).

The *dry day* indicator points out days where precipitation is below 1 mm. The maximum number of consecutive dry days is widely used as a measure of drought or water stress (Alidoost et al., 2019; NCCS, 2018; Orlowsky & Seneviratne, 2012; Zhang et al., 2011).

In Switzerland, wet and dry days have been described by NCCS (NCCS, 2018).

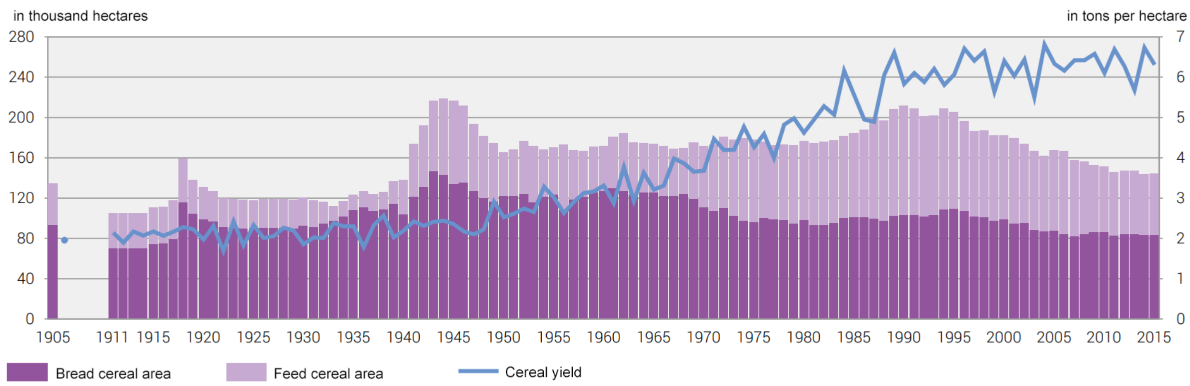
2.4 Agriculture

2.4.1 Brief History of Crop Production in Switzerland

Historically, the importance and political interest of crop production has always been very high in Switzerland because a considerable part of the national food supply dependeds on it. From 1905 onwards, the total area cultivated with crops was recorded in the federal census (see Figure 13) (BFS, 2017). A first peak in crop acreage was observed in 1944 as a consequence of the agricultural policy during the Second World War, which aimed to increase self sufficiency in food (BFS, 2017).

After a second peak in the early 1990s, the crop cultivation area declined again (BFS, 2017). This happened for several reasons: With technical and breeding progress, the amount of grain harvested increased, so that less land was needed to produce the same amount (Finger, 2008). Also, changes in agricultural policy influenced the decline of crop land (more on this in Section 2.4.4). The ratio of bread crop to feed crop also changed: In 1905, 69/% of the total cereals area was still used to produce bread grain. Today, bread cereals make up only 58/% of the total cereals area (BFS, 2017).

Crop yields per acreage more than doubled in Switzerland since the middle of the 20th century. This is due to technological development, e.g. improvements in crop varieties, adaptation to environmental conditions, mechanization, and use of fertilizers and pesticides (Finger, 2008).



Source: BFS (2017)

Figure 13: Cereal Area and Total Cereal Yield in Switzerland 1905-2015

Note: Dark violet represents bread cereal area and light violet feed cereal area (both in thousand hectares). The blue line represents cereal yield in tons/hectare.

2.4.2 Current State of Crop Production in Switzerland

Switzerland's agricultural area in 2015 was 1.05 million hectares (ha): 14/% of this was crop land and 6/% of the total crop area were organically farmed (BFS, 2017). In Switzerland, grain production is generally concentrated in the lowland, although cereals are also grown up to the highest mountain zone (BFS, 2017). Most crops were produced in the cantons of Vaud and Berne. In 2015, 21,300 agricultural companies were involved in cereal production and they cultivated 7 ha of cropland per farm on average

(BFS, 2017). In 2018, feed crop varieties accounted for 41/% of the total cereal acreage and are therefore an important branch of the arable crop production in Switzerland (BLW, 2019). Crops used for animal feed were barley, grain maize, triticale (a cross between wheat and rye), fodder wheat, oats and mixtures of fodder cereals (BFS, 2017).

2.4.3 Maize Cultivation in Switzerland

In Switzerland, a distinction is made between *grain maize*, *silage maize* and *energy maize* (Miedaner, 2014): In the case of grain maize, only the grains of the mature maize plant are used. Besides being used as feed for cattle, pigs and poultry, the grains have other uses, such as ethanol and starch production. In the case of silo maize, the whole plant is harvested in an unripe state. By mixing the plant parts, a good feed for cattle and dairy cows is produced. This was developed especially for maize cultivation in northern growing areas, where the grain maize does not mature, in the beginning of the 20th century (Miedaner, 2014). A new development is the use of maize as substrate for biogas plants (energy maize). For this purpose, the energy maize is also chopped and ensiled to have substrate available all year round (Miedaner, 2014).

In Switzerland, 171,776 tons of grain maize was produced in 2019 and the mean for the years 2015 to 2019 is 144,773 tons (SGPV, 2020b). For this, a total area of 16,015 hectares was used in 2019, or 14,391 hectares on average for 2015-2019 (SGPV, 2020a).

2.4.4 Crop Production and Agricultural Policy

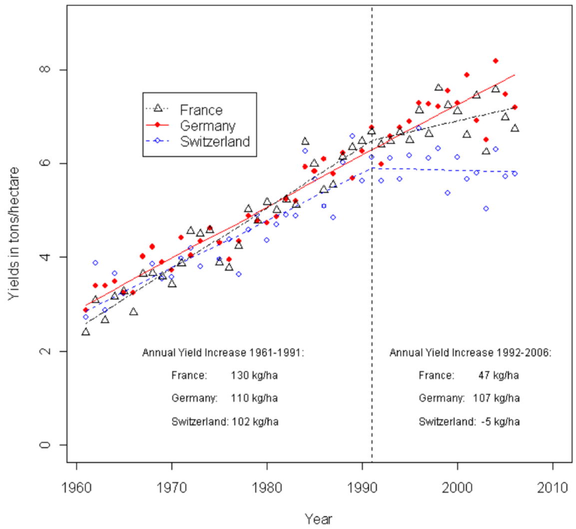
Finger (2008) looked at annual rates of crop yield in Switzerland, Germany, and France from 1961-2006. Due to technical development, crop yields in those three countries more than doubled in the studied period. Agricultural policy facilitated this growth through investments in agricultural, rural, and research infrastructure as well as price support (Khush, 1999).

Annual rates of crop yield have been stable in Europe since 1960 (Ewert et al., 2005). However, Swiss yield levelled-off after a widespread shift in production from conventional to extensive cereal production after 1991 (Figure 14) (Finger, 2008). The shift in Swiss yield was caused by newly introduced, complementary ecological payments by the Swiss government to foster environmentally-friendly (extenso) farming processes (Finger, 2008). Considering that many wheat producers in Switzerland switched to extenso subsidies, which were not available for maize, wheat yields stagnated while for maize yields no levelling-off is recognizable (Figure 15). From early to the mid 1990s, the total share of extensive area under wheat cultivation in Switzerland increased to about 45% and remained on this level there forward. Similar programs to extensify production in the European Union had much smaller effect (Finger, 2008).

The growth rate for maize in Switzerland was smaller from 1992 to 2006 compared to 1961 to 1991, even though extenso subsidies for maize were not available. The reason for this could lie in a cross compliance system (*ÖLN*) introduced into Swiss agricultural policy in 1998 which led to major changes in farming practices including maize cultivation (Mann, 2005).

In the EU, cross compliance measures became mandatory only in 2005 (Bennett et al., 2006). But Finger (2008) remarks, that with recent reforms of the EU's Common Agricultural Policy there will be more emphasis on decoupling and cross compliance policies.

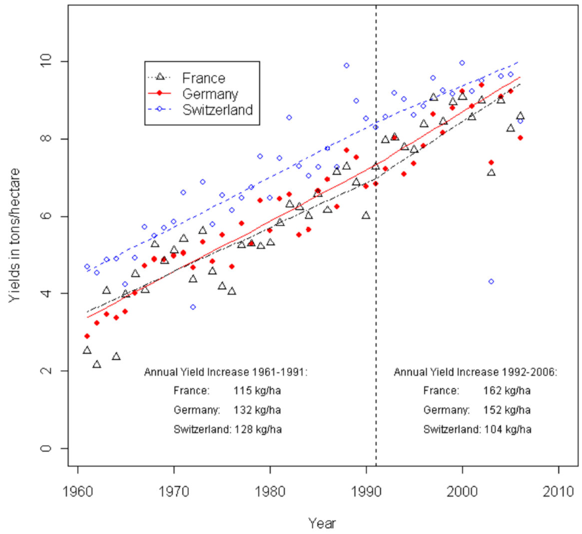
The example of Switzerland shows that widespread extensive production and cross-compliance measures could reduce crop yield growth, at least in the short term (Finger, 2008). Increases in yield, which may be necessary to meet future food needs, can therefore be limited by an agricultural policy towards environmentally friendly crop production (Finger, 2008).



Source: Finger (2008)

Figure 14: Wheat Yields for Switzerland, France, Germany from 1960 to 2007

Note: Wheat yield observations (symbols) and estimated linear trends (lines) for Switzerland, France, and Germany. The dashed vertical line symbolizes the level-off of yield growth in Switzerland.



Source: Finger (2008)

Figure 15: Maize Yields for Switzerland, France, Germany from 1960 to 2007

Note: Maize yield observations (symbols) and estimated linear trends (lines) for Switzerland, France, and Germany. The dashed vertical line symbolizes the decrease in yield growth in Switzerland.

2.5 Interferences of Agriculture and Climate Change

This subchapter brings together the topics of climate and agriculture, which have been described mostly separate so far. Fuhrer et al. (2007) argue that climate is one of the most important limiting factors for the cultivation and yield of crops and livestock. Climate change therefore changes an important framework condition.

In the following, the interferences between the (changing) climate and agriculture are discussed mainly in a Swiss context. Study results from abroad will be presented if there is a commonality with Switzerland. However, agriculture as a whole will only partly be considered. The focus is on cereal production and grain maize in particular.

2.5.1 Agriculture as Driver of Climate Change

The share of CO_2 emissions from agriculture in Switzerland is low compared to other economic sectors but rather high when compared the agricultures share of GDP (Perroud & Bader, 2013). Also, its contribution to CH_4 emissions (51%) and N_2O emissions (40%) is very high due to livestock and the use of farmyard manure (Perroud & Bader, 2013). N_2O emissions are mainly due to the biological degradation of nitrogen depositions on agricultural land – mainly due to nitrogen fertilization (Perroud & Bader, 2013).

2.5.2 Climatic Influence on Crop Production

Climate change generally leads to a shift in the areas suitable for agricultural production and brings both positive aspects (e.g. extension of the vegetation period) and negative effects (e.g. pest pressure due to more moderate winters) in the short term (BLW, 2019).

Influence of Temperature on Crop Yield

A moderate increase in temperature can have a positive effect on the yield of corn (Holzkämper et al., 2011, 2012). In the longer term, however, an increasing production risk can be assumed due to the already described enhanced weather variability (Brönnimann et al., 2014). The risk of drought, for example, will increase and lead to growing water shortages in agriculture in some regions of Switzerland (Calanca, 2007).

It can be assumed that temperature effects on yields are cumulative over time and that yield is proportional to total exposure (Schlenker & Roberts, 2009). Standard agronomic models assume that temperature effects plateau at the optimum and only through an increase in water requirements (and therefore lack of water in the soil) can even higher temperatures become harmful (Schlenker & Roberts, 2009).

However, according to Schlenker and Roberts (2009), temperature and yields are related in a nonlinear way. First, yield growth increases gradually with temperature. But above 29-32°C (depending on crop type) yield declines sharply (Schlenker & Roberts, 2009). They find that the harmful temperature effect above the optimum is the single most powerful predictor of yield (Schlenker & Roberts, 2009).

Influence of Precipitation on Crop Yield

Roberts et al. (2013) find the association between precipitation and yield to be weak. They offer the following explanation for this counterintuitive result: Corn (the crop they have analyzed in their study) is usually grown in areas that receive enough rainfall. And when rainfall is insufficient, the absence of moisture is usually better indicated by other factors that critically influence evaporation and evapotranspiration, for example VPD (Roberts et al., 2013).

Another way in which precipitation can influence crop yield was found by Schlenker and Roberts (2009): Precipitation can mitigate damages from extremely high temperatures. From their study they concluded, that when looking only at samples with greater precipitation, the decline of yield above the critical temperature threshold is less steep (Schlenker & Roberts, 2009).

For winter wheat and spring barley in Russia, Belyaeva and Bokusheva (2018) found a positive response of yields to summer precipitation. According to them, spring wheat yields and autumn and winter precipitation correlate positively. This suggests that moisture which is accumulated in those months later has a positive impact on yields (Belyaeva & Bokusheva, 2018).

Influence of Vapor Pressure Deficit on Crop Yield

VPD either directly affects yield or may be associated with weather patterns that affect yield (Roberts et al., 2013). One way for VPD to directly affect yield is through driving water loss by the plant through transpiration, which increases the water requirements of the plant (Roberts et al., 2013). Therefore, a large VPD correlates with lack of moisture which should decrease yields (if not in an irrigated system).

But higher VPD is also closely associated with diurnal temperature variation (the difference between daily minimum and maximum temperatures) (Roberts et al., 2013). This usually correlates with less cloud cover and more solar radiation – which leads to higher rate of photosynthesis and therefore is beneficial for yields (Roberts et al., 2013). Therefore, an increasing relationship between VPD and yield can be expected when soil moisture is adequate (Roberts et al., 2013). When soil moisture is lacking, Roberts et al. (2013) expect a decreasing relationship between VPD and yield, because plant growth will be limited by water scarcity.

VPD is exponentially related to temperature and increases of both minimum and maximum temperature can greatly increase VPD (Roberts et al., 2013). Consequently, it could be argued that climate change will increase VPD and plant water stress.

Roberts et al. (2013) expect VPD to be highest and most potentially damaging during the hottest months. They also found that VPD strongly interacts with degree days above 29°C and significantly improves corn yield predictions.

Extreme Weather Events and Crop Yield

In recent years, large numbers of record breaking heat waves have led to substantial yield loss in Europe (Ciais et al., 2005). However, if climate extremes will lead to extreme yield losses depends also on the timing and crop sensitivity (Ben-Ari et al., 2016). Plants may become more sensitive to damage from high temperatures when water stressed. This is because plant stoma under heat stress close to save water – but this also reduces their capability for cooling through transpiration (Roberts et al., 2013).

It should be considered that in recent years the trend towards higher temperatures has been accompanied by a pronounced variability of weather conditions (BLW, 2019). In Switzerland, this variability was accompanied by a high risk of damage caused by extreme events (BLW, 2019). Worth mentioning are in particular (BLW, 2019): The rainy spring of 2016, which caused substantial wheat yield failures after the occurrence of fungal diseases. The cold days in April 2017 which caused severe frost damage in fruit and wine growing. And the unusually warm and dry summers of 2015 and 2018, which affected fodder cultivation and livestock farming in many regions of Switzerland.

Since a record-breaking heatwave of summer 2003, Switzerland has suffered from drought several times. Although there is still no clear trend towards longer and/or more intense droughts, an accumulation of dry years has recently been observed in some regions of Switzerland (BLW, 2019): In the Jura, 2018 was the fourth consecutive year in which agriculture was affected by water scarcity. The extreme drought of 2018 first started in the eastern parts of the country, but over time spread to the whole Central Plateau and Western Switzerland. In the months of April-September it reached a similar extent as in the previous record years 2003 and 2015, whereby the intensity of the drought of 2015 was clearly surpassed by that of 2018 (BLW, 2019). In the longer term, crop failures are to be expected in Switzerland due to aridity

(BLW, 2019).

The new climate change scenarios for Switzerland show a slight decrease in cumulative precipitation in late spring and summer and an increase in the duration of drought periods (Holzkämper, 2019). A widespread use of irrigation could be considered as an adaptation option to a certain extent, but there is a risk of conflicts about water-usage with other industrial sectors (Holzkämper, 2019).

Measurements by MeteoSwiss also show an increase in heavy precipitation (Umbricht et al., 2013). A continuation of this trend over the next decades seems likely according to the new climate change scenarios for Switzerland. This leads to an increase in the risk of erosion, especially in areas that are already affected by this problem (BLW, 2019; Brönnimann et al., 2014).

Frost and heat have not yet been found to be most frequent limitations for any grain maize crop growth phases (Holzkämper et al., 2015).

2.5.3 Phenology Changes

A large number of studies in Switzerland since 1951 indicate that the *phenological development stages* of crops are shifting and that spring occurs earlier than usually expected (BLW, 2019; Brönnimann et al., 2014). The events that define the plant development stages in spring are directly dependent on temperature.

For autumn there are no clear trends regarding a time shift (Brönnimann et al., 2014). Computational studies suggest that the prolonged vegetation periods have led to an increase in net primary production of temperate grassland ecosystems (BLW, 2019).

The influence of climate and weather on crop yield depends on phenological stages. Holzkämper et al. (2015) have investigated which climate effects are most limiting to yield during certain phenological stages. Table 1 shows their results on the example of grain maize. The results of Holzkämper et al. (2015) and from other studies also, i.e. Tao et al. (2012), show the importance of considering the timing of crop phenology and how this timing interacts with crop-specific requirements.

A possibility to define the phenological stages of a crop was presented by Holzkämper et al. (2013). In their approach, seeding dates are dynamically determined within a predefined time window following the occurrence of an appropriate agronomic weather sequence. Subsequent phenological growth stages can then be assumed based on the number of GDD. See Table 1 for possible GDD requirements of grain maize for Switzerland.

Gornott and Wechsung (2016) describe another method to distinguish the influence of climate on yield over time: Instead of defining phenological stages through GDD requirements, one can also simply work with calendar months. Gornott and Wechsung (2016) differentiate between the vegetative and reproductive phases of plant growth. The daily values of the climate indicators are then summed up separately for the respective months of both growth phases. As an example, for silo maize in Germany the months May-July can be assumed for the vegetative stage and August-October for the reproductive stage (Gornott & Wechsung, 2016). The use of calendar months divided into two growth phases leads to similar results as working with phenological stages defined by GDD requirements (Dixon et al., 1994).

Table 1: Phenological Stages and Their Limiting Climate Effects for Grain Maize in Switzerland

Phenological stage	GDD requirement	Climate effects
Planting to emergence	100	Suboptimal average temperature are most frequent limitation. Also radiation limiting in some areas.
Emergence to begin of flowering	800	Radiation is the most frequent limitation. Limited water availability is most frequent limitation in the Rhone valley and in the Southwest (GE, VD, FR).
Flowering to begin of grain filling	1,100	The dominating factor across almost the entire area is limited water availability. Also, suboptimal average temperature limiting in some parts.
Maturation	1,600	Radiation and average temperature were the most frequent limitations. In the northern part mostly radiation.

Source: own representatnion of data from Holzkämper et al. (2015)

2.5.4 Pests and Diseases

The rise in temperature also favors the development of many pest organisms. Furthermore, warmer temperatures promote the spread of invasive insect pests. This has become a problem for Swiss agriculture (BLW, 2019).

Conversely, years with extremely high summer temperatures can also be problematic for some – potentially harmful – insects and may increase mortality rates of larvae and pupae (BLW, 2019).

2.5.5 Mitigation

By adapting to climate change in a forward-looking manner, agriculture can take advantage of opportunities and mitigate negative impacts on yields and the environment at least in the mid term (BLW, 2019). In Switzerland, this is intended to be accomplished through various environmental policy instruments. The instruments are related to the energy sector, agriculture, forestry, transport and environmental protection (Brönnimann et al., 2014).

In the light of the challenges posed by climate change, the Swiss Federal Office for Agriculture (BLW) has developed a climate strategy for agriculture in 2011 (BLW, 2019). By 2050, emissions are to be reduced by more than a third (compared to 1990) (BLW, 2019).

If it becomes apparent that the target will not be met, the Federal Department of Economics, Education and Research (WBF) is mandated to submit proposals to the Federal Council for a correction of the course of action (BLW, 2019). And current trends in agricultural GHG emissions show that the target actually is being missed and that therefore, additional efforts therefore are necessary to bring the emissions back on track (BLW, 2019).

3 Data Description and Preparation

3.1 Spatiotemporal Context

The case study is conducted for the Canton of Bern, which is an important grain producer in Switzerland. The time period of the study is 1990 to 2018. The analyses and interpretations in the following chapters refer to this study region and time period unless specifically written otherwise.

3.2 Agronomic Data

3.2.1 Farm Accountancy Data Network

Farm-level data for grain maize was taken from the *Farm Accountancy Data Network* (FADN). With the FADN, Agroscope conducts an analysis of the economic situation of Swiss farms on behalf of the Swiss government. For this purpose, it collects accounting data and farm structure characteristics from a sample of selected *reference farms* (Renner et al., 2018).

3.2.2 Notable Changes in Survey Methodology

The data collection and evaluation systems of the FADN are regularly revised, so that new technical possibilities and legal requirements can be continuously met (Renner et al., 2018). Although the FADN has been collecting data since the 1970s, only the period from 1990 onwards, that is relevant for this study, will be discussed here. Since 1990, significant changes in data collection methodology occurred in 1999 and 2015.

Due to the sampling methodology used in the period from 1990 to 1999, generalizations about the farm population in that period have to be made with caution (Meier, 2000). In 1999, methodological adjustments were made to enable the results from the reference farms to better represent the situation in Swiss agriculture as a whole: The sample population was revised and a weights system for the farms was introduced (Meier, 2000). The weights system improved the representativeness of the sample, but distortions remained. Nevertheless, the significance of the reference farm results for Swiss agriculture was improved by the 1999 adjustments (Meier, 2000).

In 2015, the FADN's survey system was fundamentally reformed. For samples relevant to this study, a new proportional distribution was introduced, whereby all farms are included in the calculation of the mean values with equal weights (self-weighting sample) (Renner et al., 2018). Thereby, the mean value of the sample corresponds to the mean value of the entire population. But this is only valid under the assumption that the population sample can be realized exactly according to the selection plan, which is very unlikely (Renner et al., 2018).

Irrespective of methodological improvements in the FADN survey system, the agronomic data used for the entire study period from 1990 to 2018 is not based on a purely random sample and therefore the interpretation of the data must be made with caution (Renner et al., 2018). In addition, the population of reference farms does not remain constant over the years, which can lead to some bias when comparing records of different years (Roesch, 2011).

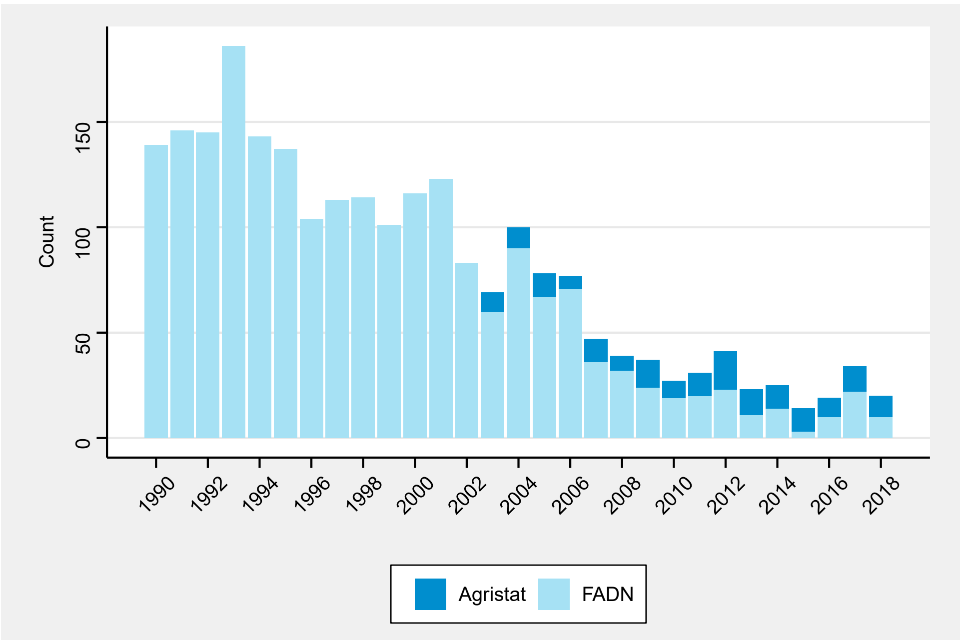
3.2.3 Inclusion of Agristat Data

The above mentioned reform of the FADN survey system and the related methodological changes have led to a break in the data time series between the years 2014 and 2015.

In order to compensate for the data gaps within the FADN survey, a second data set at farm level is included. This second data set comes from *Agristat*, the statistical service of the Swiss Farmers' Association.

Agristat has been collecting individual farm yield data since 2003. It is not a representative sample survey, but farmers remain in the survey group for several years and an attempt is made to adjust the number surveyed per canton to the size of the cantonal crop cultivation area. To ensure the accuracy of the data, the yields are reconciled with information from the branch association *swiss granum*.

Figure 16 depicts the number of reference farms with grain maize cultivation used for the study. The break in the FADN Dataset in 2014 and 2015 is well visible. It should be mentioned, however, that after 2015, fewer reference farms are needed due to the FADN reform, which explains part of the sample decrease.



Source: own representation of FADN and Agristat dataset

Figure 16: Number of Reference Farm Observations

Note: Number of reference farms in the canton of Berne with grain maize yield observations, grouped by data set.

3.2.4 Structure

The FADN data contains 2,251 farm level observations of maize harvest in kg and maize acreage in are for the canton of Bern and the period 1990-2018. The Agristat data contains 173 farm level observations of maize yield in kg/a for the canton of Bern and the period 2003-2018.

3.2.5 Yield Definition

It is common in agricultural economics to work with yields. $Yield = harvest \times area\,cultivated^{-1}$, where *harvest* is defined in kg and *area cultivated* in ares.

3.2.6 Descriptive Statistics

The following summary statistics (Table 2) refer to farm level yield observations from both datasets and to the entire study period, before outlier processing.

Table 2: Summary Statistics of Yield Data Before Outlier Removal

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Yield (kg/a)	2,424	101.011	124.398	12	86.3	110	6,133

The yield data contains some extreme values, that go up to 6,133 kg/a and are clearly invalid from an agronomic point of view. The minimum value of the dataset is 12 kg/a. However, when looking at the frequency distribution (see Figure 45 in the Appendix) and leaving aside irrational yield values above 200 kg/a, a normal distribution (with slight bimodial tendency) can be estimated.

The mean of the yield data is 101 kg/a and the median is 97 kg/a, which indicates an appropriate central tendency. The standard deviation is 124.4 kg/a which is clearly too high from a practical point of view.

The presented figures indicate that the yield data is close to normal distributed but includes distorting extreme values. This is supported by the distribution skewness, which takes on the value 47.06 and therefore indicates a strong right skew.

When looking at the same data but for each year individually one finds mostly even distributions (see Figure 46 in the Appendix). Only the year 2010 shows a slight right skew.

3.2.7 Treatment of Extreme Vaules

To prevent the manipulation of underlying time trends in the data, the extreme values (outliers) are estimated separately for each year. Outlier identification is based on the combined data from FADN and Agristat to ensure that there are enough observations to reliably detect extreme values.

The *interquartile range* (IQR) is suitable as a basis for the detection of extreme values in data sets with skewed and non-normally distributed distribution (Hubert & Van der Veeken, 2008). If *Q1* is the first and *Q3* the third quartile of a distribution, IQR is calculated as follows: $IQR = Q3 - Q1$.

All observations which lie outside of the below defined interval are classified as an outlier and removed from the dataset:

$$[\ Q1 - 1.5\, IQR\, ,\ Q3 + 1.5\, IQR\ ]$$

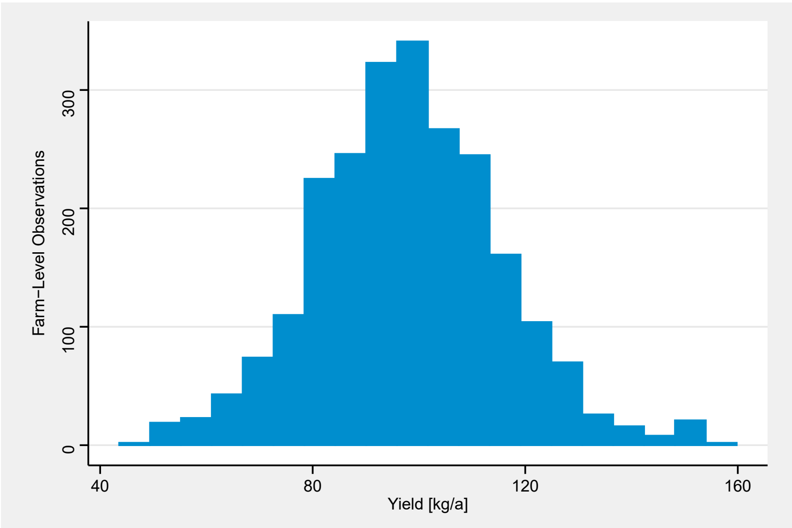
In total, 93 yield observations were classified as extreme and removed. Thus, the number of included farm-level yield observations is reduced from 2,424 to 2,331 (for the FADN and Agristat data combined).

Table 3: Summary Statistics of Yield Data after Outlier Removal

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Yield	2,326	97.862	17.486	46.164	86.803	109.091	156.571

With the removal of the outliers the median shifts to 97.7 kg/a. The mean decreases and is now 97.86 kg/a. The minimum value is 46.16 and the maximum value is 156.57 kg/a, which are much more realistic values from an agronomic point of view. See Table 3 for summary statistics after outlier removal.

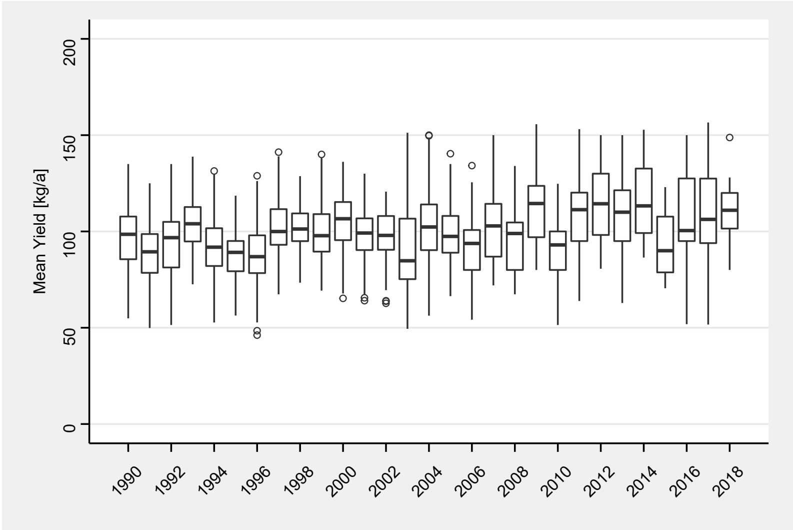
Figure 17 shows the distribution of the farm level yield observations after excluding the outliers. The data is nearly normally distributed and approximately symmetrical (skewness = 0.15). Also the standard deviation is now more realistic at 17.5 kg/a. Figure 18 shows the distribution of the yield for each year, without outliers. There are only few observations outside the IQR, which is reasonable from an agronomic perspective.



Source: own representation of FADN and Agristat datasets

Figure 17: Distribution of the Farm Level Yield Observations after Outlier Exclusion

Note: Grain maize yield observations in kg/a. Number of observations for both datasets and for the canton of Berne.



Source: own representation of FADN and Agristat datasets

Figure 18: Per-year Distribution of the Farm Level Yield Observations after Outlier Exclusion

Note: Grain maize yield observations for both datasets in kg/a, for the canton of Berne.

3.3 Meteorological Data

3.3.1 Origin

The meteorological data for this study comes from the observation network of the *Federal Office of Meteorology* (MeteoSwiss). Daily measurements for the period 1990-2018 from the meteorological station Bern/Zollikhofen are used. Table 4 provides more information about the location of that station.

Table 4: Meteorological Station Summary

Short	Location	Canton	Lat / Long	Elevation	Exposition
BER	Berne / Zollikhofen	Berne	46.990744 / 7.464061	553 m.a.s.l.	plain

3.3.2 Structure

Table 5 provides details on the structure and contents of the meteorological dataset.

Table 5: Structure of Meteorological Data

Short	Description	Unit
ea	Vapor pressure	hPa
ETo	Reference evaporation	mm
NR	Net irradiation	$W\,m^{-2}$
P	Precipitation	mm
RH	Relative humidity	%
SRad	Solar irradiation	$W\,m^{-2}$
SSD	Sun hours	h
rSSD	Relative sun hours	%
surf	Soil pressure	hPa
Ta	Temp. mean	řC
Tmax	Temp. maximum	řC
Tmin	Temp. minimum	řC
ws	Wind speed	$m\,s^{-1}$

4 Method

Multiple linear regression will be used to find out which climate indicators influence grain maize yield in the study area. This chapter describes the methods and tools used for this purpose. Linear regression has already been widely applied to similar problems in the field of agricultural economics, i.e. see Alidoost et al. (2019); Belyaeva & Bokusheva (2018); Roberts et al. (2013); Schlenker & Roberts (2009).

In addition to the regression analysis, an exploratory analysis of the yield data and climate indicators is performed. It serves the purpose of quality control and also allows to graphically depict the results of the analysis.

Calculations and statistical tests performed for this thesis were made with the programming language R in the R-Studio development environment (R Core Team, 2020; RStudio Team, 2019). Additionally used packages are listed in the bibliography. All R-Scripts used are available in the supplementary materials.

4.1 Agroclimatic Indicator Selection

The selection of climate indicators for this case study is based on the presented information in Chapter 2.3. The final selection of indicators should represent the climatic needs of grain maize in the study area in the best but most simplistic way possible. The goal is for the indicators to provide a broad view of the interactions of climate change and agriculture and address multiple aspects of crop production over different phenological phases (Walsh et al., 2020). To account for changing impacts of climate on crop yield during different phenological growth stages, the agroclimatic indicators need to be computed for specific time periods. These time periods are shown in Table 6.

The amount of precipitation in the fall, winter and spring can influence soil moisture and therefore affect yield of the next growing season (Belyaeva & Bokusheva, 2018). To account for this, the total precipitation from the months October to end of April (start of vegetative period) is included.

To achieve higher temporal precision of the indicators, vegetative and reproductive periods are included separately in the analysis in addition to the main growing season. For these three periods, a broad set of indicators is used to account for temperature and precipitation: Mean daily temperature and its square are used to explain effects of moderate and extreme temperature on yield (Schlenker & Roberts, 2009). The total amount of precipitation and its square are included as indicators of moderate and heavy precipitation.

July and August are particularly critical for plant growth because of the often very hot and dry conditions (Belyaeva & Bokusheva, 2018; Roberts et al., 2013). To take this into account, that period is included separately in the analysis. The main aim here is to reveal the effects of extreme climatic phenomena such as heat and water stress on yield. Indicators used are the number of heat days, total precipitation and its square, mean VPD and CDD.

Table 6: Phenological Time Periods

Name	Short	From-To
Pre-Season	.pre	1 October - 30 April
Growing Season	-	1 May - 20 October
Vegetative	.V	1 May - 30 June
Reproductive	.R	1 July - 20 Oct
Midsummer	.JA	1 July - 31 August

Table 7 provides a summary of all included indicators and the time periods they account for. These indicators are being calculated from the meteorological dataset based on an R-Script by Calanca (2020). The resulting agroclimatic indicators will be used as independent variables for the following regression analysis.

Table 7: Summary of Selected Agroclimatic Indicators and their Phenological Time Periods

Indicator Name	Short	Pre-Season	Growing Season	Vegetative	Reproductive	Midsummer
Consecutive dry days	ConsD					✓
Heat days	nHeat					✓
Mean temp.	mTa		✓	✓	✓	
Mean temp. squared	mTa.sqr		✓	✓	✓	
Mean VPD	mVPD					✓
Total prec.	tPrec	✓	✓	✓	✓	✓
Total prec. squared	tPrec.sqr	✓	✓	✓	✓	✓

4.2 Dependencies

To examine the independent variables for dependencies, a correlation matrix is created using the Bravais-Peason correlation coefficient.

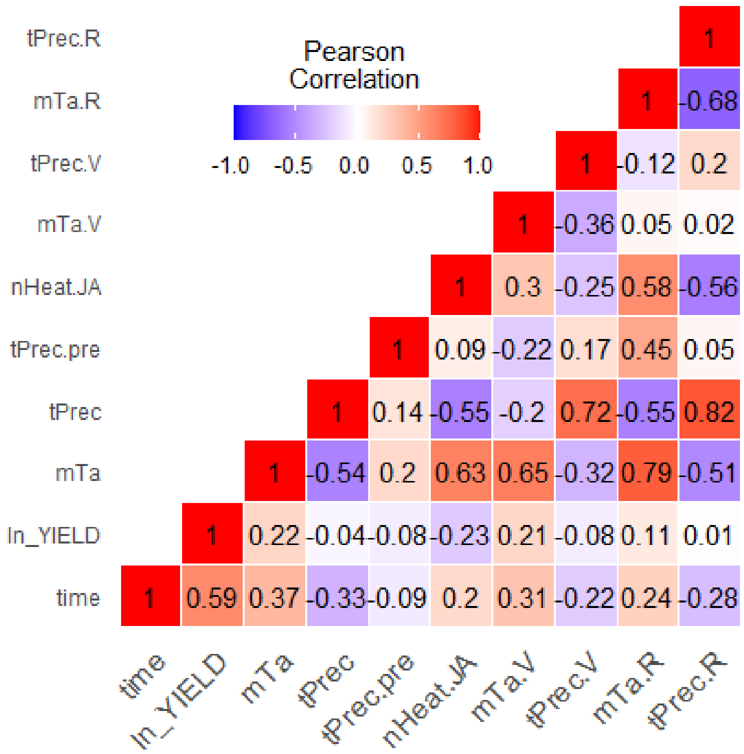
A correlation between two variables occurs when they are linearly covariant with each other. In positive correlation, high or low expressions of one varaible are associated with equal expressions of the second variable. With negative correlation, high or low values of one variable are matched by opposite values of another variable. Non-linear correlations are also possible, but a Bravais-Pearson correlation analysis is only applicable to linear correlations (Schwarz et al., 2020a). A correlation always examines the undirected linear relationship between two variables. Thus, there are no dependent and independent variables and consequently no causal statements are made (Schwarz et al., 2020a).

The Bravais-Pearson correlation coefficient is itself a measure of effect strength (Schwarz et al., 2020a). A value of 0 means no correlation at all, from $+/-$ 0.1 there is weak correlation, from $+/-$ 0.3 medium correlation and from $+/-$ 0.5 one speaks of a strong correlation. A value of 1 means a perfect correlation.

As Figure 19 shows, some of the independent variables are strongly correlated with each other. The strongest correlation (0.82) is between precipitation of the growing season $tPrec$ and the reproductive period $tPrec.R$. Also strong is the correlation (0.79) between the temperature of the growing season mTa and that of the reproductive period $mTa.R$. This can be explained by the fact that these periods partially overlap.

The combinations of precipitation or temperature of the growing season and their derivations for the vegetative period ($tPrec.V$, $mTa.V$) are also strongly correlated (0.72 and 0.65, respectively). However, having variables for the whole growing season strongly correlating with their deviations for specific periods is not a problem because these variables are not used simultaneously in a model.

The number of heat days in July and August ($nHeat.JA$) correlate strongly with mTa (0.63) and $mTa.R$ (0.58) and strongly negatively with $tPrec$ (-0.55) and $tPrec.R$ (-0.56). In addition, temperature mTa and precipitation $tPrec$ are strongly negatively correlated (-0.54).



Source: own representation

Figure 19: Bravais-Pearson Correlation Matrix of Model Variables

Note: *Time*: linear trend, *ln(YIELD)*: log. of yield, *mTa*: mean temp (growing season), *tPrec*: total precipitation (growing season), *tPrec.pre*: total precipitation pre-season, *nHeat.JA*: number of heat days July-August, *mTa.V/R*: mean temp vegetative/reproductive period, *tPrec.V/R*: total precipitation vegetative/reproductive period.

4.3 The Multiple Regression Model

Regression analysis is a statistical instrument that aims for modeling relationships between a dependent variable (also DV, y) and one or more independent variables (IV, x). In the natural sciences, there is rarely only one cause for an effect. For regression, this means that the values of a dependent variable are usually influenced by several independent variables. In *simple regression* (only one IV), it is therefore often difficult to assume validity of *ceteris paribus* (all other things being equal) for the observed effects of x on y (Wooldridge, 2020). *Multiple regression* is more suitable for ceteris paribus analysis because it allows controlling for several factors that simultaneously influence the yield and it is therefore possible to find causalities in cases where a simple regression would be misleading (Wooldridge, 2020).

The model of multiple linear regression can be generalized as follows:

$$y_i = \beta_0 + \beta_1\, x_{i\,1} + \beta_2\, x_{i\,2} + \;\dots\; + \beta_m\, x_{i\,m} + u_i \tag{3}$$

With y_i being the dependent variable for every observation i. x_1 to x_m are the independent variables. β_0 is the intercept, β_1 is the parameter associated with x_1, β_2 is the parameter associated with x_2, and so on. u is the error term.

The error term is in the model to account for the fact that the systematic part of the model $\beta_0 + \beta_1\, x_{i\,1} + \beta_2\, x_{i\,2} + \ ...\ + \beta_m\, x_{i\,m}$ will only match the observations of y with limited accuracy for a given data set (Hackl, 2013). u can contain unobserved factors that affect the dependent variable and may also include measurement (or sampling) errors in the observed dependent or independent variables (Wooldridge, 2020).

4.3.1 Ordinary Least Squares Method

Ordinary least squares (OLS) is a method used to estimate the parameters of a multiple linear regression model. OLS estimates are obtained by minimizing the sum of squared residuals (Wooldridge, 2020).

In the general case with m independent variables like in Equation 3, we look for the following equation with the OLS intercepts $\hat{\beta}_0$ and the OLS slope estimates $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\ldots$, $\hat{\beta}_m$ (Wooldridge, 2020).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1\, x_{i\,1} + \hat{\beta}_2\, x_{i\,2} + \ ...\ + \hat{\beta}_m\, x_{i\,m} \tag{4}$$

The OLS estimators are chosen so that the sum of their squared residuals

$$\sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1\, x_{i\,1} - \ \ldots\ - \hat{\beta}_m\, x_{i\,m})^2 \tag{5}$$

is minimized (Wooldridge, 2020). Squaring has the effect that positive and negative distances from the observed data points to the estimated regression line do not cancel each other out, and secondly, that larger distances thus flow into the calculation with a higher weight (Schwarz et al., 2020b).

4.3.2 Interpretation of OLS Estimates

More important than details on the calculation of OLS estimates is the interpretation of the estimated equation. The intercept $\hat{\beta}_0$ in Equation 4 is the prediction of y when all x values $(x_1, \ldots, x_m)$ are equal to zero. Sometimes this is an interesting scenario, but in most cases its interpretation will not make sense (Wooldridge, 2020). Nevertheless, the intercept is always required to obtain a prediction of y from the OLS regression line (Wooldridge, 2020).

The estimates $\hat{\beta}_1, ..., \hat{\beta}_m$ in Equation 4 have ceteris paribus interpretations, which means that changes in any x_m give the predicted change it has on y, while holding all other x_{m-1} fixed (Wooldridge, 2020).

$$\Delta\hat{y} = \hat{\beta}_1\, \Delta x_1 + \ \ldots\ + \hat{\beta}_m\, \Delta x_m\ , \tag{6}$$

For example, when $\Delta x_2,\ ...\ , \Delta x_m$ are equal to zero (i.e. held fixed), then $\Delta\hat{y} = \hat{\beta}_1\, \Delta x_1$, and coefficient $\hat{\beta}_1$ has a ceteris paribus interpretation (Wooldridge, 2020). This is how multiple regression allows controlling for several factors that simultaneously influence the yield and why one can find causalities in cases where a simple regression would be misleading (Wooldridge, 2020).

In a *log-level model*, the dependent variable is expressed as its natural logarithm. This allows for a more convenient interpretation of the coefficients, since a unit increase in an independent variable approximately is a one percent increase in the dependent variable (semi-elasticity) (Wooldridge, 2020). Taking the log can also mitigate problems of skewness or *heteroskedasticity* in the distribution of the dependent variable and make estimates less sensitive to extreme observations because taking the log narrows the range of the dependent variable (Wooldridge, 2020).

4.3.3 Conditions of Multivariate Regression Analysis

Before analyzing the results of the regression analysis, prerequisites are to be checked. For that, five assumptions of multiple linear regression (MLR) are discussed. Results for the necessary tests are presented in Section 5.2.

If MLR 1 to 4 are valid, the OLS method is not biased. However, there may be other unbiased estimators under these four assumptions that have greater explanatory power than OLS. Only if the MLR assumptions 1 to 5 are true, OLS is with certainty the best linear unbiased estimator (BLUE) (Wooldridge, 2020).

MLR 1: Linearity in Parameters (Gauss-Markov Assumption 1)

This simply means that the postulated model (Equation 3) is linear in the coefficients. However, this assumption is not strongly limiting, since the y and x variables may well be log-transformed or squared, respectively (Wooldridge, 2020).

MLR 2: Random Sampling (Gauss-Markov Assumption 2)

MLR 2 assumes that the observations that go into the model (Equation 3) are based on random sampling (Wooldridge, 2020). The answer to whether this condition is met is found based on background knowledge of the data set (Schwarz et al., 2020b).

MLR 3: Zero Conditional Mean (Gauss-Markov Assumption 3)

This assumption requires that the error value u has the expected value 0 for each observation of the independent variable (Wooldridge, 2020).

$$E(u \mid x_1, x_2, ..., x_m) = 0 \tag{7}$$

To test this assumption, a scatter plot of the standardized estimates of y and the standardized error values (residuals) is generated (Schwarz et al., 2020b). It is then visually checked whether over the entire range of estimated values the error is 0 on average.

MLR 4: No Perfect Collinearity (Gauss-Markov Assumption 4)

This assumption requires that none of the independent variables in the sample is constant and that there are no exact linear relationships among the independent variables (Wooldridge, 2020). This assumption only concerns the independent variables. If one of them has an exact linear correlation with another IV, the model suffers from perfect collinearity and OLS is not a valid estimation method (Wooldridge, 2020). The validity of this statement is checked by using a correlation- or scatterplot matrix of all independent variables (Schwarz et al., 2020b).

MLR 5: Homoscedasticity (Gauss-Markov Assumption 5)

Homoscedasticity means that the error has the same variance for each value of the independent variable (Schwarz et al., 2020b). If this assumption fails (i.e., the variance of the observed error u changes with any of the independent variables), the model exhibits heteroskedasticity (Wooldridge, 2020).

This condition is often tested in the same scatter plot of the residuals, in which the zero conditional mean assumption has already been tested (Schwarz et al., 2020b). If the residual plot does not clearly distinguish between homo- and heteroskledasticity, the *Goldfeld-Quandt-Test* can be applied. This compares the variances of two sample halves. In this test, the null hypothesis implies that homoscedasticity is present (Kosfeld, 2015).

MLR 6: Normality

Here it is assumed that the error u is not influenced by the independent variables $x_1, x_2, ..., x_m$ and follows a normal distribution (Wooldridge, 2020). Whether the error value is normally distributed can be checked using a *quantile-quantile* plot (Q-Q plot).

The Case of Multicollinearity

Multicollinearity describes correlation between the independent variables in a multiple regression model. A certain degree of multicollinearity is usually unavoidable. But it should not be too large, because multicollinearity leads to inaccurate estimates of the affected regression parameters (Schwarz et al., 2020b). However, multicollinearity does not break any of the MLRs described above, and there is no absolute value with which to define problematic multicollinearity (Wooldridge, 2020).

As the correlation matrix (Figure 19) showed, there is some multicollinearity among the independent variables. To check if the level of multicollinearity is higher than appropriate, the *variance inflation factor* (VIF) can be calculated:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{8}$$

where R^2 is the coefficient of determination for the model j. The coefficient of determination is described in more detail in the next section. The variance inflation factor should not be greater than 10 (Schwarz et al., 2020b). If the value is smaller, the level of multicollinearity is not too high.

4.4 Model Design

In total, four *log-level models* are proposed, with the natural logarithm of yield as the dependent variable. The independent variables are expressed in their original form.

The climate indicators, whose selection and calculation were discussed in Section 4.1, act as independent variables. For each of the three models, different combinations of indicators will be tested.

In addition to the agroclimatic indicators, a linear time trend over the entire period 1990-2018 is included as independent variable in the models. The aim of this time trend is to explain technological progress over time. A linear time trend starting from the introduction of agricultural policy changes 1998 (to explain for policy effects, as described in Chapter 2.4.3) was tested but not found to be meaningful for any of the proposed models.

The agroclimatic indicators mean VPD and CDD were tested for July-August but did not have a significant effect on yield for any of the proposed models.

Model 1

$$\begin{aligned} ln(yield)_t = \beta_0 + \beta_1\; time_{\,t} + \beta_2\; mTa_{\,t} + \beta_3\; mTa.sqr_{\,t} \\ +\beta_4\; tPrec_{\,t} + \beta_5\; tPrec.sqr_{\,t} + \beta_6\; tPrec.pre_{\,t} + u_{\,t} \end{aligned} \tag{9}$$

With $time_{\,t}$ being a linear time trend, $mTa_{\,t}$ being mean temperature, $mTa.sqr_{\,t}$ being mean temperature squared, $tPrec_{\,t}$ being total precipitation, $tPrec.sqr_{\,t}$ being total precipitation squared (all for the entire growing season) and $tPrec.pre_{\,t}$ being total precipitation for the pre-season.

The goal of Model 1 is to map basic plant needs throughout the growing season. Differing plant needs depending on the phenological stage are not yet considered. An exception is pre-season precipitation, which is included in the model to incorporate any accumulated moisture in the soil before sowing.

Model 2

$$\begin{aligned} ln(yield)_t = \beta_0 + \beta_1\; time_{\,t} + \beta_2\; mTa.V_{\,t} + \beta_3\; mTa.sqr.V_{\,t} + \beta_4\; mTa.R_{\,t} \\ +\beta_5\; mTa.sqr.R_{\,t} + \beta_6\; tPrec_{\,t} + \beta_7\; tPrec.sqr_{\,t} + u_{\,t} \end{aligned} \tag{10}$$

Model 2 is very similar to the first model. However, the indicators temperature and temperature squared are included separately for the vegetative and reproductive phases ($mTa.V_{\,t}$, $mTa.sqr.V_{\,t}$ and $mTa.R_{\,t}$, $mTa.sqr.R_{\,t}$). Thus, it should become apparent whether there are differences in the influence of temperature on yield between these periods. The indicators for precipitation are left the same. The precipitation of the pre-season is not included in this model in order not to have too many independent variables in the model.

Model 3

$$\begin{aligned} ln(yield)_t = \beta_0 + \beta_1\, time_{\,t} + \beta_2\, mTa_{\,t} + \beta_3\, mTa.sqr_{\,t} + \beta_4\, tPrec.V_{\,t} \\ +\beta_5\, tPrec.sqr.V_{\,t} + \beta_6\, tPrec.R_{\,t} + \beta_7\, tPrec.sqr.R_{\,t} + u_{\,t} \end{aligned} \tag{11}$$

In model 3, the precipitation indicators are split between the vegetative and reproductive periods ($tPrec.V_{\,t}$, $tPrec.sqr.V_{\,t}$ and $tPrec.R_{\,t}$, $tPrec.sqr.R_{\,t}$) and the temperature indicators are included over the entire growing season. In a way, model 3 is an inversion of model 2. The aim is to determine whether there are differences in the effect of precipitation (normal and squared) on yield between the vegetative and reproductive periods.

Model 4

$$\begin{aligned} ln(yield)_t = \beta_0 + \beta_1\, time_{\,t} + \beta_2\, mTa.V_{\,t} + \beta_3\, mTa.sqr.V_{\,t} + \beta_4\, nHeat.JA_{\,t} \\ +\beta_5\, tPrec_{\,t} + \beta_6\, tPrec.sqr_{\,t} + \beta_7\, tPrec.pre_{\,t} + u_{\,t} \end{aligned} \tag{12}$$

This model aims to capture the effects of temperature in the vegetative phase and specifically of extreme heat in midsummer (by means of the Heat Days indicator $nHeat.JA$). Also, precipitation and its square for the whole growing season as well as precipitation in the pre-season are included.

4.5 Model Analysis

After the prerequisites of the MLR are checked and the models are set up, the model coefficients are estimated (see Section 5.3 for results). The resulting model equations are then examined for their significance and quality by applying tests that are described in the following. The results of these tests are presented in Section 5.4.

4.5.1 Significance of the Regression Model

To check whether the regression model is overall significant, an F-test is performed (Schwarz et al., 2020b): The test proves if the complete model contributes an explanation in contrast to the basis model. The basis model considers only the intercept. The F-test checks whether the model has an overall explanatory effect (Schwarz et al., 2020b). The null hypothesis for this test is $\beta_1 = \beta_2 = ... = \beta_m = 0$, and H_1 states that one of the parameters is not equal to zero. Results of the F-test are shown in Table 8.

4.5.2 Significance of the Regression Coefficients

To check if the regression coefficients have a significant effect, a t-test is performed for each of the regression coefficients (Schwarz et al., 2020b). The results are shown in the summary of the regression models (Table 8). The significant coefficients of the independent variables mean that their regression coefficients are not 0 and thus these variables have a significant effect on the dependent variable (Schwarz et al., 2020b).

4.5.3 Goodness of Fit

The *coefficient of determination*, or *R-squared* (R^2), shows how well an estimated model fits the sample data (Wooldridge, 2020). R^2 is always between 0 and 1. To interpret R^2, it is usually multiplied by 100 to get a percentage value. $100 \times R^2$ is the percentage of sample variation in the dependent variable that is explained by the independent variables (Wooldridge, 2020). An R^2 of 0 means that the model has no explanatory power, a value of 1 means that the model perfectly predicts the observed values.

R^2 is affected by the number of independent variables in the model. This is problematic in the case of multiple regression. The R^2 increases with the number of independent variables, even if additional variables have no explanatory value (Schwarz et al., 2020b). Therefore, R^2 is corrected downward (*adjusted* R^2).The correction becomes larger as more variables are in the model, but smaller as the sample size increases (Schwarz et al., 2020b).

To estimate how meaningful the goodness-of-fit result is, the *Cohen effect size* can be calculated (Schwarz et al., 2020b):

$$f^2 = \frac{R^2}{1-R^2} \tag{13}$$

For the effect size f^2 after Cohen (1992) there are the following categories: An f^2 of 0.02 corresponds to a weak effect, an f^2 of 0.15 corresponds to a medium effect, and an f^2 of 0.35 corresponds to a strong effect (Schwarz et al., 2020b).

To evaluate which of the proposed models is the best fit to the data, the *Akaike Information Criterion* (AIC) can be consulted. On a side note, comparing the models by performing an ANOVA F-test is not useful here because the proposed models are not clearly nested.

Gordon (2015) describes a simple formula to calculate the AIC within an OLS framework:

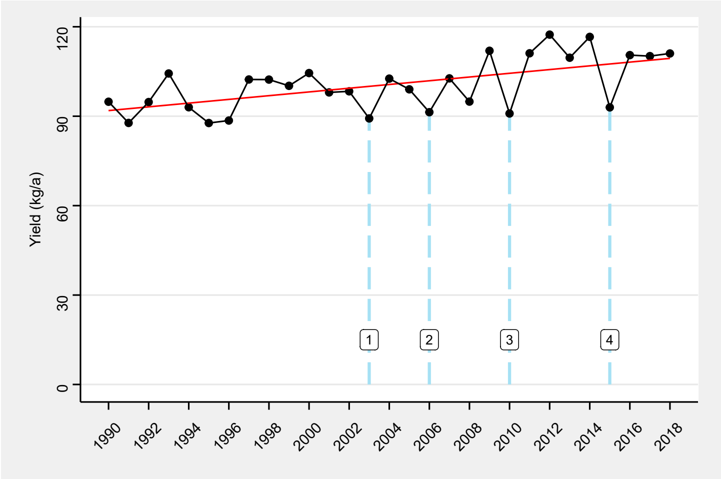
$$AIC = n \times ln(\frac{SSE}{n} + 2k) \tag{14}$$

Where SSE represents the *Sum of Squared Errors* ($\sum(Y_i - \hat{Y}_i)^2$), n represents the sample size, and k represents the number of independent variables in the model. If the SSE in the above formula decreases while everything else remains the same, the AIC will also decrease. Therefore, the model with the lowest AIC is to be preferred.

5 Results

5.1 Exploratory Analysis

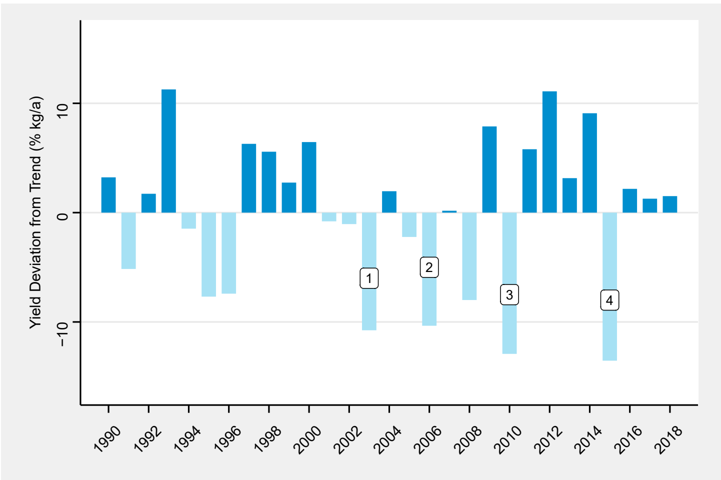
This exploratory analysis is intended to increase understanding of the regression parameters and reveal relationships that are apparent by eye. To do this, the yield (Figures 20 and 21) and the weather variables (Figure 22 to 34) are plottted over time. The yield plots show numbered labels indicating extreme yield variations that are defined by a deviation of more than 10% from the expected value (linear time trend).



Source: own representation of FADN and Agristat data

Figure 20: Yield over Time

Note: Yield for the canton of Berne. The numbers and dashed lines represent years with yield anomalies (identified by negative deviation from linear trend > 10%). The red line depicts a linear trend over time. Data from FADN/Agristat for the canton of Berne.



Source: own representation of FADN and Agristat data

Figure 21: Yield Deviation from Trend in Percent

Note: Yield Deviation from the linear time trend in percent. The number labels refer to the same yield anomalies as mentioned in the figure above. Data from FADN/Agristat for the canton of Berne.

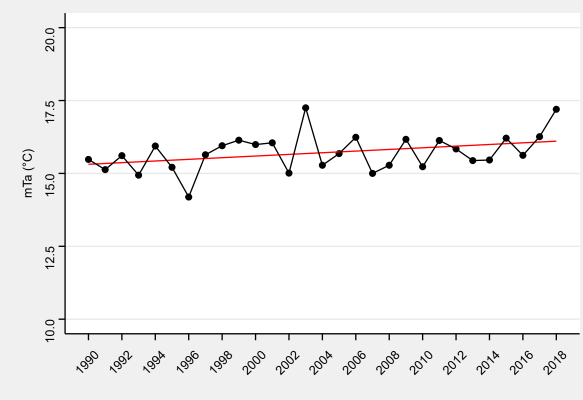


Figure 22: mTa over Time

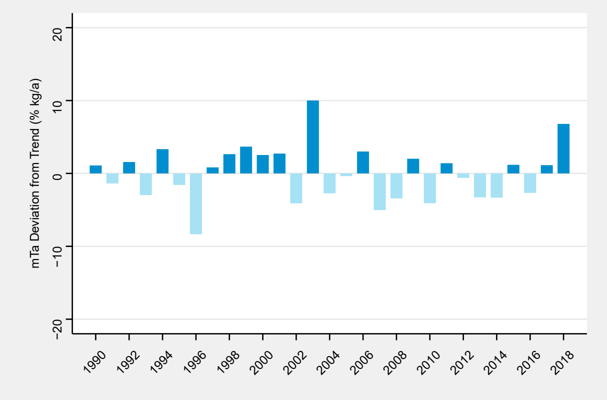


Figure 23: mTa Deviation from Trend

Note: Mean Temperature (mTa) over time: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate mTa over the full growing season. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.

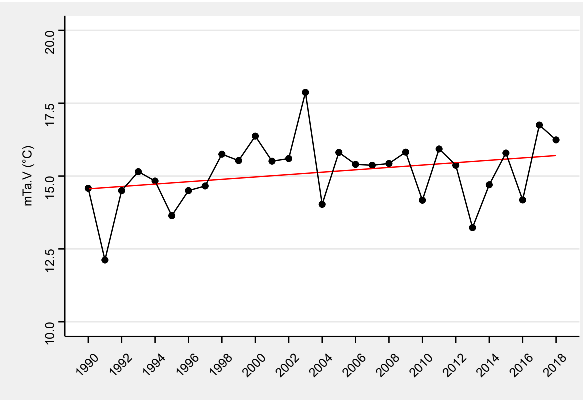


Figure 24: mTa.V over Time

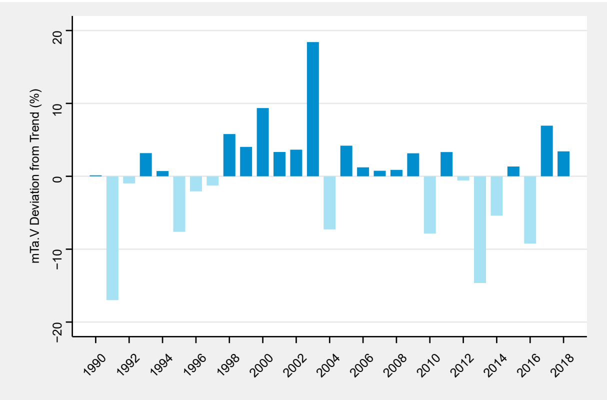


Figure 25: mTa.V Deviation from Trend

Note: Mean Temperature of the vegetative period (mTa.V) over time: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate mTa.V only for the vegetative phase. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.

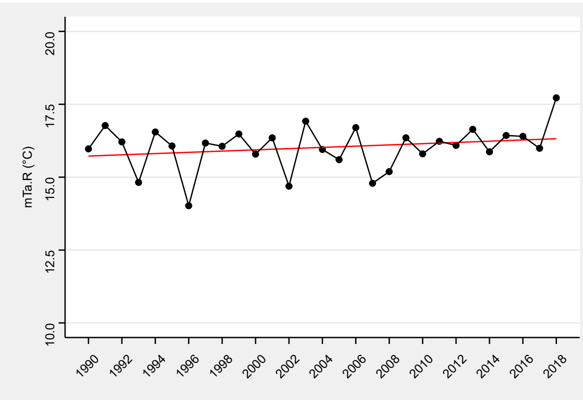


Figure 26: mTa.R over Time

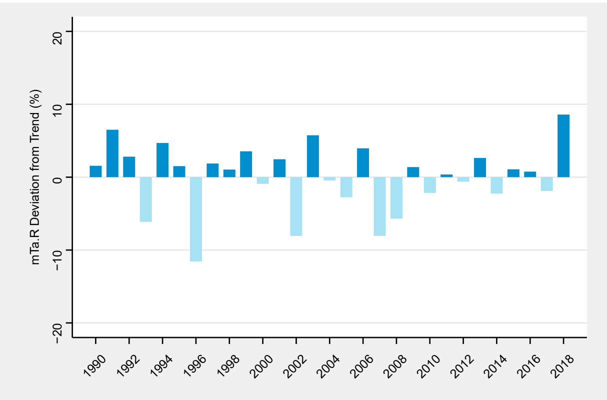
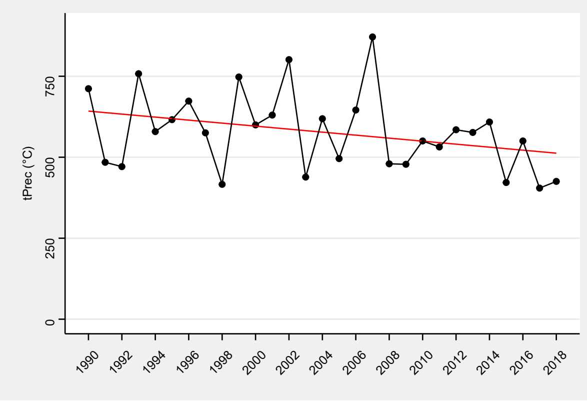


Figure 27: mTa.R Deviation from Trend

Note: Mean Temperature of the reproductive period (mTa.R) over time: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate mTa.R only for the reproductive phase. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.



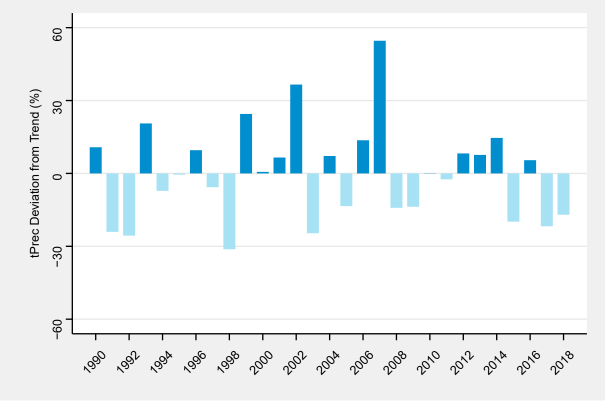
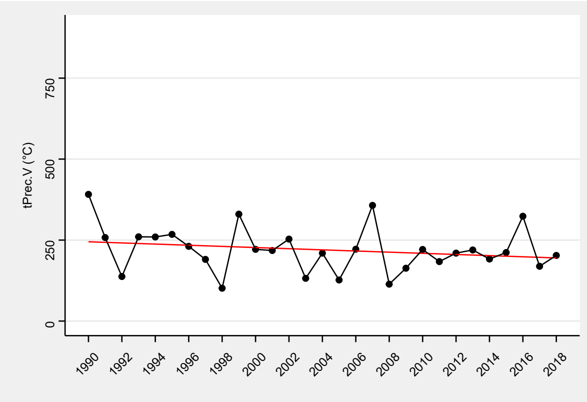


Figure 28: tPrec over Time

Figure 29: tPrec Deviation from Trend

Note: Total precipitation (tPrec) over time: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate tPrec for the full growing season. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.



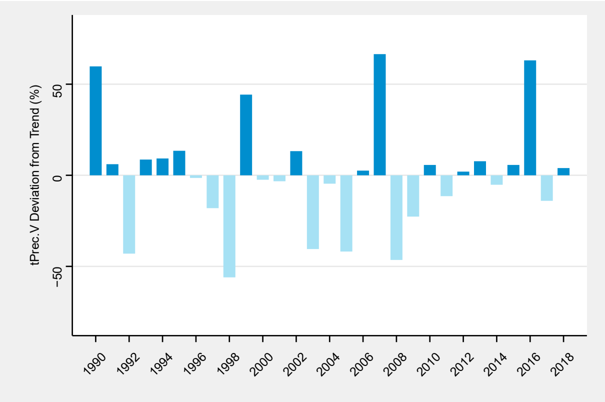
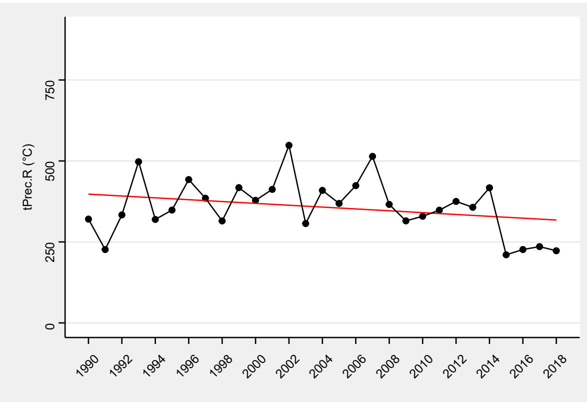


Figure 30: tPrec.V over Time

Figure 31: tPrec.V Deviation from Trend

Note: Total precipitation (tPrec.V) over time for the vegetative period: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate precipitation for the vegetative growing season. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.



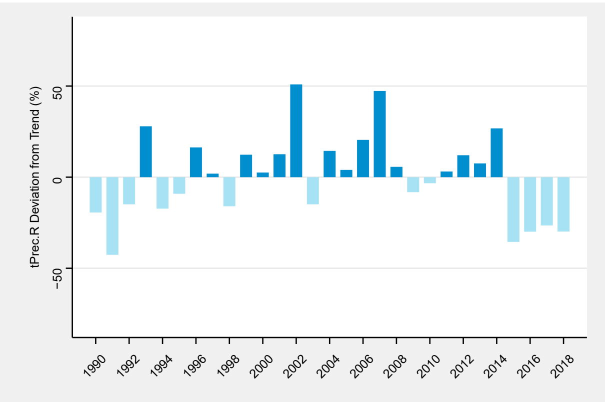
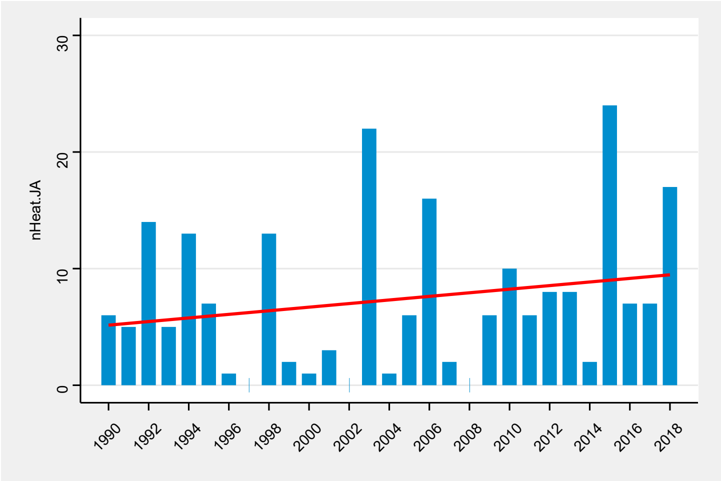


Figure 32: tPrec.R over Time

Figure 33: tPrec.R Deviation from Trend

Note: Total precipitation (tPrec.R) over time for the reproductive period: The red line indicates a linear time trend, which is also used to calculate deviation. Both graphs illustrate precipitation for the reproductive growing season. Source: own representation of MeteoSwiss data from their Berne/Zollikhofen station.



Source: own representation of MeteoSwiss data from Berne/Zollikhofen

Figure 34: Number of Heat Days in July-August over Time

Note: Number of heat days in July-August (nHeat.JA) for the canton of Berne. The red line depicts a linear trend over time.

5.2 Test of the Model Conditions

In this section, the test results of the MLR conditions (as described in Section 4.3.3) are presented.

First, it is to be checked whether the linearity of the correlation is given. For this purpose a scatterplot matrix is used (see Figure 47 in the Appendix).

The scatterplot matrix provides an introductory overview of the bivariate relationships between the dependent variable and each of the independent variables. It can be seen that at least for each of the independent variables a bivariate linear relationship is plausible.

MLR 1 can be checked by simply looking at the proposed models. Since all parameters β are linear, this precondition is fulfilled.

MLR 2 requires that the data used in the model are randomly generated. The challenges regarding the collection of FADN yield data at farm level (described in Section 3.2.3) therefore lead to a potential violation of MLR 2. However, it should be added that fulfilling all OLS assumptions requires an ideal data set, which often does not exist in reality.

To check MLR 3, a scatterplot of standardized estimates of the dependent variable and the standardized error is viewed. This plot is shown below for each of the proposed models (Figures 35 to 42). According to the figures, it is likely that the mean of the error values is approximately 0, since the negative and positive deviations from 0 on the y-axis approximately balance each other out on average.

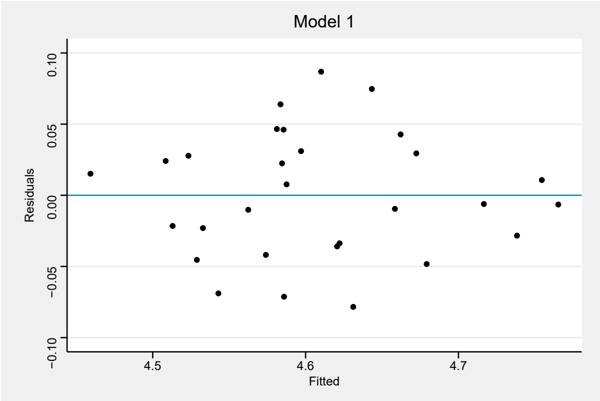


Figure 35: Fitted vs. Residuals Model 1

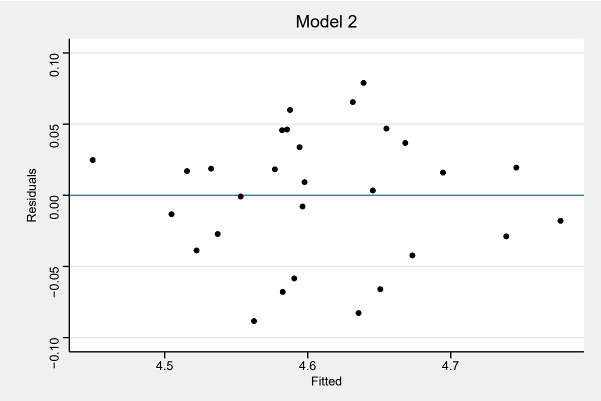


Figure 36: Fitted vs. Residuals Model 2

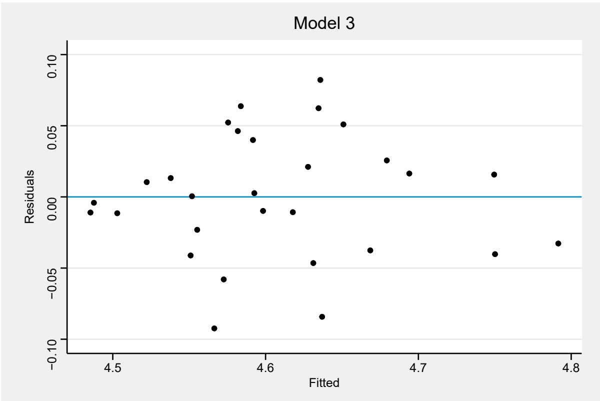


Figure 37: Fitted vs. Residuals Model 3

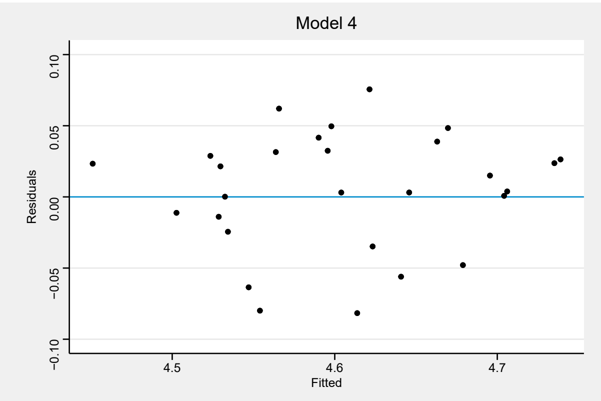


Figure 38: Fitted vs. Residuals Model 4

Source: own representation

MLR 4 requires that there is no perfect collinearity between the independent variables. This can be checked using the correlation matrix (Figure 19) or the scatterplot in the Appendix (Figure 47). Based on this, there is no reason to believe that MLR 4 may be violated.

At this point, however, the squared variables of temperature and precipitation should be mentioned. Because these depend directly on their non-squared counterparts, a strong correlation is naturally expected. To account for this, those interrelated pairs of variables are given special consideration in the interpretation, and ceteris paribus conclusions for a separate variable whose square is also included in the model equation are not allowed (Wooldridge, 2020).

As described in the Methods chapter, the VIF test can also be applied to test for multicollinearities. This is of limited use for a model with x and x^2 as independent variables, since a high VIF value is to be expected. However, if the squared variables are not included in the VIF analysis, the test yields results ($VIF < 2$ for all variables in all 4 models) that allow one to rule out problematic multicollinearities.

In order to determine whether homoscedasticity is present, the figures 35 to 42 are used again. No clear patterns can be recognized in the scatter of the points, therefore homoscedasticity may be assumed. In addition, the Goldfeld-Quandt test was applied: With $p > 0.05$ for all models, the null hypothesis cannot be rejected. Thus, there is no reason to believe that the assumption of homoscedasticity is not satisfied.

Figures 39 to 42 show the Q-Q plots for the four proposed models. The observed values of the standardized residuals and the theoretical quantiles are similar enough that it is reasonable to assume that the error values are approximately normally distributed.

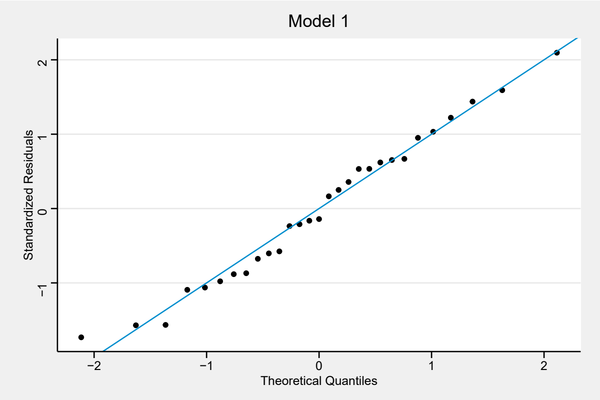


Figure 39: Q-Q Plot Model 1

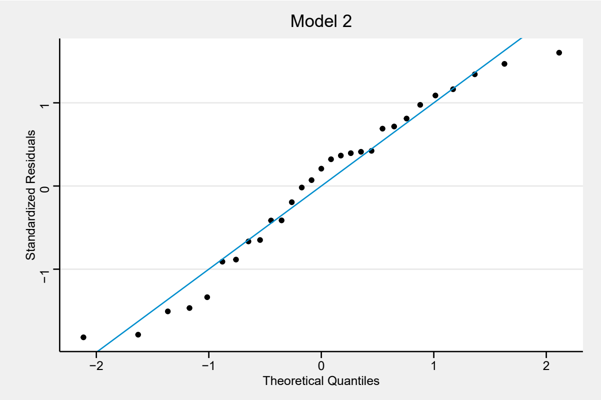


Figure 40: Q-Q Plot Model 2

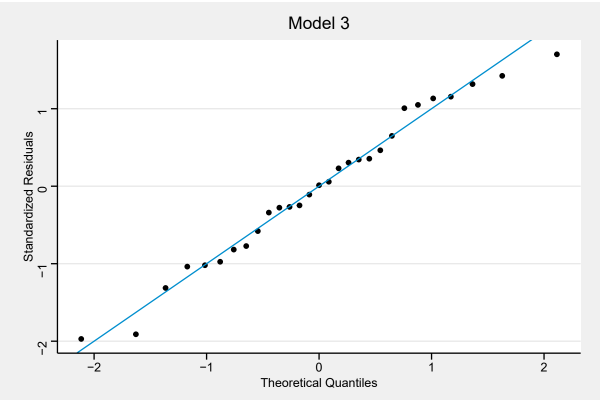


Figure 41: Q-Q Plot Model 3

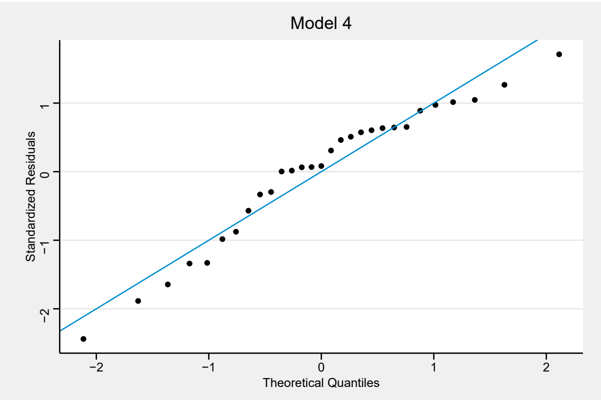


Figure 42: Q-Q Plot Model 4

Source: own representation

5.3 Model Fitting

The model estimation results are presented in Table 8. For Model 1 and 3, the model estimates of mTa and its square ($mTa.sqr$) imply an inverted U-shaped response of yield on mean temperature. The optimal mean temperature over the entire growing season is estimated to be 17°C. As shown by Model 2 and 4, yield also seems to responds to mean temperature and its square during the vegetation phase ($mTa.V$ and $mTa.sqr.V$) as inverted U-curve (Figure 43). The optimal mean temperature for yield in the vegetative phase is 14°C according to the estimates. A similiar response is visible for the reproductive stage, where the optimal mean temperature is estimated to be 18°C (Figure 43).

Model 4 finds a weak negative influence of extremely hot days ($nHeat$) in July and August on yield. According to its estimate, each additional heat day in this period reduces the yield of grain maize by

0.005%.

Accumulated precipitation of autumn, winter and spring (*tPrec.pre*) prior to the growing season has a negative impact on yield according to Models 1 and 4, but these estimates are not significant.

For precipitation over the entire growing season (*tPrec* and *tPrec.sqr*), estimates of Models 1, 2 and 4 indicate also an inverse U-shaped response of grain maize yield. Over the full growing season can be observed that accumulated precipitation above 25 mm/day seems to have a negative impact on yield. According to Model 3, yield also responds with an inverted U-curve to accumulated precipitation in the vegetative period (*tPrec.V*). As can be seen in Figure 44, precipitation has a beneficial effect on yield up to 13 mm/day. Higher values lead to a reduction of yield.

The estimate for accumulated precipitation in the reproductive stage (*tPrec.R*) in Model 3 lacks significance. However, the squared precipitation parameter for the same stage (*tPrec.sqr.R*) is significant. Both estimates combined indicate that during the reproductive period, daily precipitation sums above 20 mm have a downward effect on yield.

The linear time trend is slightly positive in all four models.

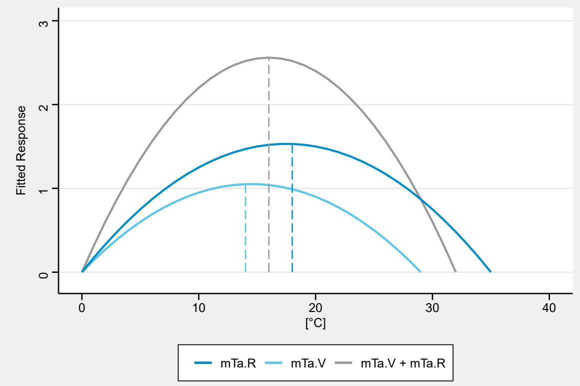


Figure 43: Estimated Temperature Curve

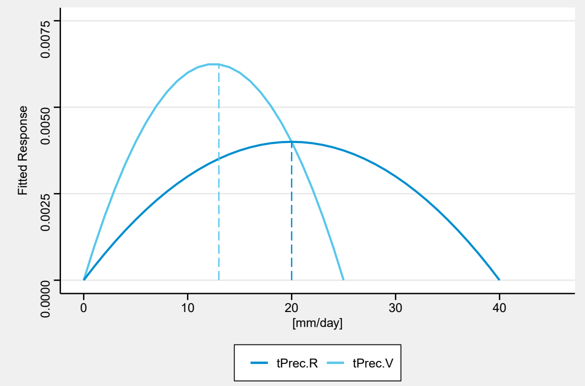


Figure 44: Estimated Precipitation Curve

Source: own representation

Note: Figure 44 shows the estimated functions of the combined regression coefficients mTa.V/mTa.sqr.V and mTa.R/mTa.sqr.R (blue lines) and also their sum (grey line) from Model 2. Figure 55 shows the estimated functions of the combined regression coefficients tPrec.V/tPrec.sqr.V and tPrec.R/tPrec.sqr.R (blue lines) from Model 3. The dashed vertical lines mark the maxima of the respective functions. The regression coefficients are taken from Model 2 and 3 in Table 8.

Table 8: Summary of Regression Models

	Dependent variable:			
	ln(yield)			
	(1)	(2)	(3)	(4)
time	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
mTa	0.333***		0.334***	
	(0.078)		(0.081)	
mTa.sqr	−0.010***		−0.010***	
	(0.002)		(0.002)	
mTa.V		0.144**		0.146**
		(0.052)		(0.053)
mTa.sqr.V		−0.005**		−0.005**
		(0.002)		(0.002)
mTa.R		0.175**		
		(0.068)		
mTa.sqr.R		−0.005**		
		(0.002)		
nHeat.JA				−0.005**
				(0.002)
tPrec	0.001**	0.001**		0.001**
	(0.0002)	(0.0002)		(0.0002)
tPrec.sqr	−0.00002***	−0.00002***		−0.00002***
	(0.00001)	(0.00001)		(0.00001)
tPrec.pre	−0.0001			−0.00002
	(0.0001)			(0.0001)
tPrec.V			0.001**	
			(0.0004)	
tPrec.sqr.V			−0.00004**	
			(0.00002)	
tPrec.R			0.0004	
			(0.0002)	
tPrec.sqr.R			−0.00001**	
			(0.00001)	
Constant	1.832***	2.027***	1.848***	3.351***
	(0.616)	(0.652)	(0.629)	(0.386)
Observations	29	29	29	29
R^2	0.751	0.733	0.753	0.718
Adjusted R^2	0.683	0.645	0.670	0.624
Residual Std. Error	0.050 (df = 22)	0.052 (df = 21)	0.051 (df = 21)	0.054 (df = 21)
F Statistic	11.045*** (df = 6; 22)	8.255*** (df = 7; 21)	9.128*** (df = 7; 21)	7.644*** (df = 7; 21)
Note:				*p<0.1; **p<0.05; ***p<0.01

5.4 Model Analysis

Model 1

From the regression table (Table 8) it can be concluded that the independent variables $time$, mTa, $mTa.sqr$, $tPrec$ and $tPrec.sqr$ of Model 1 have a significant effect on grain maize yield, $F(6, 22) = 11.045$, $p < 0.01$, $n = 29$. The variable $tPrec.pre$ is not significant. Model 1 explains 68.3% of the variability, which corresponds to a medium effect size according to Cohen (1992).

Model 2

All the independent variables of Model 2: $time$, $mTa.V$, $mTa.sqr.V$, $mTa.R$, $mTa.sqr.R$, $tPrec$ and $tPrec.sqr$, have a significant effect on grain maize yield, $F(7, 21) = 8.255$, $p < 0.01$, $n = 29$. 64.5% of the variability can be explained, which corresponds to a medium effect size according to Cohen (1992).

Model 3

For Model 3, the independent variables $time$, mTa, $mTa.sqr$, $tPrec.V$, $tPrec.sqr.V$, and $tPrec.sqr.R$ are significant with respect to maize yield, $F(7, 21) = 9.128$, $p < 0.01$, $n = 29$. The variable $tPrec.R$ is not significant. Model 3 can explain 67% of the variance, corresponding to a medium effect size according to Cohen (1992).

Model 4

It can be concluded that the independent variables $time$, $mTa.V$, $mTa.sqr.V$, $nHeat.JA$, $tPrec$ and $tPrec.sqr$ of Model 4 have a significant effect on grain maize yield, $F(7, 21) = 7.644$, $p < 0.01$, $n = 29$. The variable $tPrec.pre$ is again not significant. The model explains 62.4% of the variability, which corresponds to a medium effect size according to Cohen (1992).

Model Comparison

At this point, an attempt will be made to find the best of the four proposed models, although this is not directly related to the research questions posed in this paper. The best model is to be determined on the basis of the adjusted R-squared and AIC criteria.

It is important to mention that AIC should not be understood as an absolute measure of quality. Even the best model according to the AIC score can have a very poor fit to the data – it is then simply a better fit than in the alternative models (Skarke & Kluge, 2019).

Table 9 shows the AIC and R^2adj values of the proposed models. Model 1 has the lowest AIC score and at the same time the largest R^2adj value, and thus can be considered the best of the four models. Also in favor of Model 1 is that it requires one less independent variable and thus is less complex. The second lowest AIC value is achieved by Model 3, which also has the second highest R^2adj. Model 2 performs slightly worse than Model 3 in terms of AIC and R^2adj. The lowest fitting model according to the criteria applied here is Model 4.

Table 9: Model Comparison Summary

	Model 1	Model 2	Model 3	Model 4
Num. of IV	7	8	8	8
AIC	-168.2682	-164.3209	-166.4864	-149.7381
$R^2adj.$	0.683	0.645	0.670	0.624

6 Discussion

Exploratory Analysis

In Figures 20 and 21, the years 2003, 2006, 2010 and 2015 are defined as years with unusually low grain maize yields for the canton of Berne. The threshold for this classification is defined by a negative deviation of more than 10% from the linear time trend for the 1990-2018 period. In the following, potential causes of these below average yields are searched for within Figures 22 to 34.

For the year 2003 the explorative plots can provide a few indications on why the yield was low. The year was characterized by extremely high mean temperatures, especially during the sensitive vegetative growth period. Also, the year was overly dry throughout the growing season and recorded the second largest number of heat days in July and August for the considered period. In the literature, the year 2003 is also recognized as an extremely hot and dry year (Büntgen, SCNA, BLW 2019). In 2006, yields were nearly as low as in 2003 but mean temperature values were in a normal range. However, there was a high number of heat days in July and August 2006, which may have had a negative impact on yield. According to MeteoSwiss (2020), the year was also subject to excessive precipitation within a few days, something that the mean precipitation indicator probably does not capture. Another year with a particularly low grain maize yield was 2010. But with the climate indicators mapped in the explorative analysis, little explanation can be found by eye. Apart from an unusually cold vegetative period, the climate indicators are inconspicuous. However, it is possible that the low average temperatures in spring have negatively affected the yield. 2015 is the year with the smallest yield in the considered time series. Average temperatures are unobtrusive, and precipitation in the vegetative period is also not exceptional. The year is characterized by a very large number of heat days in July and August. Literature also describes it to be an extremely hot year (SCNAT). It could be assumed that the heat partly overlapped with an exceptional dryness in the reproductive phase. In that way, 2015 is a good example to demonstrate the difficulties of capturing extreme climate events by using indicators of the mean, as also noted by Zhang et al. (2011).

To summarize, it is very difficult to reliably find correlations between climate and yield only by performing an exploratory analysis. For this purpose, a multiple regression is much better suited, the results of which will be discussed in the following.

Temperature and Yield

Regression Model 1 was designed to capture the influences of temperature and precipitation over the entire growing season in the simplest possible form. According to the model analysis results presented the previous chapter, it is the model with the best performance. From Model 1 it can be concluded that the optimal average temperature over the entire growing season would be 17°C. During the period from 1990 to 2018, this value was only exceeded in the heat years 2003 and 2018, with the observed average for that period being 15.7°C. Therefore, it can be stated that a moderate increase of about 1.5°C in average temperature over the entire growing season would have a positive impact on yield in the canton of Berne.

However, since the effects of temperature on yield depend on the growth stage of the crop, it is questionable whether mean temperature over the entire growing season provides a sufficient foundation for the above statement. For this reason, mean temperatures for the vegetative and reproductive periods were included separately in Model 2.

According to Model 2, the estimated temperature optimum for the vegetative growth stage is 14°C. This value is already clearly exceeded with the observed temperature mean for that period being 15.1°C. This indicates that it is probably not sufficient to study the effects of temperature on yield only for the entire growing season because early growth stages seem to be more sensitive to mean temperature rise. This finding is consistent with Holzkämper et al. (2013), who state that grain maize is particularly sensitive to suboptimal average temperatures in between planting and emergence (both in vegetative stage).

For the reproductive period, the estimated temperature optimum is 18°C according to Model 2. The observed temperature mean for the same time frame is 16°C. This leads to the suggestion that in the reproductive period the maize plants would still benefit from an average temperature increase of 2°C according to the model estimates.

By looking at the summed effects of mean temperature for the vegetative and reproductive periods on yield, as estimated by Model 2, a statement about the effect of mean temperature over the total growing season can be made (Figure 43). According to this approach, the optimal mean temperature for the total growing season is estimated to be 16°C. So, the effect of temperature on yield that Model 1 assessed for the whole growing season and the sum of the effects for the vegetative and reproductive periods, as estimated by Model 2, are very comparable. This bears evidence to a certain robustness of the estimates of these two models.

Model 4 was designed to capture the influences of heat days in the hottest time of the growing season. According to its estimates, the number of heat days in July and August have a negative impact on yield: for each additional heat day, the yield is assumed to decrease by 0.005%. Although the estimated reduction is fairly small, it shows that the tolerance for heat days in July and August has already been exceeded. With trends of the frequency and magnitude of heat days projected to increase, it is therefore likely that yield loss will occur in the canton of Berne more often in the medium and long term. Yield reductions during the hottest months of the year can furthermore be amplified by water shortages and drought, an issue discussed further below.

To summarize the effects of temperature on yield, it can be concluded that a moderate, uniform increase of about 1.5°C over the entire growing season is positive for yield. However, increasing mean temperatures specifically during the vegetative period or additional heat days from July to August would weaken the beneficial effect or even turn it into a negative one. In the reproductive phase from August onwards, there is still potential for yield gains through moderate mean temperature increases. This assumptions are consistent with findings by Holzkämper et al. (2011, 2012).

Precipitation and Yield

Before interpreting the regression results for precipitation, a brief side note on precipitation variables is appropriate. As mentioned, daily precipitation was summed over the relevant season length to be included in the regression. To account for heavy rainfall, however, the daily precipitation sums were squared before they were also summed over the season length. This approach was chosen to be able to measure at what level daily precipitation becomes damaging to the culture, because uncovering the effects of extreme precipitation in a short time is an important aspect of this work. If the daily precipitation totals are first added up to the seasonal total and only then are being squared, day-to-day resolution of precipitation effects are being lost and statements can only be made concerning the precipitation pattern of the entire season. The downside of the chosen approach is, that it is not possible to draw conclusions about the optimum precipitation sums for the entire season, which would also be very interesting.

Besides temperature, Model 1 should also control for the influence of precipitation on grain maize yield. According to its estimates, it can be argued that precipitation has a positive effect on the yield over the entire growing season, but heavy precipitation has a negative impact.

Model 1 also controls for precipitation during fall, winter, and spring before the growing season. According to this variable, it is likely that too much precipitation tends to occur during this time. However, the variable itself did not turn out to be significant, so this statement is made very cautiously. Nevertheless, the variable improved the explanatory power of the entire model, and therefore it was retained in the model. Since precipitation intensity in Switzerland is expected to increase especially in the winter months, one could expect the variable for pre-season precipitation to increase in explanatory power in the future (Brönnimann et al., 2014; NCCS, 2018).

As for temperature, it can also be assumed for precipitation that the mean over the entire growing season does not have a sufficiently high temporal resolution to make robust conclusions of its effects on yield. The timing of precipitation and especially of extreme rainfall events, plays a major role in its effect on yield. This assumption is reinforced by Model 3. There, the influence of the precipitation during the vegetative and reproductive period is examined separately. In the vegetative period, the peak from which the positive effect of precipitation starts to decrease is already at 13 mm per day and precipitation becomes harmful above 25 mm per day (Figure 44). A possible reason for these low values could be that the early crops are not yet very resistant in spring. For the reproductive period, the peak is at 20 mm and precipitation becomes harmful at 40 mm per day. These thresholds being larger than for the vegetative period can be explained by the fact that the crops are already well matured in the reproductive period and are consequently less susceptible to extreme weather events.

To find out if the damaging precipitation amounts estimated by Model 3 possibly influence yield, more information on precipitation in Berne needs to be provided: The mean intensity of wet days observed for the period 1990 to 2018 is 9.7 mm/day. For the same period, 7.3% of wet days bring a sum greater than 25 mm. The wettest days of the growing season averaged 45.5 mm of rain, although this value is subject to considerable variability. Based on these values, one can conclude that it is rather unlikely for heavy rainfall to be a limiting factor for yield. However, if one assumes that a major rain event in spring is sufficient to severely damage early crops, it cannot be ruled out. It might be helpful to increase the temporal resolution of heavy rainfall events in subsequent studies to improve understanding of this issue.

There are two additional points to consider from literature in this regard: It is expected that there will be more extreme precipitation events in the future, which will increase the risk of damage caused to yield (Umbricht et al., 2013). At the same time, it is assumed that the amount of precipitation in late spring and summer will decrease, which may lead to an increased risk of drought (Holzkämper 2019).

More Variables and Further Thought

It has been shown that summer precipitation can mitigate the adverse effects of high temperatures (Belyaeva & Bokusheva, 2018; Schlenker & Roberts, 2009). No interaction term to capture this effect was included for this work, however. One reason for this is the rather small number of observations, which also required keeping the number of independent variables relatively small. For a future analysis, it would be of interest to investigate this effect. This could be done as suggested by Schlenker & Roberts (2009) by running a separate regression, including only observations with high rainfall in the summer months, and then comparing the estimated temperature effects with those of the main group.

Changes in pest pressure and increased incidence of plant diseases due to climate change were not considered in this thesis. Since there is evidence in the literature that increased average temperature can promote or inhibit pests, it would be inappropriate to draw quick conclusions. Also, rainfall can have an impact on pests and especially on fungal disease emergence (BLW, 2019). Therefore, for a more comprehensive analysis of yield changes due to climate change in the canton of Berne, these factors should be considered in more detail.

As per Roberts et al. (2013), VPD significantly improved yield estimates during the hottest months. For this work, VPD was also tested as a regressor for the months of July and August, but the variable failed to improve any of the tested models. The number of heat days, that correlates strongly with VPD, has outperformed, and therefore replaced VPD. It was also tested whether the number of consecutive dry days would improve the model estimates as an indicator of drought. Again, this indicator did not produce significant improvements for any model. In a similar way, GDD has also produced less effective model improvements than mean temperature. Overall, it can be said that the simple indicators showed better performance than the more complex ones. This is in line with a finding by Ben-Ari et al. (2016) that simple indicators often outperform more complex counterparts.

The results discussed here confirm that the canton of Bern is still well suited for the cultivation of grain maize today and that a moderate, uniform increase in mean temperature would still have a positive effect on yield. However, depending on the timing, a rise in mean temperature or an increase in heavy precipitation events could turn out to be problematic. The vegetative period and the months of July and August have proven to be particularly sensitive. But to make accurate predictions for the future, one would need to compare the coefficients estimated by the models with actual climate projection scenarios for the future – a task that would be very interesting for future studies.

Limitations

Although climatic processes often occur on a large spatial scale, the low spatial resolution is one of the major limitations of this work. Here, the measurement series of only one weather station provides the basis for inferring the grain maize yield of the entire canton of Berne. This simplification results in the loss of information on microclimatic processes that do not occur in the immediate vicinity of the weather station. As temperature is often homogeneous over larger areas, it is less affected by this limitation. Extreme precipitation events, on the other hand, often occur very locally and spatially heterogeneous, so this limitation is particularly important for the latter (Donat et al., 2013).

Another limitation stems from the data basis. The time series from 1990 to 2018 is rather short for climatic analyses, which makes it difficult or impossible to reliably identify climatic trends. During the study period, there were also agricultural policy reforms whose enforcement took place over several years. With little observations before and after the policy implementations, it is therefore also difficult to identify the impact of those policy changes on yield. Furthermore, with 29 observations the number of independent variables is somewhat limited. For a bachelor thesis, however, this point has a positive side effect. Because it is not possible to include every variable in the regression, it is necessary to get a better understanding of the strengths and weaknesses of the individual variables.

Another challenge the data poses is the number of reference farms. Especially in the years before and after the FADN reform in 2015, their number is rather small. This limitation was partially mitigated by including the Agristat data. Also, it must be recognized that in a study with real and complex data, there are no perfect data sets.

The last limitation to be mentioned is that the results of this work were not subjected to verification. One reason for this is the lack of data already described. This deficiency would have been further reinforced by the creation of a data set for verification. However, there was once an intention to compare the results from the canton of Berne with data from the canton of Vaud, which would have been available. But the number of reference farms in Vaud was considerably smaller than in the canton of Berne. In the end, it was also a consideration of additional effort that would likely have exceeded the scope of a bachelor's thesis.

7 Conclusion

In the present work, an assessment of climatic suitability for the cultivation of grain maize in the canton of Berne is made. This succeeds in explaining up to 68.3% of the variability in yield. The unexplained part is probably due to factors such as pest and disease activity, individual fertilizer use, soil properties or agronomic practices. The spatial uncertainty, which means that there is only one measuring station for the whole canton, is also likely to increase the error term. However, it was possible to estimate the influence of temperature and precipitation on the yield to a realistic extent and to gain knowledge about the influence of extreme weather events on grain maize yield. The results of this thesis confirm that the canton of Bern is still well suited for the cultivation of grain maize today. How suitability will change in the future can only be approximated roughly: In order to make confident predictions for the future, the method used would have to be extended.

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Directories

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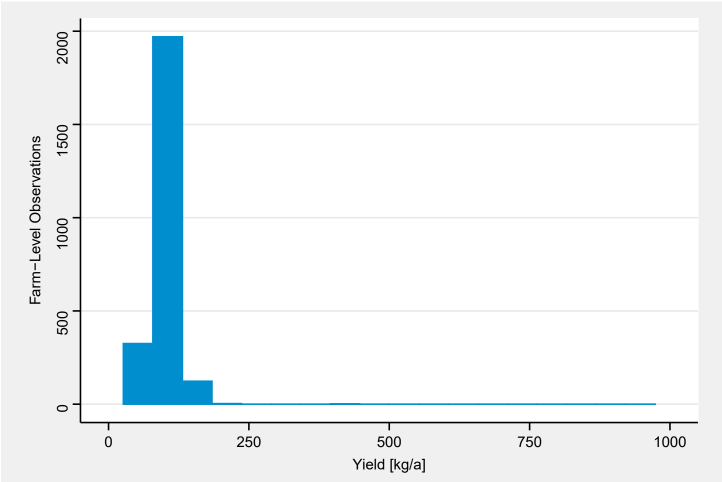
Appendix

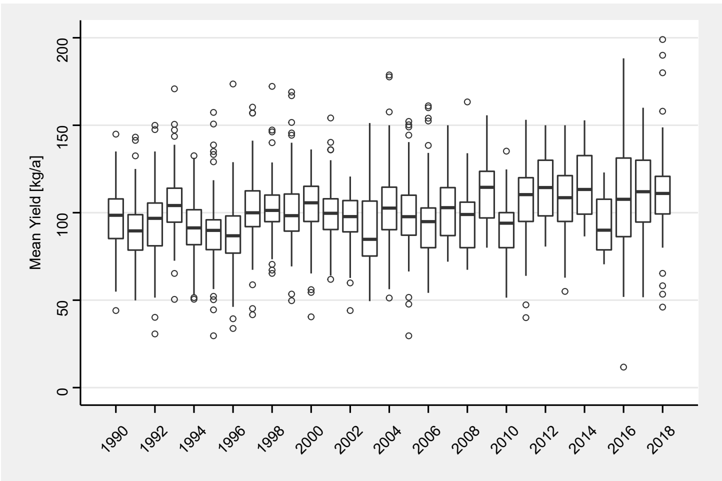
A Additional Figures



Source: own representation

Figure 45: Distribution of the Farm Level Yield Observations Before Outlier Exclusion

Note: Grain maize yield observations in kg/a. Number of observations for FADN and Agristat datasets and for the canton ofBerne.



Source: own representation

Figure 46: Per-year Distribution of the Farm Level Yield Observations Before Outlier Exclusios

Note: Grain maize yield observations for FADN and Agristat data in kg/a, for the canton of Berne.

Source: own representation

Figure 47: Scatterplot of Regression Variables

B Declaration of Originality

Zürcher Hochschule
für Angewandte Wissenschaften

N-AA-Abfassung studentischer Arbeiten

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Stabsbereich Bildung

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Winterthur, 13.01.2021
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Fortsetzung

Titel der Arbeit: How Climate Change Influences Grain Maize Yield: A Case Study for the Canton of Berne

Name der/des Studierenden: Linus Meier

Name der/des 1. Korrigierenden: Raushan Bokusheva

Welche Schlagwörter schlagen Sie für die öffentliche online Suche vor?

Climate Change	Extreme Weather Events	Switzerland
Grain Maize	Agroclimatic Indicators	Berne
Linear Regression	Crop Yield	Agriculture

Das Original dieses Formulars ist bei allen abgegebenen Bachelorarbeiten im Anhang mit Original-Unterschriften und -Datum (keine Kopie) einzufügen.

C Poster

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Life Sciences and
Facility Management
Institute of
Natural Resource Sciences

How Climate Change Influences Grain Maize Yield: A Case Study for the Canton of Berne

Linus Meier, Bachelors Thesis
2020/21

Institute of Natural Resource Sciences
Agricultural and Resource Economics Group

1 Introduction

Climate change is altering patterns of mean climate and increases the occurrence of extreme weather events. Since agricultural productivity is strongly dependent on climate, farmers need reliable crop yield forecasts to help them adapting to climate change. This Bachelor's Thesis aims at identifying the effects of relevant agroclimatic indicators on grain maize yield in the canton of Bern (Switzerland) for the period 1990 to 2018 by means of regression analysis.

2 Data

Yield for the canton of Berne is provided by *Agroscope* and *Agristat*. In total, 2,326 observations of farm-level yield from 1990 to 2018 are analyzed. Daily meteorological data is available from *MeteoSwiss* for the station at Berne/Zollikhofen.

3 Method

Climate indicators used to measure the effects of climate are:

- Mean temperature
- Mean temperature squared
- Total precipitation
- Total precipitation squared
- Number of heat days

To consider the changing influence of climate on maize yield in different growth stages, agroclimatic indicators are calculated specifically for the vegetative and reproductive period in addition to the total growing season. The following four regression models are proposed, using an Ordinary Least Squares framework to estimate the model coefficients.

Model 1

$$\ln(yield)_t = \beta_0 + \beta_1 time_t + \beta_2 mTa_t + \beta_3 mTa.sqr_t + \beta_4 tPrec_t + \beta_5 tPrec.sqr_t + \beta_6 tPrec.pre_t + u_t$$

Model 2

$$\ln(yield)_t = \beta_0 + \beta_1 time_t + \beta_2 mTa.V_t + \beta_3 mTa.sqr.V_t + \beta_4 mTa.R_t + \beta_5 mTa.sqr.R_t + \beta_6 tPrec_t + \beta_7 tPrec.sqr_t + u_t$$

Model 3

$$\ln(yield)_t = \beta_0 + \beta_1 time_t + \beta_2 mTa_t + \beta_3 mTa.sqr_t + \beta_4 tPrec.V_t + \beta_5 tPrec.sqr.V_t + \beta_6 tPrec.R_t + \beta_7 tPrec.sqr.R_t + u_t$$

Model 4

$$\ln(yield)_t = \beta_0 + \beta_1 time_t + \beta_2 mTa.V_t + \beta_3 mTa.sqr.V_t + \beta_4 nHeat.JA_t + \beta_5 tPrec_t + \beta_6 tPrec.sqr_t + \beta_7 tPrec.pre_t + u_t$$

Where *time* is a linear time trend, *mTa* is mean temperature, *mTa.sqr* is mean temperature squared, *tPrec* is total precipitation, *tPrec.sqr* is total precipitation squared, *.V* abbreviates vegetative period only, *.R* abbreviates reproductive period only, *tPrec.pre* is total precipitation preseason, *nHeat.JA* is number of heat days in July-August

4 Results

	Dependent variable:			
	ln_YIELD			
	(1)	(2)	(3)	(4)
time	0.007^{***} (0.001)	0.007^{***} (0.001)	0.007^{***} (0.001)	0.006^{***} (0.002)
mTa	0.333^{***} (0.078)		0.334^{***} (0.081)	
mTa.sqr	-0.010^{***} (0.002)		-0.010^{***} (0.002)	
mTa.V		0.144^{**} (0.052)		0.012 (0.013)
mTa.sqr.V		-0.005^{**} (0.002)		
mTa.R		0.175^{**} (0.068)		
mTa.sqr.R		-0.005^{**} (0.002)		
nHeat.JA				-0.006^{**} (0.003)
tPrec	0.001^{**} (0.0002)	0.001^{**} (0.0002)		-0.00004 (0.0001)
tPrec.sqr	-0.00002^{***} (0.00001)	-0.00002^{***} (0.00001)		
tPrec.pre	-0.0001 (0.0001)			0.0001 (0.0001)
tPrec.V			0.001^{**} (0.0004)	
tPrec.sqr.V			-0.00004^{**} (0.00002)	
tPrec.R			0.0004 (0.0002)	
tPrec.sqr.R			-0.00001^{**} (0.00001)	
Constant	1.832^{***} (0.616)	2.027^{***} (0.652)	1.848^{***} (0.629)	4.367^{***} (0.225)
Observations	29	29	29	29
R^2	0.751	0.733	0.753	0.494
Adjusted R^2	0.683	0.645	0.670	0.384
Residual Std. Error	0.050 (df = 22)	0.052 (df = 21)	0.051 (df = 21)	0.069 (df = 23)
F Statistic	11.045^{***} (df = 6; 22)	8.255^{***} (df = 7; 21)	9.128^{***} (df = 7; 21)	4.493^{***} (df = 5; 23)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 1 Model Summaries Source: own representation

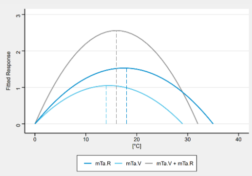

Figure 2 Estimated Temperature Curves

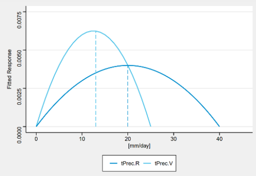

Figure 3 Estimated Precipitation Curves

Figure Note Figure 2 visualizes the estimated response of grain maize yields on average temperature for the vegetative (*mTa.V*) and reproductive (*mTa.R*) stages (blue lines). The gray line represents the estimated response of maize yield to mean temp. for the entire growing season. Figure 55 shows the estimated response of grain maize yields on daily precipitation for the vegetative (*tPrec.V*) and reproductive (*tPrec.R*) period. The dashed vertical lines mark the maxima of the respective functions. Source: own representations.

5 Discussion

It is found that a uniform increase of mean temperature of about 1.5°C during the growing season is positive for yield. But increasing mean temperature only during the vegetative period or additional heat days from July to August have a negative effect on yield. In the reproductive phase from August onwards, there is still potential for yield gains through moderate mean temperature increases. For precipitation over the entire growing season, the model estimates indicate a positive effect of moderate precipitation and a negative effect of heavy precipitation on yield. The adverse effect of heavy precipitation is more pronounced for the vegetative period than for the reproductive period. It is confirmed that the canton of Bern is suitable for the cultivation of grain maize momentarily and in the medium term. However, more research will be needed to better assess the risks of climate change in the future.