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Michael Peichl | Climate Change Impacts on Crop Yield – Development and evaluation of ...

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Climate Change Impacts on Crop Yield – Development and evaluation of fundamental models as a basis for economic assessment

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Helmholtz Centre for Environmental Research – UFZ
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Climate Change Impacts on Crop Yield

Development and evaluation of fundamental models as a basis for economic assessment

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Für meine Familie.

Abstract

Physical climate changes due to greenhouse gas emissions are well understood. However, quantifying the economic consequences remains a major challenge. Nevertheless, such quantification is crucial for the development of effective climate protection and adaptation strategies. Especially at local and regional levels, there is insufficient knowledge about the multiple impacts of climate change on economic sectors and regions.

This is particularly true for the agricultural sector, which is considered to be vulnerable to the effects of global climate change. Since climate change not only changes temperature but also precipitation patterns in space and time, a higher variability of individual weather and the resulting extreme events (e.g. storms, flooding or droughts) is expected. Accurate models that depict the weather and crop yields are important not only for projecting the effects of agriculture, but also for projecting the impact of climate change on the associated economic and ecological consequences and thus for mitigation and adaptation policies.

There are various methodological approaches to modelling climate impacts on agriculture. On the one hand, there are holistic approaches such as integrated assessment models. On the other hand, there are process-based or mechanistic models that capture the relevant biophysical relationships. Finally, there are empirical or statistical models that explain the relationship between meteorological variables and agricultural yields. These modelling approaches are rooted in very different disciplines and involve different emphases and assumptions, often resulting in a lack of consistency.

Based on this scientific discussion, the thesis aims at the design of statistical approaches in order to allow a convergence of the results of the different methods. The aim is to identify missing aspects in current statistical approaches, such as the absence of important variables (e.g. soil moisture) and addressing the timing of the occurrence of extreme events that affect plant growth. In addition, new statistical approaches from the field of machine learning will be introduced to complement the existing methods, which are mainly based on econometrics. Furthermore, the approach presented here enables a Germany-wide impact assessment for the main crops. Finally, the development of such statistical damage functions promotes the management of the effects of extreme events on the agricultural sector on several time scales and can be used for climate change impact assessment. The work is cumulative and consists of three scientific articles.

List of Publications

Paper 1: The effect of soil moisture anomalies on maize yield in Germany

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Publication Outlet	Natural Hazards and Earth System Science
Publication Type	Journal Paper
Publication Year	2018
5-year impact factor	3.321
Publication status	Published
DOI	10.5194/nhess-18-889-2018
Abstract	Crop models routinely use meteorological variations to estimate crop yield. Soil moisture, however, is the primary source of water for plant growth. The aim of this study is to investigate the intra-seasonal predictability of soil moisture to estimate silage maize yield in Germany. It is also evaluated how approaches considering soil moisture perform compared to those using only meteorological variables. Silage maize is one of the most widely cultivated crops in Germany because it is used as a main biomass supplier for energy production in the course of the German Energy Transition. Reduced form fixed effect panel models are employed to investigate the relationships in this study. These models are estimated for each month of the growing season to gain insights into the time varying effects of soil moisture and meteorological variables. Temperature, precipitation, and potential evapotranspiration are used as meteorological variables. Soil moisture is transformed into anomalies which provide a measure for the inter-annual variation within each month. The main result of this study is that soil moisture anomalies have predictive skills which vary in magnitude and direction depending on the month. For instance, dry soil moisture anomalies in August and September reduce silage maize yield more than 10 % other factors being equal. On the contrary, dry anomalies in May increase crop yield up to 7 % because absolute soil water content is higher in May compared to August due to its seasonality. With respect to the meteorological terms, models using both temperature and precipitation have higher predictabilities than models using only one meteorological variable. Also, models employing only temperature exhibit elevated effects.

Paper 2: Climate impacts on long-term silage maize yield in Germany	
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Publication Outlet	Scientific Reports
Publication Type	Journal Paper
Publication Year	2019
5-year impact factor	4.525
Publication status	Published
DOI	10.1038/s41598-019-44126-1
Abstract	In this study, we examine the impacts of climate change on variations in the long-term mean silage maize yield using a statistical crop model at the county level in Germany. The explanatory variables, which consider sub-seasonal effects, are soil moisture anomalies for June and August and precipitation and temperature for July. Climate projections from five regional climate models (RCMs) are used to simulate soil moisture with the mesoscale Hydrologic Model and force the statistical crop model. The results indicate an average yield reduction of −120 to −1050 (kilogram/hectare)/annum ($kg\,ha^{-1}a^{-1}$) for the period 2021–2050 compared to the baseline period 1971–2000. The multi-model yield decreases between −370 and −3910 $kg\,ha^{-1}a^{-1}$ until the end of the century (2070–2099). The maximum projected mean loss is less than −10% of average yields in Germany in 1999–2015. The crop model shows a strong ability to project long-term mean yield changes but is not designed to capture inter-annual variations. Based on the RCMs outcomes, July temperature and August soil moisture anomalies are the main factors for the projected yield anomalies. Furthermore, effects such as adaptation and CO_2 fertilization are not included in our model. Accounting for these might lead to a slight overall increase in the future silage maize yield of Germany.

Paper 3: Machine learning methods for predicting winter wheat yield in Germany	
Authors & Affiliations	Michael Peichl (1), Stephan Thober (1), Luis Samaniego (1), Bernd Hansjürgens (2) & Andreas Marx (1) (1) UFZ-Helmholtz Centre for Environmental Research, Department Computational Hydrosystems, Permoserstrasse 15, D-04318, Leipzig, Germany. (2) UFZ-Helmholtz Centre for Environmental Research, Department Economics, Permoserstrasse 15, D-04318, Leipzig, Germany.
Publication Outlet	Environmental Research Letters
Publication Type	Journal Paper
Publication Year	submitted 2020
Impact Factor	6.192 (2018)
Publication status	Submitted (ID: ERL-108788)
Abstract	Agricultural production is highly dependent on the weather. This critical relationship is modelled in a constantly growing empirical literature. Instead of the commonly used parametric linear statistical models, this study employs machine learning, i.e. random forests, to achieve higher predictive capacity for the inter-annual variation of winter wheat yield anomalies on district level in Germany. Furthermore, the interpretability of these black box models is introduced by using accumulated local effect (ALE) plots to visualize the sensitivity of crop yields to specific features. To consider sub-seasonality, monthly aggregates of daily hydro-meteorological variables, which account for extreme environmental conditions, as well as monthly soil moisture are used as predictors. Spatial clustering of the counties under consideration is applied to account for the various spatially dependent yield potentials in Germany. Different damage potentials are shown for the two clusters considered, such as a higher susceptibility to drought damage from April to July in eastern Germany compared to the rest of the country. Without clustering, this drought signal is alleviated. In general, soil moisture explains more yield variations than the meteorological variables. The top 25 cm soil moisture is a better yield predictor than the entire soil column or a combination of both. Compared to other studies, the importance of heat (number of days with maximum temperature above 30°C) is underrepresented. The highest average test R-squared is 0.70, not accounting for time-invariant effects on crop yield. The approach has proven to be suitable to identify extreme yield anomalies for years with extraordinary high losses (2003, 2018) and gains (2014) and to reproduce the spatial distribution of these anomalies. Furthermore, the sensitivity of crop yield variation to soil moisture and extreme meteorological conditions revealed by ALE plots contributes to the promotion of targeted decision support systems.

Table 1: Share of the authors' workload for each paper.

	Peichl, Michael	Thober, Stephan	Meyer, Volker	Samaniego, Luis	Marx, Andreas	Hansjürgens, Bernd
The effect of soil moisture anomalies on maize yield in Germany	70%	20%	5%	5%	--	--
Climate impacts on long-term silage maize yield in Germany	75%	10%	--	3%	10%	2%
Machine learning methods for predicting winter wheat yield in Germany	80%	5%	--	3%	10%	2%

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Chapter 1

General introduction

1.1 Topic focus and research problem

Physical climate changes due to greenhouse gas emissions are well understood (Stocker et al., 2013). However, quantifying the economic consequences of changes in temperature,precipitation, sea level and other climate variables remains a major challenge. Nevertheless, such quantification is crucial for the development of effective climate protection and adaptation strategies. Especially at local and regional levels, there is insufficient knowledge about the multiple impacts of climate change on economic sectors and regions. In particular, there is a lack of socio-economic models that take up information from hydrology and other natural sciences and provide information on the effects of global climate change for specific sectors and/or regions or the (regional) economy (Burke et al., 2016). This is particularly true for the agricultural sector, which is considered to be vulnerable to the effects of global climate change, as changes in meteorology and trace gas concentrations have a direct impact on crop yields and agricultural ecosystems (Porter et al., 2014; Gömann et al., 2017). Since climate change not only changes temperature but also precipitation patterns in space and time (Brasseur and Jacob, 2017), a higher variability of individual weather and the resulting extreme events (like storms, flooding or droughts) is expected. Data from a recent study show that the time under drought conditions in Germany will increase by about 50% with a global warming of 3°C (Samaniego et al., 2018). Accurate models that depict the weather and crop yields are important not only for projecting the effects of agriculture, but also for projecting the impact of climate change on the associated economic and ecological consequences and thus for mitigation and adaptation policies (Crane-Droesch, 2018). There are various methodological approaches to modelling climate impacts on agriculture (Ciscar et al., 2018). On the one hand, there are holistic approaches such as integrated assessment models (Nelson et al., 2014). On the other hand, there are process-based or mechanistic models that capture the relevant biophysical relationships (Rosenzweig et al., 2014). Finally, there are empirical or statistical models that explain the relationship between meteorological variables and agricultural yields (Auffhammer and Schlenker, 2014; Blanc and Schlenker, 2017). These modelling approaches are rooted in very different disciplines and involve different emphases and assumptions, often resulting in a lack of consistency. These include, among other things, the magnitude of the impacts on agriculture at different degrees of global warming, the role of carbon fertilization in their role for production, and the consideration of adaptation in the model. Furthermore, key issues such as the empirical basis behind the model projections have not yet been adequately addressed (Ciscar et al., 2018).

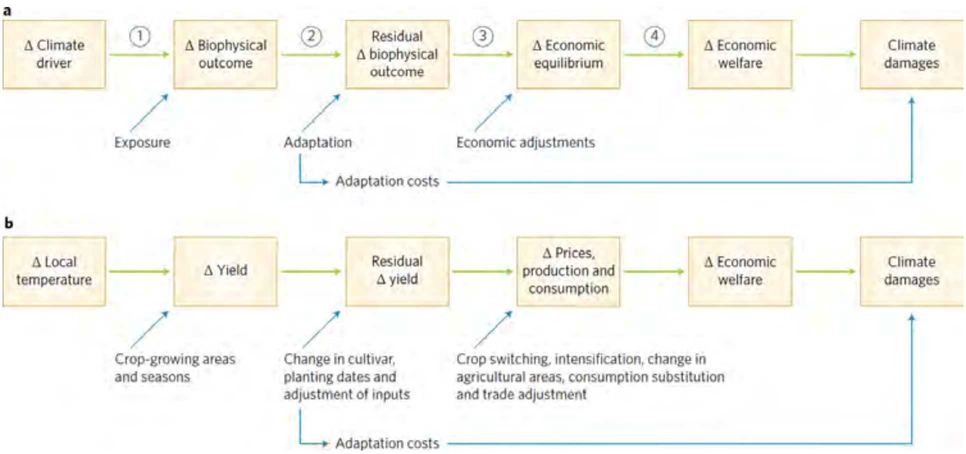
1.2 Goal of the doctoral thesis and road map of this chapter

Based on this scientific discussion, the thesis aims at the design of statistical approaches in order to allow, to the extent possible, a convergence of the results of the different methods. The aim is to identify missing aspects in current statistical approaches, such as the absence of important variables (e.g. soil moisture) and addressing the timing of the occurrence of extreme events that affect plant growth. In addition, new statistical approaches from the field of machine learning will be introduced to complement the existing methods, which are mainly based on econometrics. Furthermore, the approach presented here enables a Germany-wide impact assessment for the main crops. Finally, the development of such statistical damage functions promotes the management of the effects of extreme events on the agricultural sector on several time scales and can be used for climate change impact assessment. The work is cumulative and consists of three scientific articles. This introductory text is intended to provide an introduction to the topic of agricultural impact modelling and to examine in more detail statistical approaches in this context. To this end, it presents the three general modelling approaches that address the impacts of climate change on the agricultural sector, i.e. integrated assessment models, process-based models and statistical/empirical models, and highlights their respective advantages and disadvantages. Furthermore, the extent to which these models are interrelated will be assessed. For example, process-based and statistical models can be used as damage modules in integrated assessment models. Conversely, an integral economic consideration of climate change is only possible with the latter approach. Furthermore, it is shown to what extent statistical approaches are preferable in this context and how the research here contributes to the development and dissemination of these approaches. Subsequently, the general approach and the specific contributions to the research topic of the three articles presented in this thesis are summarized. Finally, the limitations and further research are outlined.

1.3 Three model approaches addressing climate change impacts on the agricultural sector

As explained above, there are three approaches that model the effects of extreme weather events related to climate change on the agricultural sector. An overview is given below. First, the most holistic approach, i.e. Integrated Assessment Models (IAM), is presented. Secondly, process-

Figure 1.1: Schematic representation of the complex series of physical and socioeconomic processes and relationships encompassed by a damage function. a, Generalized stages involved in determining damages, where Δ represents the change in the parameter and numbered connections represent (1) biophysical sensitivity to climate driver, (2) adaptation effectiveness, (3) general-equilibrium effects, and (4) economic preferences. b, Specific example for the agriculture sector. Depicted from Diaz and Moore (2017).



based models are described. Third, the respective statistical models are outlined, which serve as a basis for the approaches and developments undertaken in this thesis.

1.3.1 Social cost of carbon and integrated assessment models

IAMs model the global economy, the climate system and the links between them via greenhouse gas emissions and climate impacts (Füssel, 2010; Clarke et al., 2014). The goal of IAMs is to gain insights into how climate change could affect future global welfare, which is estimated using the social costs of carbon (Carleton and Hsiang, 2016; Nordhaus, 2017). The social cost of carbon (SCC) is a monetary estimate of the damage that an additional ton of carbon dioxide will cause to society over time as a result of climate change, including the effects on market (agricultural productivity, energy costs and infrastructure damages), and the impacts on non-marketed goods such as ecosystem services and human health (Diaz and Moore, 2017). They are useful tools for policy makers, scientists and economists seeking to understand the relationship between climate (and energy) policy and the costs of the damages caused by climate change (Moore et al., 2018). For example, the federal government of the United States uses estimates of SCC reported by three IAMs, as do Canada and several US states (Moore et al., 2018). In addition, these models are also used to inform global policies (Interagency Working Group on Social Cost of Greenhouse Gases, 2015; Revesz et al., 2014; Burke et al., 2016).

IAMs are well suited to address climate change impacts on society. They are the most holistic one of the three approaches presented in this introductory chapter, as they take into account the entire economic system and its interdependencies. A typical structure of IAMs can be seen in Figure 1, depicted from Diaz and Moore (2017). In this figure (part (a)) you see the processes typically incorporated in an IAM. Those are the change in a climate driver which causes a change in biophysical outcome and associated the change of the residual biophysical outcome after adaptation, and a shift in the economic equilibrium which subsequently affects the economic welfare. Thus, economic losses due to climate change in a sector are the sum of welfare changes that remain after taking into account the sector's exposure and sensitivity to climate change, its capacity for natural or technological adaptation, the available scope for economic adaptation and the structure of economic preferences, as well as the costs of adaptation (Diaz and Moore, 2017).

In addition, as shown in Figure 1b, IAMs that are specifically designed for or designed to include the agricultural sector, capture socio-economic feedbacks on agricultural yields, such as price changes due to the effects of climate change, which can alter factor input and production decisions and trigger technological innovation. Therefore, these models are also capable of taking economic adaptation into account by considering all the related effects implied by a change in the biophysical outcome (Moore et al., 2017b). Strictly defined, adaptation is an action that reduces the negative impacts of climate change or amplifies positive ones (Lobell, 2014). Neither statistical nor process-based methods capture the feedback loops between different sectors as a whole that are necessary to model such adaptation (Ciscar et al., 2018). For example, Moore et al. (2017b) could not find adaptation in process-based models, which often take into account adaptation at the farm level - i.e. in process-based models no change in management is implemented that is beneficial only under global warming but would not be beneficial under current circumstances (Lobell, 2014).

There are many critical aspects in deriving SCC from IAMs, such as how to take socio-economic drivers into account, how to translate future damage into current monetary values and how to include tipping points within the earth or socio-economic system (Diaz and Moore, 2017; Revesz et al., 2014). The main criticism of the IAMs addressed in this thesis is that they are usually based on theoretical "damage functions" that represent a simplified relationship between climate variables (temperature change or CO_2 concentrations) and their impact on relevant outcome variables such as sea-level rise and economic welfare (Diaz and Moore, 2017; Hsiang et al., 2017). These aggregated functions generally have (i) a simplified functional form, are (ii) based rather on modelling intuition, rough estimates, and theoretical effects instead of systematic calibration to observed human-climate relationships (Diaz and Moore, 2017; Hsiang et al., 2017), and (iii) are often calibrated to only a few data (Carleton and Hsiang, 2016; Hsiang et al., 2017). Other relevant criticisms of the damage functions are:[1]

- Firstly, IAMs only model on coarse spatial and sectoral scales. For example, standard IAMs like DICE (e.g. Nordhaus, 1993), FUND (e.g. Anthoff and Tol, 2013), and PAGE (Hope, 2011) comprise 1 global and 8 or 16 regions (Rose et al., 2017; The National Academies of

[1] for further information on aspects such as the parameterization of the economic utility function, see Table 2 of Diaz and Moore (2017)

Sciences Engineering and Medicine, 2017). Such a resolution prohibits the consideration of local and regional impacts of climate change. Furthermore, the damage functions are usually based on underlying impact studies that focus disproportionately on a few regions (US, EU) and are then extrapolated to other regions to provide global coverage. Similarly, only 2, 14 and 4 sectors are considered (Diaz and Moore, 2017). Thus, damage functions only incompletely cover the categories of climate impacts, often because the underlying studies for calibration are missing. In addition, represented sectors may have secondary effects that are omitted, such as health effects of malnutrition due to effects in the agricultural sector. Furthermore, the interregional and intersectoral interaction between the damage functions of the respective sectors and regions is not taken into account (Diaz and Moore, 2017).

- Secondly, and similar to process-based approaches, IAMs are calibrated to a snapshot in time (Ciscar et al., 2018). The production of a snapshot does not reflect the probability of the occurrence of adverse climate impacts, which depends strongly on both the time of occurrence and the evolution over time. In particular for the agricultural sector, seasonal effects are of high relevance in order to allow a precise damage assessment.

- Thirdly, these simplified damage functions cannot cover the whole range of parametric and stochastic uncertainty (Diaz and Moore, 2017). Underlying studies used for calibration typically estimate the effects of equilibrium changes in mean temperature (or sea level), but not necessarily the effects of extremes. It has been shown that empirical approaches are particularly suitable for the agricultural sector to capture these extremes (Diaz and Moore, 2017).

- Fourthly, IAM damage functions are based on outdated scientific understanding. In most cases the scientific basis of IAMs is undocumented, based on damage functions from earlier versions of the models, or dated 10 to 20 years ago and may therefore have been overtaken by more recent results (The National Academies of Sciences Engineering and Medicine, 2017; Burke et al., 2016). For instance, current agricultural damage functions in IAMs use studies from the early to mid 1990s, which are now outdated and largely obsolete (Moore et al., 2017b). Because of that the National Academies of Sciences, Engineering and Medicine of the United States (The National Academies of Sciences Engineering and Medicine, 2017) recommended improvements to the IAMs in terms of damage modules (or damage functions) so that they reflect the current state of scientific knowledge.

In recent years there have been several approaches to derive better informed damage functions in IAMs. These are detailed process impact IAMs, model comparison framework to align mechanistic and process-based models and empirical studies (Diaz and Moore, 2017).

The first comprises IAMs designed for specific purposes, such as assessing global scenarios instead of deriving climate change SCC. These models often do not provide results in economic terms, but are based on physical measures. These IAMs are less stylized for the cost-benefit analysis of climate change, but rather include a higher spatial resolution and a better understanding of mechanistic processes that influence the relevant outcome variables. Such models therefore combine detailed bio-geophysical and economic models to represent climate impacts on a finer scale and can be used to calibrate damage functions for different sectors in IAMs (Diaz and Moore, 2017).

Accordingly, the calibration of the damage function is both data- and resource-intensive. Furthermore, given the research developments of recent years, both model comparison projects and empirical studies are of greater relevance to the agricultural sector (Diaz and Moore, 2017). A recent explosion of empirical work suggests that these global policy models can now be calibrated to real-world relationships that characterize the many social impacts of climate (Carleton and Hsiang, 2016). This opens the avenue for the next section. There, process-based models will first be discussed before the statistical damage functions for the agricultural sector are described in more detail. These process-based models aim to model different processes explicitly, including the effects of individual adaptation (generally on farm-level). However, this type of modelling is very resource-intensive and rather difficult to implement, as it usually involves knowledge from different disciplines, which is often not available (Diaz and Moore, 2017). On the other hand, empirical studies that parameterize the effects in a reduced relationship between climate and outcome are developing very rapidly (Diaz and Moore, 2017).

1.3.2 Process-based models

For the agricultural sector, the most important model comparison framework of the process-based models is the Agricultural Model Intercomparison and Improvement Project (AgMIP, Rosenzweig et al., 2014). This project aimed at evaluating and comparing models for the agricultural sector under different criteria, and at deriving pathways for improving these models.

Of particular interest for the use of process-based models in an economic valuation framework such as IAMs is the scope (scale and regional coverage) and coverage (e.g. crops simulated) (Ewert et al., 2015) of the models used. Process-based plant growth simulation models have been developed since the 1960s (Monteith, 1965; de Wit and de Wit, 1965; Duncan, W.G., Williams, W.A., Loomis, 1967) to better understand and manage crops and, increasingly, farming systems. Thus, these models are based on the understanding of biophysical processes and growth stages of plants (Ewert et al., 2015; Ruane et al., 2017; Moore et al., 2017b). This involves the empirical parameterization of one or more simplified processes that require crop- or region-specific calibration (Challinor et al., 2014; Ewert et al., 2015). This calibration process opens the opportunity for evaluating the mechanisms by which plants respond to environmental changes, emphasizing their sensitivity to basic stresses (ambient CO_2 effect, temperature, heat stress, frost damage, tropospheric ozone effect, drought and excess water stress, effect of snow and hail, lodging due to wind and rain), which in turn can be used with climate projections (Ewert et al., 2015; Ruane et al., 2017).

Recent developments within the AgMIP framework have expanded these process-based approaches to networks of those sites (Ruane et al., 2017). But sampling with site-specific information is still being carried out: aggregation to regional or global damage functions is a challenge due to gaps in geographical site-specific data and underrepresented systems. It is also difficult to validate these models because they rely on prior model calibration and on a preference for common crop models (Ruane et al., 2017). Meanwhile, the development of computing power allows for working with great data sets and to advance high-resolution, grid-based, process-based models at the national or even global level, so that they can be used in an integrated environment, taking into account climate, economic and process-based models (Ruane et al., 2017). In contrast to site networks, these approaches rely, among other things, on rasterized data sets of soil and weather to capture rather spatially averaged conditions instead of site-specific information (Elliott et al., 2015). Global gridded crop models provide comprehensive coverage, but with major challenges for calibration and quality control of inputs (Ruane et al., 2017). Furthermore, the process of transforming data from crop models into inputs for economic modelling poses challenges, such as (i) deriving yield effects for crops not included in the crop models (most model evaluations and testing in climate studies have been strongly biased towards wheat, maize, rice and soybean), (ii) assigning crops to commodities used in the economic model to allow for trade, (iii) determining yield effects over time, and, in particular, (iv) aggregating high-resolution raster-based crop model outputs to lower-resolution country or regional units of the economic models (Nendel et al., 2013; Nelson et al., 2014; von Lampe et al., 2014; Ewert et al., 2015). Other critical aspects of model integration for climate risk assessment concern the link between the level for assessing food production which considers farm level management and the regional or global scales of IAMs (van Ittersum et al., 2008; Ewert et al., 2015). In terms of geographical coverage, most studies focus on Europe, America and Asia (Ewert et al., 2015). As far as the time scale is concerned, process-based crop models usually simulate in daily time steps. Therefore, large-scale simulations over several years necessary for climate assessment may require considerable computational time. However, for many economic models only final yields are actually needed as input (Ewert et al., 2015; Ruane et al., 2017). In general, these process-based modelling approaches are data-intensive and their ability to be generalised to larger areas (upscaling) and thus allow for application within IAMs or other integrated assessment tools is limited (Ewert et al., 2015; Moore et al., 2017b). The underlying problem is that crops react differently at selected sites due to unique soils, weather conditions, cultivars and management practices. Approaches exist which use integrated approaches based on economic, climatic, and raster-based process-based crop models (Müller and Robertson, 2014; Nelson et al., 2014; Wiebe et al., 2015). However, these are based on only a small subset of crop models (Ruane et al., 2017), which makes it difficult to use model ensembles that are commonly used to quantify the structural uncertainty inherent in process-based crop models. For example, it is suggested that at least five models are required for robust assessments of the impact of climate change on yield effects at increases of up to 3 degrees and 540 ppm CO_2 (Asseng et al., 2013).

A more direct coupling of agricultural reactions within the IAMs is facilitated by the use of crop model emulators (Ruane et al., 2017). These statistical models (Blanc, 2017; Mistry et al., 2017; Moore et al., 2017b) estimate the yield derived from process-based models (for instance at different locations) as a function of climate variables with varying degrees of detail (Ruane et al., 2017). They are similar to statistical models for crops, but instead of relying on observed crop yields, the results of the models are assumed to be a fair representation of actual yields (Blanc, 2017). It is difficult for crop model emulators to unravel basic damage mechanisms from these results because there are many types of changing and interacting environmental conditions, such as temperature and precipitation, the treatment of subseasonality, and the consideration of meteorological extremes (Ruane et al., 2017). Emulation modeling is also complicated by the fact that some models include a farm-level adaptation (field workability, tillage practice, crop rotation, fertilization, sowing date, irrigation, change of cultivar, change of crop, water savings techniques, nutrient optimization, pest, disease and weeds), while other models do not (Rosenzweig et al., 2014; Ewert et al., 2015).

Another approach, which is computationally more efficient and applicable than process-based crop models, is statistical crop models based on observational data. These are a valid tool for deriving damage functions to estimate the socio-economic consequences of meteorological and climatological variations on the agricultural sector (Carleton and Hsiang, 2016; Diaz and Moore, 2017; Moore et al., 2017b,a). These are described in more detail in the next section. First, the models are introduced using the general approach of statistical modelling and its applications for impact assessment in different sectors. Then, the specific role of the statistical damage function in the agricultural sector is described in more detail. There the state of the art is outlined. The limitations of current approaches are also highlighted, such as the dependence on certain variables or the lack of seasonal effects. Finally, the own contributions of this thesis to the research field are described.

1.3.3 Statistical models

From the above paragraph it has become clear that recent advances in the empirical modeling of climate data on societies and economies have been rapid. For statistical approaches they are facilitated by increased computing power, access to data and advances in the statistical theory of causal inference, relying heavily on the design of research from non-experimental studies (Holland, 1986; Hsiang, 2016; Carleton and Hsiang, 2016). This opens up a new generation of models based on these statistical data. It has been shown that classical statistical models outperform process-based models in predictive power, especially on a large scale (Lobell and Asseng, 2017). Damage functions, or so-called dose-response functions, have been developed for various areas, such as health (mortality, morbidity, early life), economic effects (labour supply and productivity, energy supply and demand, trade), social interactions (women and girls, interpersonal violence and aggression, violence between groups, institutional collapse and state failure), demographic effects (migration, population structure and growth) and coastal damage (Carleton and Hsiang, 2016; Hsiang et al., 2017; Diaz and Moore, 2017). These empirical studies open up opportunities for investigating climate impacts in sectors that have so far been excluded from the damage functions, such as conflicts, political instability or labour productivity (Diaz and Moore, 2017). In the following two sections some more details about the role of these statistical models in the agricultural sector will be provided. In the first section the focus is put on the state-of the art of these models, presenting what has been achieved so far by applying them, and where their limits are. In the second section it is demonstrated which progress has been achieved by the three papers which are subject of this PhD thesis.

1.3.3.1 State-of-the-art research literature on statistical models in the agricultural sector

From an economic perspective, at the interface of natural sciences and agricultural economics, structural and reduced form models are employed (Auffhammer and Schlenker, 2014) to assess the impact of changing weather or climate conditions on the agricultural sector. Both allow the general the identification of causal climate drivers on the agricultural sector. Structural approaches, such as IAMs or processed-based crop models, have the "the ability to make predictions about counterfactual outcomes and welfare" (Chetty, 2009). On the other hand have reduced form approaches the advantage of being transparent and allowing credible identification (Chetty, 2009). They exploit the exogenous within-sample variation of key parameters, with as few structural assumptions as possible. This reduces the reliance on these assumptions, which assists in establishing causality in the relationship of interest (Timmins and Schlenker, 2009). In this type of modeling, commonly regression analysis is used to estimate the variation in the dependent variable by dose-response functions (Carleton and Hsiang, 2016; Hsiang, 2016; Kolstad and Moore, 2020). Reduced form models aim on avoiding issues in causal inference due to factors based on endogeneity such as confounding variables, feedback loops (structural assumptions) and systematic treatment assignment (selection bias). Further, reduced form approaches under the premise of jointly demeaning the dependent and independent variables (as for instance in a fixed effects approach) can be interpreted as natural experiments, because it is only relied on period-to-period variation, which is not anticipated by the farmers (Auffhammer and Schlenker, 2014). Natural experiments are considered a valid method to reveal causal effects when randomized field experiments are not available, which commonly is the case in disciplines such as social science and public health research (Angrist and Pischke, 2008). In contrast to process-based models, statistical crop yield models usually reduce the processes that influence plant development to the main features (Timmins and Schlenker, 2009; Kolstad and Moore, 2020). Despite very long experience in agriculture, one surprising result of statistical models is the importance of temperature, which often dominates precipitation, for the production of staple foods (Carleton and Hsiang, 2016). In this context, most progress on dose-response functions has been achieved by developing temperature estimates with high spatial and temporal resolution (Hsiang, 2016). Based on these data, many studies in the agricultural context use a precise term that integrates cumulative exposure to specific temperature ranges during the growing season as an important explanatory variable. These are defined as growth degree days (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2006) and cumulative measures of extreme heat above a certain threshold, such as killing degree days (Annan and Schlenker, 2015; Burke and Emerick, 2016; Roberts et al., 2013; Schlenker and Roberts, 2006, 2009, among others). Schlenker and Roberts (2009) showed that the time a plant is exposed to a temperature above a threshold value can explain almost half of its yield variation. Along with the USA, this correlation of nonlinear yield losses and hottest days was observed for many regions, e.g. for Africa (Schlenker and Lobell, 2010), Europe (Moore and Lobell, 2015), Southeast Asia (Welch et al., 2010) and India (Burgess et al., 2014).

However, the inference based on these often aggregated measurements of meteorological variables is critical, since they can be confounded by missing or only roughly represented variables (Peichl et al., 2018; Roberts et al., 2017). Apparently, causal relationships of weather determinants with yield variations can obscure the underlying physiological mechanisms (Roberts et al., 2017). For example, the influence of heat on crop yields is not fully understood. Recent research suggests that the main reason for the importance of high temperature measurements is the high correlation with measurements of cumulative evaporation demand (Urban et al., 2015), such as the vapour pressure deficit (VPD, Lobell, 2013; Roberts et al., 2013). There is evidence that the effect of high temperature measurements and measures of evaporation demand is overestimated when adequate control of water supply is neglected (Basso and Ritchie, 2014; Ortiz-Bobea, 2013). Urban et al. (2015) highlight the impact of interactive effects between VPD and water supply to further improve the predictability of the model. In Germany, the most recent statistical impact assessment of weather fluctuations in maize and winter wheat recognizes water shortage as a major limiting factor (Gornott and Wechsung, 2015, 2016; Conradt et al., 2016). Instead of relying on the primary water source for plants, i.e. soil moisture, these studies use proxies such as precipitation and measures of evapotranspiration demand. Important factors such as the water holding capacity of the soil and the persistence of soil moisture are not considered.

A global study based on process-based models for maize and wheat, for example, found that for most countries, such as Germany, water stress is a major cause of the observed yield variations (Frieler et al., 2017). In addition, it has been shown that several unfavourable environmental conditions such as frost, heat, drought and excessive soil moisture during sensitive growing seasons influence plant development, and this should be taken into account when assessing the effects of climate change (Trnka et al., 2014; Albers et al., 2017; Schauberger et al., 2017; Mäkinen et al., 2018; Peichl et al., 2018, 2019). One explanation for the differences that occur in climate impact assessment between process-based and statistical models is the factors used in the individual modelling approaches. A recent study concluded that using the best features of both approaches can improve the predictive power (Ciscar et al., 2018). Sub-seasonal patterns of precipitation, vapour pressure deficit and solar radiation are implemented in process-based models, but are often simplified or neglected in statistical approaches (Roberts et al., 2017). It is likely that aggregated measures of water supply commonly used in statistical models, such as precipitation averaged over the entire vegetation period, are less sensitive than those found in process-based models, since seasonal effects and extremes can be averaged out (Lobell and Asseng, 2017). An approach that uses a semi-parametric machine learning approach to explain crop yields in the Midwest of the USA and takes into account the complexity of the underlying reaction mechanism surpasses classical parametric statistical methods (Crane-Droesch, 2018). Furthermore, the predicted climate impacts were less severe than those found by linear models that rely mainly on heat as the main predictive variable.

1.3.3.2 Own contributions and scientific progress

Contribution 1: The effect of soil moisture anomalies on maize yield in Germany (NHESS, 2018)

Based on the analysis outlined above, the main objective of the first step (i) is to investigate the intra-seasonal predictability of soil moisture to estimate silage maize yield in Germany. It will also be assessed how (ii) approaches that take soil moisture into account perform compared to those that use only meteorological variables. The hypothesis investigated is that (a) models using soil moisture are better able to predict yield variations than purely meteorological approaches, and that (b) temporal patterns play a role in the seasonal effects of the explanatory variables, i.e. there is no additive substitutability. To analyse these hypotheses, the intra-seasonal effects of soil moisture and meteorological variables are investigated for non-irrigated arable land in Germany. To answer these research questions, the nonlinear intra-seasonal partial effects of soil moisture anomalies and the meteorological variables temperature, potential evapotranspiration and precipitation are investigated in a reduced form panel approach. For this purpose, a new data set is generated, which additionally contains data on soil moisture anomalies. Soil moisture anomalies are calculated as an index and are based on the results of the mesoscale Hydrologic Model (mHM). Soil moisture and each derived index is strongly autocorrelated in time and thus provides an integrated signal of the meteorological conditions in the preceding and following months (Orth and Seneviratne, 2012; Samaniego et al., 2013). This persistence does not allow cumulative measures as used for temperature, but it avoids the inflation of error terms. In general, the predictive power of models that use only meteorological variables can be improved by taking into account the region-specific temporal distribution of phenological stages (Dixon et al., 1994). However, the integrated signal of meteorological conditions provided by each variable derived from soil moisture allows the use of monthly averages to take into account these intra-seasonal effects.The model selection is based on Bayesian Information Criterion and the adjusted coefficient of determination. This study provides a proof of concept that (a) soil moisture improves the ability of models to predict silo maize yields compared to purely meteorological approaches and (b) temporal patterns in the seasonal effects of the explanatory variables are important. The results show that soil moisture anomalies improve model fitting in all model configurations, according to both validation criteria, i.e. Bayesian Information Criterion (BIC) and the adjusted R-square. The SMI has the highest explanatory power in all months except May (most explained by temperature) and July (most explained by precipitation). This illustrates that soil moisture provides different information than meteorological variables. All time invariant variables show seasonal patterns in accordance with each individual growth stage of silage maize. Furthermore, the dynamic patterns over the vegetation period of the SMI effects are derived from seasonality in absolute soil moisture. These results support the assumption that it is necessary to control the intraseasonal variability in both soil moisture index and meteorology to derive valid impact assessments. The comparison of different meteorological effects based on the BIC also shows that potential evapotranspiration compared to the average temperature has no explanatory power. Furthermore, in controlling intraseasonal variability, the partial effects of precipitation outweigh those of temperature.

Contribution 2: Climate impacts on long-term silage maize yield in Germany (Scientific Reports, 2019)
This study examines the effects of climate change on the variations in the long-term mean value of silo maize yields for all districts in Germany. The reduced form model is further developed by explicitly considering the most important factors of the approach presented in contribution 1. These are dry and wet soil moisture anomalies for June and August and temperature and precipitation for July. Drivers of extreme annual yield variations, such as drought or extreme temperatures, are not explicitly considered in this study. Five hydro-meteorological simulations are used to drive the statistical yield model. For scenario A1B, climate data for two climate periods were derived from five different RCMs. The model is able to explain long-term average yield changes, but is not designed to simulate extreme crop losses in individual years. The maximum absolute projected long-term average yield loss of silage maize in Germany was estimated to be less than 10% of average yield. Taking into account adaptation and CO_2 fertilization, positive yields are expected.

Contribution 3: Machine learning methods for predicting winter wheat yield in Germany (submitted to ERL, 2020)
In a third step, the approach is generalized for other winter crops such as winter wheat. Winter wheat has the largest share in cultivated area (2018: 46%) and total production (2018: 51% of quantity harvested) (Statistisches Bundesamt (Destatis), 2018) amongst all crops in Germany. The main difference thereby is the extended season of winter wheat (ten months of season starting in autumn) compared to silage maize (five months starting in spring). Because of this long period, which also extends over the winter months, it is assumed that the interaction of the effects within the season is important. The reason is that weather patterns can fundamentally change due to the longer period of time. This should be included in statistical modeling. Furthermore, it has been shown that it is necessary to account for multiple adverse environmental conditions such as frost, heat, drought and excessive soil moisture during sensitive growth phases (Trnka et al., 2014; Albers et al., 2017; Schauberger et al., 2017; Mäkinen et al., 2018; Peichl et al., 2018, 2019).

Similarly, this study applies a statistical framework that does not rely on a key predictive variable, but takes into account a range of potentially harmful factors to cover the full spectrum of potential damage. The aim is to increase the forecasting capacity of the model to allow for a better prediction of inter-annual yield fluctuations (for example, in comparison to contribution 2), while at the same time allowing for a representation and thus interpretation of the damage mechanisms. The latter is usually carried out using parametric approaches, as the parameters are easy to interpret (see contributions 1 and 2). Machine learning, on the other hand, is largely focused on maximizing predictive capacity by generating high-dimensional and highly non-linear functions while waiving interpretability (Breiman, 2001; Zhao and Hastie, 2019). This is where model agnostics comes into play, which compromises various methods that allow the interpretation of approaches to machine learning (Ribeiro et al., 2016). In particular, accumulated local effect plots are used to show sensitivities of features that determine plant growth that are comparable to the coefficients in linear regression models. In doing so, it is still possible to rely on machine learning algorithms, which usually exceed the classical statistical model in predictive power and at the same time allow for interpretability.

For this purpose, different subseasonal hydro-meteorological extremes and their interaction with the yield variation of winter wheat are mapped using random forests. Monthly aggregates of meteorological extremes for frost, heat and precipitation extremes as well as soil moisture are used as predictors, which takes into account the subseasonality in the model. Within this framework, plant growth is considered as a non-linear system, since the time of occurrence and the different features themselves interact. For this reason, random forests are used, which are particularly suitable for nonlinear systems (James et al., 2013; Breiman et al., 1984). Neural networks are not considered because model agnostics are not fully capable of revealing the structures in the hidden layers of these models (Molnar, 2020). In order to further refine the model, it is based on spatial clustering, which takes into account regional differences in climate, soil moisture and soil properties and thus contributes to increase the predictive power of the models (Conradt et al., 2016) and to identify spatially dependent damage mechanisms.

Here, for the first time a machine learning algorithm was used to predict crop yields in Germany. It is the statistical model that is not relying on time-invariant factors but only on the variation of yield anomalies, with the highest predictive capacity for all of Germany (as shown in contribution 1, a large proportion of the explained variation in statistical yield is due to the fixed effects). Compared to other models, this approach performs better in regions with low yield variance. Moreover, this is the first time that model agnostics has been applied in such a context. Various clustering algorithms and cluster sizes were applied to improve the predictive power of the model from 65% in the average test R-square to 70%. In general, it is able to explain the general pattern of district losses and gains, even in particularly extreme years such as 2003, 2014 and 2018, with only slight underestimation of the most extreme yield variations. Because of its predictive power, the model is considered suitable to be used, for example, for annual yield forecasting. In Germany, moreover, yield data are reported more than six months later than the actual time of harvest. The predictions generated by this model can bridge that gap in time and support the design of tailor-made and above all timely support mechanisms for major losses caused by extreme values. The approach also helps to unravel the damage spectrum for each clustered region in Germany. Soil moisture dominates in the ranking of variable importance, especially in Western Germany. Preference is given to the upper 25 cm of the soil moisture column over the entire column or a combination of both. While the northeastern part of Germany is rather driven by damage due to water shortage, excess water in the soil is problematic for winter wheat growth in the other parts of Germany. The water shortage effects for the smaller cluster remain undetected with an approach not relying on clustering to form subregions. Heat-related measures are underrepresented in explaining the effects on yield anomalies in winter wheat.

This information is useful for tailoring management and adaptation measures. For example, it is particularly useful for the insurance industry to offer index-based insurance products, as they help to identify harmful features and thresholds in these features that cause damage (Albers et al., 2017). Furthermore, such an approach, which explicitly captures the complexity of the underlying response mechanism rather than relying on a key determinant, is suitable for the projection of climate impacts, as GCMs explicitly capture the dynamics of several hydro-meteorological variables (Crane-Droesch, 2018).

1.4 Limitation of the research and further research

Despite the ability of the model to explain a large part of the yield variability, which is shown in contribution 3, further improvements can be implemented to increase the predictive capacity. Increasing predictive power is especially useful to better reflect the extreme yield variations that are increasingly expected to occur as a result of climate warming. In particular, further research is needed to better account for small-scale events such as hail and thunderstorms. Likewise, a higher temporal resolution in the variables can be applied to take better account of the vegetation periods in the different subregions considered. Similarly, the meteorological extremes in this approach are based on features that use expertly defined thresholds. A sensitivity analysis of these expert-based thresholds may help to improve the model. In addition, the use of deep learning instead of classical machine learning can help to further increase predictive power.

Furthermore, the damage functions are to be integrated into a framework that allows an economic assessment of the effects of climate change on the agricultural sector in Germany. For this purpose, a similar framework to that used in IAMs will be created. The statistical approach of modelling yield functions based on machine learning will first be transferred to the other main crops available for Germany. In a next step, climate projections will be applied to determine global warming of 1.5, 2 and 3 degrees. Similar to contribution 2, the model uses the projected meteo-hydrological variables to project crop yield variations to these warming intervals. These damage assessments are then integrated into an economic framework. However, instead of relying only on a standard economic module that considers only general or partial equilibrium models, it is planned to additionally use an individual-based modelling approach to enable management decisions at farm level. Thus, the aim is to capture both the impacts and costs of adaptation at farm level and of general economic adaptation, in order to allow for a more comprehensive conclusion to be drawn on the social costs of carbon in the agricultural sector.

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Chapter 2

The effect of soil moisture anomalies on maize yield in Germany

2.1 Introduction

In the course of the German Energy Transition, the demand for biomass has increased considerably with silage maize being an important plant for high dry matter yields. The share of the total production in agriculture was 18 % in 2014 (Die Landwirtschaft Band 1, 2014), with an increasing share of agricultural area used for silage maize from 15.4 % in 2010 to 17.7 % in 2015 (Statistisches Bundesamt (Destatis), 2011; Statisitisches Bundesamt, 2016). With that in mind, the observed susceptibility of silage maize towards extreme dry conditions during summer time supports the detection of relevant factors for yield variation (as for instance in 2015, Becker et al., 2015; Bundesministerium für Ernäherung und Landwirtschaft, 2015). Knowing the determinants of maize variation can help to mitigate welfare losses. For instance, detrimental effects of soil moisture shortage and abundance can be mitigated by the means of irrigation and drainage and thus are key for targeted and efficient development of adaptation measures (Chmielewski, 2011).

In general, two different kinds of modeling approaches are employed to assess the impact of weather or climate on the agricultural sector. These are structural (integrated assessment) models and reduced form models (Auffhammer and Schlenker, 2014). Whilst structural approaches specify the economic behavior based on theoretical models and assumptions and thus have "the ability to make predictions about counterfactual outcomes and welfare" (Chetty, 2009), the advantage of reduced form approaches is "transparent and credible identification" (Chetty, 2009) by exploiting the exogenous variation of key parameters (Timmins and Schlenker, 2009). Regression models are used to estimate the variation in the dependent variable within various sectors by the means of *damage* or *dose-response functions* (Hsiang, 2016; Carleton and Hsiang, 2016). In the agricultural sector, the major explanatory variables are temperature based (Carleton and Hsiang, 2016; Lobell and Burke, 2008; Lobell et al., 2011b; Schlenker et al., 2005; Schlenker and Lobell, 2010). The use of temperature as the main explanatory variable is questioned in this study by using reduced form models to identify the impact of different determinants on crop yield.

In the agricultural context, most advances have been made regarding dose-response functions through the development of temperature estimates on high spatial and temporal resolutions (Hsiang, 2016). Based on this data, many studies employ a precise term which integrates cumulative exposure to specific temperature ranges over the growing period as major explanatory variable. Those are defined as growing degree days (Schlenker et al., 2006; Deschenes and Greenstone, 2007) and accumulated measures of extreme heat above a certain threshold, as for instance extreme, heat, killing, or damage degree days (Annan and Schlenker, 2015; Burke and Emerick, 2016; Butler and Huybers, 2013, 2015; Lobell et al., 2011a, 2013; Ortiz-Bobea and Just, 2013; Roberts et al., 2013; Urban et al., 2012, 2015a; Schlenker and Roberts, 2006, 2009; Schlenker et al., 2013; Teixeira et al., 2013). Schlenker and Roberts (2009) showed that the time in which a plant is exposed to a temperature above a threshold during each day of the growing season can explain almost half of its yield variations. For corn, this threshold is estimated to be 29 °Celsius. Thus, it is highly recommended to account for nonlinearity in temperature. This is particularly important in the context of climate change, as the likelihood of significant and non-marginal changes in relevant factors increases. Currently, non-linear measures with thresholds such as extreme degree days (EDD) are considered to be the best predictor of crop yield variation (Auffhammer and Schlenker, 2014; Carleton and Hsiang, 2016).

Recent research suggests, that the main reason of the importance of EDD is the high correlation with measures of cumulative evaporative demand (Urban et al., 2015a), as for instance vapor pressure deficit (VPD, Roberts et al., 2013; Lobell et al., 2013). There is evidence, that the effect of EDD and measures for evapotranspirative demand is overstated when neglecting proper control for water supply (Ortiz-Bobea, 2013; Basso and Ritchie, 2014). For instance, soil moisture is considered a major limiting factor to maize growth (Andresen et al., 2001). Extremely high temperature amplifies the impact of soil moisture deficit because of surface-atmosphere coupling (Mueller and Seneviratne, 2012), but the opposite is not necessarily the case as droughts occur independently of heat (Basso and Ritchie, 2014). Urban et al. (2015b) highlight the impact of interactive effects between VPD and water supply to further improve model predictability. In Germany, a recent statistical impact assessment of weather fluctuations affecting maize and winter wheat recognizes water shortage as major limiting factor (Gornott and Wechsung, 2015, 2016; Conradt et al., 2016). These studies employ proxies to control for the primary source of water, such as precipitation and measures for evapotranspirative demand. The water holding capacity of the soil and the persistence of soil moisture is often not considered.

One basic assumption in EDD is that temperature effects are additively substitutable, which means that their impact is constant for all development stages of the plant. This assumption is rejected in both agronomic studies (de Bruyn and de Jager, 1978; Sinclair and Seligman, 1996; Tubiello et al., 2007; Wahid et al., 2007) and large-scale empirical analyses (Lobell et al., 2011a; Ortiz-Bobea, 2011; Ortiz-Bobea and Just, 2013; Berry et al., 2014). For example, the susceptibility to high temperatures is increased during flowering (i.e. tasseling, silkening, and pollination) and the reproductive period. Similar to heat measurements, the sensitivity to water stress is dependent on the development stage of the plant (FAO, 2019). For instance, it is shown for climate projections in India that a more uneven distribution of precipitation within a season overturns positive effects of an increase in total precipitation (Fishman, 2016). It is argued to control for intra-seasonal varying weather induced effects on crop yield variation. This issue is amplified for precipitation controls compared to temperature. The distribution of measures such as EDD partially overlaps with the sensitive phase of plant growth (see Figure A14 of Schlenker and Roberts, 2009), but precipitation, as control for water supply, is commonly aggregated for the entire growing season (Annan and Schlenker, 2015; Burke and Emerick, 2016; Roberts et al., 2013; Schlenker and Roberts, 2006, 2009, among others). These studies do not explicitly account for seasonality of water supply related effects. Overall, controls for meteorological effects averaged over the entire season may bias the estimated dose-response function and diminish the predictive power of the models, because they do not account for the seasonal interaction between water supply and water demand (Urban et al., 2015b).

Based on this analysis, it is the main aim of this study to investigate the intra-seasonal predictability of soil moisture to estimate silage maize yield in Germany. It is also evaluated how approaches considering soil moisture perform compared to those using meteorological variables. The examined hypothesis are, that a) models with soil moisture are better able to predict yield than meteorology-only approaches and that b) temporal patterns in the seasonal effects of the explanatory variables matter, i.e. there is no additive substitutability. In order to analyze these hypotheses, the intra-seasonal effects of soil moisture and meteorological variables for non-irrigated arable land in Germany are examined in this study. In detail, the following research questions are addressed: 1) Is there predictability of soil moisture additionally to meteorology? 2) If so, how does it compare to the one by meteorological determinants? 3) Is there temporal pattern in the seasonal effects of all explanatory variables (meteorology and soil moisture)? Along this analysis we also evaluate 4) how models based on different meteorological determinants perform compared to each other.

To answer this research questions, a reduced form panel approach is employed to examine the non-linear intra-seasonal partial effects of soil moisture anomalies and the meteorological variables temperature, potential evapotranspiration, and precipitation. For this purpose, we use a new data set which is additionally comprised of soil moisture anomaly data. The aim is to evaluate whether soil moisture anomalies have predictive skills and how the effects differ from those using only meteorological variables. Soil moisture and any derived index is highly autocorrelated in time and thus provide an integrated signal of the meteorological conditions in the preceding and subsequent months (e.g., Orth and Seneviratne, 2012; Samaniego et al., 2013). This persistence does not allow for cumulative measures as those used for temperature, but it avoids the inflation of the error terms. Commonly, the predictive power of models only employing meteorological variables can be improved by accounting for the regional specific temporal distribution of the phenological stages (Dixon et al., 1994). The integrated signal of the meteorological conditions provided by any measure derived from soil moisture, however, allows the employment of monthly averages to account for these intra-seasonal effects. In our study, it is implicitly controlled for the interaction of both variables controlling for water supply and water demand, because these show high correlation on a monthly basis. Different model configurations for each month of the growing season are compared by model selection criteria to allow conclusions about the effect of soil moisture anomalies on the explanatory power of the model and to test the assumption of additive substitutability. Further, the difference in explanatory power of models either using potential evapotranspiration or average temperature is evaluated. The partial effects of all covariates of the best model for each month are examined. For the purpose of a comprehensive examination, we also investigate the effects of wet anomalies.

2.2 Data

2.2.1 Yield data

Annual yield data for silage maize are provided by the Federal Statistical Office of Germany for the administrative districts (rural districts, district-free towns, and urban districts) since the year 1999 (Statistische Ämter des Bundes und der Länder, 2019). The yield data are de-trended using linear regression for the period 1999 to 2015 to control for technical progress. A log transformation is applied to yield to better satisfy the normality assumption. This transformation also mitigates issues related to heteroscedasdicity and the estimates are less sensitive to outliers. All administrative districts with less than nine observations are removed from the analysis, because the influence of single observations points is too strong in these cases. The threshold nine has been chosen after exploring Cook's distance and evaluating the systematic omission of yield data by the administrative districts (Cook, 1977, 1979).

2.2.2 Soil moisture anomalies and meteorology

The explanatory variables used in the study are the observed meteorological variables precipitation (P), average temperature (T), and potential evapotranspiration (E), as well as model-derived soil moisture. The mesoscale Hydrologic Model (mHM) has been used to estimate the soil moisture (Samaniego et al., 2010; Kumar et al., 2013). The model uses grid cells as primary unit and it accounts for various hydrological processes such as infiltration, percolation, evapotranspiration, snow accumulation, groundwater recharge and storage as well as fast and slow runoff. The parametrization process of the model is based on physical characteristic, as for instance soil texture. Three different forms of land cover are also integrated in the model, which are based on the CORINE Land Cover maps of 2006 (European Environmental Agency, 2009). However, no endogenous processes of land use management, as for instance drainage or irrigation, are considered within the model. The depth of the soil in each grid depends on the soil type used in mHM. Details can be found in Zink et al. (2017).

Soil moisture is further transformed into a soil moisture index (SMI), which is a non-parametric cumulative distribution function (cdf) derived from the absolute soil moisture estimated by mHM. A non-parametric kernel smoother algorithm has been used for the calculation of the cdf for each calendar month in accordance to the proposed method by Samaniego et al. (2013). It ranges from zero to one and represents an anomaly with respect to the monthly long term median in soil water (SMI = 0.5). Low values represent extreme dry soils and high values extreme wet ones. The SMI is calculated for entire Germany at a spatial resolution of 4 km. Monthly values of soil moisture are transformed to SMI for the period from 1951 to 2015. These values have also been used for drought reconstruction (Samaniego et al., 2013). A similar procedure has been applied for the seasonal forecasts of agricultural droughts (Thober et al., 2015).

The monthly SMI values are categorized into seven classes which follow the notion of the US drought monitor and the German Drought Monitor (Zink et al., 2016). This stepwise approach allows to measure nonlinear effects of soil moisture. The dry categories SMI ≤ 0.1, $0.1 <$ SMI ≤ 0.2, and $0.2 <$ SMI ≤ 0.3 are denoted as severe drought, moderate drought and abnormally dry, respectively. The wet quantile intervals between $0.7 <$ SMI ≤ 0.8, $0.8 <$ SMI ≤ 0.9, and $0.9 <$ SMI are labeled as abnormally wet, abundantly wet and severely wet, respectively. The interval between $0.3 <$ SMI ≤ 0.7 serves as reference and characterizes normal situations. This classification uses location dependent cdfs and thus allows comparison of classes across locations. In the rest of this, the terms soil moisture anomalies and soil moisture index (SMI) are used synonymously because of this categorization.

Daily data of precipitation and temperature are obtained from a station network operated by the German Weather Service (Deutscher Wetterdienst, 2019). Details on interpolation can be found in Zink et al. (2017). These daily values are also used to force mHM. For the analysis in this study, all daily values are aggregated to monthly ones conserving the mass and energy of the daily observations.

Further, we introduce Potential Evapotranspiration (E) as a measure for evaporative demand. E is calculated by the equation of Hargreaves and Samani (1985) based upon extraterrestrial radiation and temperature and is estimated in millimeter per day:

$$E = \kappa R \sqrt{T_\delta}(T + 17.8), \tag{2.1}$$

where κ is a free parameter ($^\circ C^{-1.5}$) that compensates for advection of water vapor (mm d^{-1}), R is extraterrestrial radiation converted into equivalent water evaporation, and T_δ is the temperature difference between daily maximum and daily minimum temperature ($^\circ$C). The term $T+17.8$ is an approximation of saturated vapour pressure, whereas the term T_δ is an approximation of cloudiness. 17.8 is an empirical constant found by calibration.

More complex alternatives exist, as for instance the standard method of United Nations Food and Agriculture Organization after Penman and Monteith (Monteith, 1981). These data for example use net radiation that is more difficult to estimate at the national scale in comparison to temperature particularly due to the lack of consistent observations. Similar to Vapor Pressure

Table 2.1: Mean and standard deviation of the meteorological variables, averaged over Germany. P is precipitation, T is mean temperature, and E is potential evapotranpiration. Data are obtained by the Germany Weather Service.

	P (monthly sum in mm)		T (monthly average in °C)		E (monthly average in mm)	
	Mean	SD	Mean	SD	Mean	SD
May	75.74	39.84	13.46	1.42	115.23	12.15
June	69.71	33.15	16.52	1.45	133.42	12.21
July	89.48	39.72	18.48	1.74	139.10	16.52
August	84.04	43.68	17.90	1.57	115.24	13.55
September	63.88	32.62	14.07	1.63	70.33	8.73
October	57.72	27.28	9.64	1.83	36.82	4.69

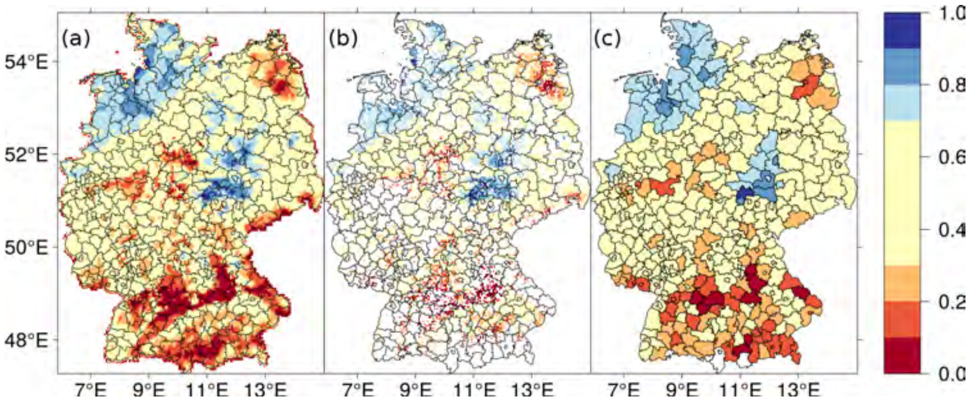
Deficit, which has been introduced as effective crop yield predictor (Roberts et al., 2013; Lobell, 2013), potential evapotranspiration has a more direct physical link to crop water requirements than temperature. One goal of this study is to evaluate whether potential evapotranspiration provides improved yield estimates in comparison to temperature.

All meteorological variables are standardized to ease the comparison among different months. After this transformation, the variables have a mean of zero and a standard deviation of one. The original mean and standard deviation of the meteorological variables are depicted in Table 2.1 for completeness.

2.2.3 Spatial processing

The explanatory variables (meteorology and soil moisture) are mapped onto the level of administrative districts to align with the spatial scale of the yield data. Maps st the different processing steps are shown in Fig. 2.1. Figure 2.1a depicts the 4×4 km^2 grid. These absolute soil moisture fractions are masked for *non-irrigated arable land*-class of the CORINE Land Cover (2006) at a 0.1×0.1 km^2 resolution to account for the variability due to heterogeneous land use within the administrative districts (Fig. 2.1b). The 0.1 km values are then averaged for each of the administrative district to obtain district level values (Fig. 2.1c). Blank administrative districts occur because of the absence of *non-irrigated arable land* grid cells. These processing steps are also applied to the meteorological variables (P, T, E). The soil moisture fractions of each administrative district is then transformed into a percentile index (SMI) using the kernel density estimator explained above (Samaniego et al., 2013; Thober et al., 2015; Zink et al., 2016). An index reduces the probability of measurement errors and the estimated coefficients in the regression models are supposed to be less prone to attenuation bias (Fisher et al., 2012; Auffhammer and Schlenker, 2014; Hsiang, 2016).

Figure 2.1: Illustration of the spatial processing of the SMI data of May 2003. On the left side, one can see the SMI with the 4×4 km^2 grids. In the middle, the data are masked with the 0.1×0.1 km^2 *non-irrigated arable land*-class of the CORINE Land Cover. Those data are than averaged over all the grid cells which are inside an administrative district. This is done for each district and the map on the right is derived. The processing steps shown in panel (a) and (b) are shown here exemplary for the soil moisture index for consistency, but these processing steps are applied to soil moisture fractions.



2.3 Regression analysis

The main aim of this study is the identification of the monthly effects of soil moisture anomalies on crop yield. The model relates silage maize yield deviation (Y) to a stepwise function of soil moisture anomalies (SMI) and polynomials of the meteorological variables (P, T, E). Also, an error term is included which is composed of the fixed effects (c), a time-invariant categorical administrative district identifier, and the observation-specific zero-mean random-error term, which is allowed to vary over time (ϵ). Each monthly model can be written as:

$$\begin{aligned} Y_{ik} = & \sum_{n=1}^{6} \alpha_n \mathrm{I}(SMI_{ikm} \in \mathrm{C_n}) \\ & + \sum_{j=1}^{3} \beta_j (\mathrm{P}_{ikm})^j + \sum_{j=1}^{3} \gamma_j (\mathrm{T}_{ikm})^j + \sum_{j=1}^{3} \delta_j (\mathrm{E}_{ikm})^j \\ & + c_{im} + \epsilon_{ikm}. \end{aligned} \tag{2.2}$$

The index i represents the administrative districts, k the years, and m each month of the growing season, while the superscript j refers to degrees of the polynomials. $\mathrm{I}(\cdot)$ is the indicator function of the soil moisture categories $\mathrm{C_j}$, being 1 if the SMI belong to class n and 0 otherwise. The six classes are defined as severe drought ($\mathrm{SMI} \leq 0.1$), moderate drought ($0.1 < \mathrm{SMI} \leq 0.2$), abnormally dry ($0.2 < \mathrm{SMI} \leq 0.3$), abnormally wet ($0.7 < \mathrm{SMI} \leq 0.8$), abundantly wet

Table 2.2: Comparison of Pearson correlation coefficients of the exogenous variables. Absolute values of the Pearson Correlation Coefficients are employed to calculated the averages presented in the last two columns.

	May	June	July	August	September	October	Average	Avg. June to Aug.
E / T	0.84	0.86	0.92	0.84	0.65	0.4	0.75	0.87
E / P	−0.38	−0.38	−0.52	−0.52	−0.56	−0.15	0.42	0.47
P / T	−0.31	−0.22	−0.54	−0.47	−0.47	−0.06	0.35	0.41
SMI / E	−0.27	−0.28	−0.44	−0.49	−0.46	−0.02	0.33	0.40
SMI / P	0.19	0.31	0.43	0.43	0.5	0.09	0.33	0.39
SMI / T	−0.04	−0.16	−0.35	−0.35	−0.27	0.13	0.22	0.29

($0.8 < \text{SMI} \leq 0.9$) and severely wet ($0.9 < \text{SMI}$), respectively. The estimated coefficients of the model are α, β, γ, and δ and are constrained to be the same for all administrative districts. Time-invariant differences between administrative districts are taken into account by the fixed effects. These consist of the district specific mean values of the individual variables on the right and left hand side of the equation.

The explanatory variables are correlated to each other (Table 2.2). Thus, higher non orthogonal polynomials induce singularity in the moment matrix which cannot be inverted as required by the ordinary least-squares estimation of the coefficient. The polynomials are limited to degree three to avoid this and other detrimental consequences of multicollinearity such as the inflation of the standard errors. Additionally, E and T are treated as mutually exclusive because of the high correlation of E and T (Table 2.2). The coefficients γ or δ are set to 0, accordingly.

In addition to soil moisture, a meteorological and a fixed effect term is included. The fixed effects potentially reduce omitted variable bias, because they take into account the time-variant confounding factors specific to each spatial unit, such as average weather conditions and the water storage capacity of the respective soil. It is also assumed that farmers have optimized the entire production process at their location given their experience about that location. Soil and plant management, such as the choice of varieties, is adapted based on this long term experience. Therefore, the coefficients of the exogenous variables are determined on the basis of year-to-year variations. By restricting the coefficients to be identical in all administrative districts, it is implicitly assumed that the response of plants to inter-annual stressors is the same across all locations. Differences in the sensitivity to exogenous weather and soil moisture fluctuations implied by the use of different silage maize varieties might thus be neglected by the model. If it is also assumed that these interannual fluctuations in weather and soil moisture are not fully taken into account by the farmer in the cultivation decisions, this corresponds to a randomised allocation of the farmer to a treatment group and can therefore be regarded as a natural experiment (Auffhammer and Schlenker, 2014; Schlenker and Roberts, 2009). The outlined interpretation of the coefficients is particularly suitable for SMI, because this index, which describes deviations from the median, is per definition an anomaly.

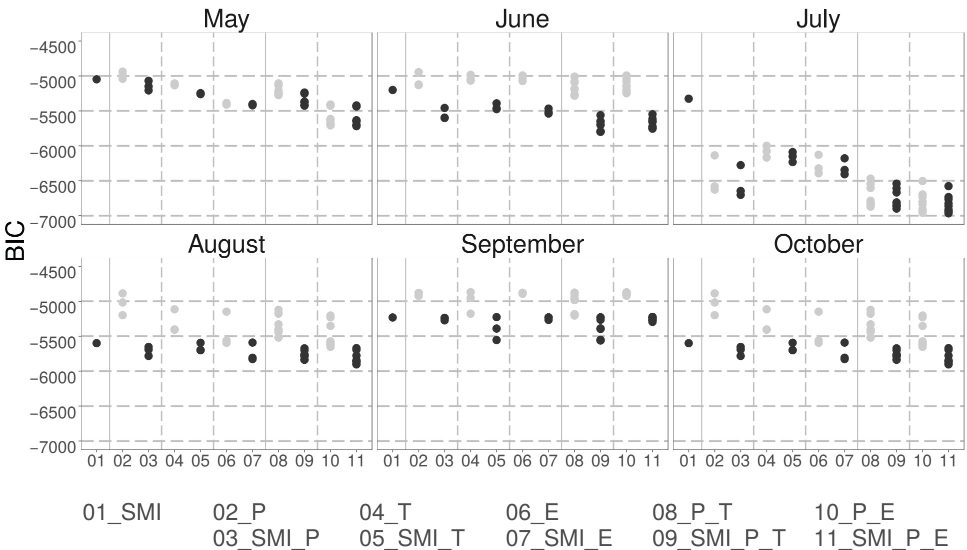
Endogenous variables are not included because these are considered as bad control in frameworks as those defined by Angrist and Pischke (2008). For instance, prices are affected by weather realizations and climate and are thus defined as endogenous (Hsiang et al., 2013; Hsiang, 2016; Gornott and Wechsung, 2015, 2016). Other studies additionally use annual fixed effects and interaction terms of both time and entity specific fixed effects to control for time specific confounding factors (e.g., Moore and Lobell, 2014). These terms are not used in this study because annual variation should be explicitly accounted for by the weather variation of the exogenous variables. Annual fixed effects would diminish the entity specific inter-annual variation of the exogenous variables and thereby potentially amplify measurement errors (Fisher et al., 2012).

Various estimation approaches are used to evaluate the quality of the models. Models can be distinguished by the explanatory variables they use and the degree of polynomials in the meteorological terms. The maximum number of parameters estimated in a model is 12. The Bayesian Information Criteria (BIC) is used for model selection in the next section. The BIC is composed of the maximum of the likelihood function for a particular set of variables as well as a penalty term (Schwarz, 1978). The latter adjusts the model selection criterion for the number of parameters to account for over-fitting. This allows to choose across models with different number of variables. The BIC criterion imposes a higher penalty on over-fitting compared to other model selection criteria based on maximum likelihood such as the Akaike Information Criterion (Akaike, 1973). The penalty particularly affects the soil moisture anomaly term because it always adds six parameters. Overall, the model with the lowest BIC is preferred. To derive the BIC, a generalized linear model is fitted using the *glm* function (R Core Team, 2015).

Additionally, the models are evaluated according to their adjusted coefficient of determination (adj. R^2, Section 2.4.2). Ordinary least squares using the *lm* function (R Core Team, 2015) are employed with a dummy variable for each administrative district to explicitly account for the fixed effects. As default, a demeaning framework (Croissant and Millo, 2008) has been applied to investigate the model performance in terms of R^2. The demeaning framework involves converting the data by subtracting the administrative district average from each variable. The estimated coefficients are the same for the least squares dummy variable regression, a demeaning framework, and maximum likelihood (BIC). This is in accordance to theory that normal distributed error terms estimators based on maximum likelihood and least squares are the same.

The standard errors of the coefficients are corrected for spatial autocorrelation. For this purpose, the Robust Covariance Matrix Estimator proposed by Driscoll and Kraay (1998) is employed to construct standard errors based on asymptotic formulas. No weights capturing decaying effects in space are used because the administrative districts have different areas and the spatial extent of SMI occurrences is heterogeneous. This can be regarded as comparable to block-bootstrapping on country-level, which has been used in many comparable studies relying on re-sampling methods (e.g. Butler and Huybers, 2015; Moore and Lobell, 2014, 2015; Urban et al., 2015a,b). Further, serial correlation and heteroskedasdicity is also controlled for (White, 1980; Arellano, 1987). Overall, this approach is rather conservative but in alignment with the proposal of Angrist and Pischke (2008) to take the largest robust standard error as measure of precision.

Figure 2.2: Each panel shows the BIC distribution of one month. Within the panels various models are compared, whilst the lowest marker is preferred. Each column represents a particular selection of variables. The markers represent different degrees of the polynomials in the meteorological term. The gray markers denote those models that neglect the SMI, whilst the black include it.



2.4 Results and discussion

2.4.1 Qualitative evaluation of different model configurations within the growing season

In this section, the Bayesian Information Criterion (BIC) is applied to evaluate the best combination with respect to soil moisture, meteorological variables, and the polynomial degrees of the latter. The BIC is calculated separately for each month to assess the intra-seasonal variability.

The distribution of the BIC for the various model configurations is presented in Fig. 2.2, which shows one panel for each month of the growing season. Within the panels, models with different variable combinations in the meteorological term are separated by vertical lines. A model configuration is defined by a set of meteorological variables, the polynomial degree of each variable, and the stepwise function of the soil moisture anomalies. The complexity of the configurations increase stepwise from the left to right within each panel. The model employing SMI as single explanatory variable is represented by a point on the left in each panel. The black markers indicate the models with soil moisture and gray markers without. The models 02 - 07 employ one meteorological variable each. These have three markers for the different degrees of the polynomials. The models 08 - 11 entail two meteorological variables and thus have nine markers.

The explanatory power is different across the months as indicated by the lowest marker within each panel. Overall, July has the highest explanatory power. Nonlinear meteorological terms improve the fit of the model on the data in all model configurations (not shown). The preferred polynomial in the meteorological term is of degree three. The only exception is June, where the best model employs a second degree polynomial for P. These observations are consistent with agronomic studies. Curvilinear relationships between maize yield and meteorological variables are already investigated in previous research. The rationale behind this is that optimal conditions exist for certain growth stages and deviations from them are detrimental. For example, Thompson (1969) found for corn in the U.S. Corn Belt that precipitation in July above and temperature in August below the monthly average is desirable. Nonlinear configurations have been neglected so far in comparable approaches employing constant elasticity models in Germany (Gornott and Wechsung, 2015, 2016; Conradt et al., 2016).

The composition of the meteorological term is evaluated by comparing the gray markers in Fig. 2.2. It is possible to asses the impact on the model fit of the single variables P, T, and E by the comparison of the configurations 02, 04, and 06, respectively. In May, most of yield variation is explained by E. In June and July, P contributes to model fit the most. In July, for instance, the explanatory power of a nonlinear P term is almost as good as the best combined configuration. September and October are determined by T. However, in most months, using more than one meteorological variable results in the highest explanatory power. The only exception is October, where model 05 (SMI & T) exhibits the lowest BIC.

The difference in BIC between configuration 08 (P & T) and 10 (P & E) is small from June to August. This result can be expected because T and E are highly correlated in our sample (Table 2.2). The models with mixed meteorological terms in July and August slightly prefer E, while in June it is T. In the other months, the difference between T and E is comparatively larger. In May, E is preferred, and in September and October T is the better measure. Both measures, T and E, account for similar determinants of silage maize growth. The latter, however, is more complex because it contains information on sub-daily radiation additionally to daily temperature (Hargreaves and Samani, 1985). It can be assumed that this additional information are averaged out using monthly values and monthly temperature becomes a close estimate of monthly E. This is in alignment with results on different time resolutions, which indicate that measures of evapotranspirative demand are highly correlated with temperature extremes (Roberts et al., 2013; Lobell et al., 2013). Therefore, it is sufficient to account for temperature when simultaneously controlling for water supply (P, SMI) because it is easier to measure temperature data and there is a smaller chance of attenuation bias.

The extent of the model improvement by adding soil moisture anomalies varies across the months. This can be evaluated by comparing the gray and black markers in Fig. 2.2. Including soil moisture anomalies only improves model fit to a little extent in May and July. In all the other months, large improvement can be made when additionally controlling for soil moisture. In the second half of the season, i.e. August and September, the models using only SMI have a similar or even lower BIC compared to all meteorology-only models.

These results indicate that soil moisture builds memory over the season that adds relevant information, which are not integrated in the monthly meteorological variables. There are several reasons for this postulation remark. First, the seasonality of soil moisture must be considered. The fraction of the saturated soil changes over time and thus the base value for the index. For Germany, this seasonality is depicted in Fig. 4 in Samaniego et al. (2013). In March, soil water content is the highest while soils are usually driest in August and September. This also implies, that an agricultural drought has a lower absolute soil moisture in August and September compared to the preceding months. Second, the anomalies in the later months integrate information about the water balance in the preceding months because of the persistent character of soil moisture (evident from the autocorrelation of the soil moisture indexes). For instance, extreme dry conditions during flowering and grain filling are reflected in a dry soil moisture anomaly in the second half of the agricultural season of silage maize. The observation, that the SMI represents additional information to the meteorology is also pronounced by the fact that the pairwise correlations including SMI are lower compared to any other combination of the exogenous variables (Table 2.2). Further, dry anomalies in the late part of the season may indicate a long lasting water shortage condition, as soil moisture drought lasts over several month or potentially even years (Sheffield and Wood, 2011; Samaniego et al., 2013; Zink et al., 2016).

Similar results may be achieved by cumulated measures of the meteorology or the climatic water balance. However, the comparison of soil moisture measurements and different cumulates of precipitation (one to six months) shows that it would be necessary to consider different precipitation accumulations for different sites in order to include the same information as for soil moisture (not shown). For example, Southern Germany exhibits higher water retaining capacities and also higher correlation with three month precipitation as compared to Eastern Germany. Further, a substantial share of the variability of soil moisture is not explained by precipitation (the mean coefficient of determination is at most 50 %). One advantage of using soil moisture in such a study is that the coefficients can be restricted to be the same at all locations, whilst assuming that the water retaining capacity is not the same everywhere.

In summary, soil moisture anomalies improve the model fit in all model configurations. This is the case even though soil moisture is strongly affected by the penalty for additional parameters within the BIC. Further, the evidence of nonlinear effects in the meteorological terms is confirmed. The results also indicate that there is substantial seasonal variability in the impact of exogenous variables. This is investigated further quantitatively in the next sections for the meteorological variables and soil moisture.

2.4.2 Quantitative assessment: Coefficient of determination for models using different explanatory variables

In this and the next section (2.4.3), we present the quantitative results for the "full" model with polynomials of degree three of the variables temperature (T) and precipitation (P) in the mete-

Table 2.3: Comparison of the adjusted coefficient of determination R^2. The results from the demeaning framework serve as reference to the ones obtained by Least Square Dummy Variable Regression (LSDV). The latter explicitly accounts for the fixed effects. Additionally model configurations without either T, P, or SMI are shown.

	May	June	July	August	September	October	Average	June - August
(a) Adjusted R^2 demeaning	0.11	0.16	0.31	0.17	0.13	0.12	0.16	0.21
(b1) Adjusted R^2 LSDV	0.56	0.59	0.66	0.59	0.57	0.56	0.59	0.61
(b2) ((b1) − (a)) / (a) in %	409.1	268.8	112.9	247.1	338.5	366.7	290.5	209.6
(c1) Adjusted R^2 no T	0.07	0.13	0.28	0.16	0.08	0.08	0.13	0.19
(c2) ((c1) − (a)) / (a) in %	−36.4	−18.8	−9.7	−5.9	−38.5	−33.3	−23.7	−11.4
(d1) Adjusted R^2 no P	0.08	0.11	0.22	0.14	0.12	0.12	0.13	0.16
(d2) ((d1) − (a)) / (a) in %	−27.3	−31.3	−29.0	−17.6	−7.7	0.0	−18.8	−26.0
(e1) Adjusted R^2 no SMI	0.07	0.08	0.30	0.11	0.06	0.07	0.11	0.16
(e2) ((e1) − (a)) / (a) in %	−36.4	−50.0	−3.2	−35.3	−53.8	−41.7	−36.7	−29.5

orological term and additionally the soil moisture anomalies (SMI). Using the same model configuration for each month allows the comparison of partial effects and ensures that the source of variation is the same within the meteorological term (Auffhammer and Schlenker, 2014). In this section, the coefficient of determination is employed to evaluate the share of the sample variation only explained by the exogenous variables. Additionally, it is used to assess the in-sample goodness of fit of the models 03 (SMI & P), 05 (SMI & T), 08 (P & T), and 09 (SMI & P & T), each using polynomials of degree three.

The coefficients of determination for two model settings are evaluated to show the ability of exogenous explanatory variables, e.g. the meteorological term and the soil moisture anomalies, to improve the in-sample goodness of fit of the full model: first, the model that only accounts for the variation in the exogenous explanatory variables, which is derived by the demeaning framework (row (a) in Table 2.3); second, the least squared dummy variable model that accounts for both the variation in the exogenous explanatory variables and the administrative district specific average yield (row (b1) in Table 2.3). The ratio of the coefficient of determination derived by these two model setups is investigated (row (b2) in Table 2.3) to quantify the share of variance explained only by the exogenous explanatory variables, e.g. the meteorological term and soil moisture anomalies. Expectedly, the exogenous variation in weather and soil moisture improves the model fit in all months, but the level of improvement varies. The month which gains the least in explanatory power when additionally accounting for the share of variation explained by the average crop yield of each administrative district is July (+ 112.9 %). This suggests that a large part of the yield variation is explained only by exogenous explanatory variables. The month with the greatest variation, which is explained only by the average yield of the districts, is May. During this month, 409.1 % of the explanatory power is added if the average yield of each county is explicitly taken into account in comparison to the models that only use soil moisture and weather variation as explanatory variables (line (b2) in table 2.3).

The adjusted R^2 presented in this study explicitly including fixed effects for each month of the period June (0.59), July (0.66), and August (0.59) is comparable to related approaches. Urban et al. (2015b), who employed a comparable period to estimate their results, reported R^2 of 0.65 and 0.67 for a model that successfully accounts for the interaction between heat and moisture for a 61 - 90 day period following sowing for Iowa, Illinois, and Indiana. Their study additionally employed time fixed effects which usually lead to higher R^2. The seminal approach employing extreme degree days (EDD, Schlenker and Roberts, 2009) reported R^2 between 0.77 and 0.78. In their sample, a comparatively large share of the variation was explained by the fixed effects and trend, which exhibited an R^2 of 0.66. A study using updated data of Schlenker and Roberts (2009) and controlling for evaporative demand in July and August achieved adjusted R^2 between 0.66 and 0.72 (Roberts et al., 2013).

In the previous section, all the models have been evaluated with respect to the BIC criterion which penalizes over-fitting. The focus here is on reducing the sample bias of the model. The in-sample adjusted R^2 of the models is additionally compared when either one of the variables SMI, P, or T is not considered (rows (c1) - (e1) in Table 2.1). The according relative change in model fit when one variable is removed from the full model can be found in rows (c2) - (e2) of Table 2.3. In all months but May and July, the strongest loss in in-sample goodness of fit is seen for removing soil moisture (for instance - 50.0 % in June and - 35.3 % in August). In July, which is the month with the highest overall in-sample-goodness of fit, the largest effects is accounted for by precipitation (- 29.0 %). The average relative model loss is largest for soil moisture for the entire season (-36.7 %) as well as the period June to August (-29.5 %). As observed in the section before, the effect of each particular variable is dependent on the month. For instance, the largest relative loss in adjusted R^2 for SMI is estimated in June (- 50.0 %) and September (- 53.8 %). The largest effect of precipitation is observed in June (- 31.3 %) and July (- 29.0 %). Temperature is relevant the most in September (- 38.5 %) and May (- 36.4 %).

To summarize, the in-sample explanatory power of the full models are comparable to those reported in the previous literature. The largest average gain in goodness of fit is achieved by including SMI. In July, the month with the largest in-sample goodness of fit, most of the variation in yield is explained by precipitation. This section has only presented a quantitative analysis of the explanatory power in terms of adjusted R^2. A detailed assessment of the partial functional form of individual explanatory variables is presented in the next section to better understand their ceteris paribus impact on the crop yield.

2.4.3 Quantitative assessment: Partial effects of the meteorological variables

A better understanding of the relationship between individual explanatory variables allows to design effective adaptation measures. The partial functions of the meteorological covariates are presented in the next two sections and those of soil moisture in section 2.4.3.3. Those functional forms, which are significant at least in the first or second order, are presented for individual months in Fig. 2.3. The range of the meteorological variables is depicted from - 2 to + 2 standard deviations (SD). It can be assumed that larger deviations from the mean are related to higher

Table 2.4: Results of Regression Models employing precipitation and temperature to account for meteorology (both with polynomials of degree 3, superscripts denote the degree of individual polynomials) and a stepwise function of SMI.

	Dependent Variable: log(Silage Maize)					
	Model of the month					
	May	June	July	August	September	October
Precipitation^1	0.004	0.036^{***}	0.039^{***}	−0.014	−0.011	−0.003
	(0.011)	(0.014)	(0.013)	(0.011)	(0.013)	(0.010)
Precipitation^2	-0.023^{*}	-0.014^{*}	-0.023^{***}	-0.019^{***}	−0.005	0.002
	(0.014)	(0.007)	(0.004)	(0.006)	(0.005)	(0.008)
Precipitation^3	0.004	0.001	0.005^{***}	0.004^{***}	0.002	−0.0001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Temperature^1	0.024	−0.006	-0.036^{*}	−0.003	0.038	−0.002
	(0.021)	(0.015)	(0.021)	(0.014)	(0.024)	(0.018)
Temperature^2	−0.005	−0.006	-0.007^{***}	-0.008^{**}	-0.009^{*}	-0.016^{**}
	(0.007)	(0.006)	(0.002)	(0.003)	(0.005)	(0.008)
Temperature^3	0.0004	−0.002	0.004^{*}	−0.002	-0.013^{*}	0.005
	(0.003)	(0.003)	(0.003)	(0.002)	(0.006)	(0.003)
SMI: severe drought	0.068^{***}	0.024	-0.044^{**}	-0.110^{***}	-0.126^{***}	-0.149^{***}
	(0.012)	(0.020)	(0.019)	(0.035)	(0.028)	(0.037)
SMI: moderate drought	0.044^{***}	0.016	−0.007	-0.055^{***}	-0.041^{*}	−0.024
	(0.011)	(0.017)	(0.011)	(0.017)	(0.023)	(0.030)
SMI: abnormal dry	0.011	0.023^{***}	−0.005	-0.024^{**}	−0.017	−0.005
	(0.011)	(0.007)	(0.007)	(0.011)	(0.015)	(0.017)
SMI: abnormal wet	−0.007	-0.034^{***}	−0.011	0.026^{***}	0.007	−0.006
	(0.014)	(0.011)	(0.007)	(0.008)	(0.011)	(0.019)
SMI: abundant wet	−0.014	-0.052^{**}	−0.004	0.027^{***}	0.012	−0.001
	(0.020)	(0.025)	(0.009)	(0.008)	(0.017)	(0.015)
SMI: severe wet	−0.009	-0.202^{***}	-0.041^{***}	0.037^{***}	0.030	0.025
	(0.019)	(0.047)	(0.016)	(0.013)	(0.027)	(0.017)
Observations	5,376	5,376	5,376	5,376	5,376	5,376
R^2	0.113	0.173	0.326	0.179	0.136	0.129
Adjusted R^2	0.105	0.162	0.305	0.168	0.127	0.121
F Statistic	53.151^{***}	87.531^{***}	203.025^{***}	91.409^{***}	65.891^{***}	62.296^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01	

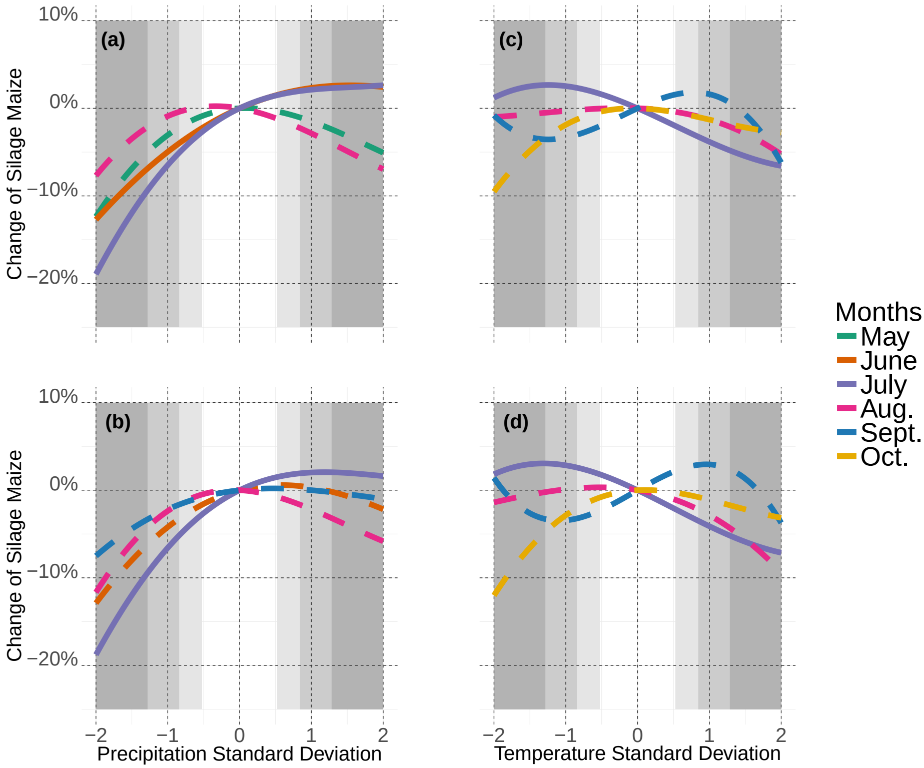
uncertainties in the estimated crop yield. A table with the estimated coefficients and standard errors of all models can be found in Table 2.4.

2.4.3.1 Partial effects of precipitation

The partial precipitation effects for the months May to August are shown in Panel a) of Fig. 2.3[1]. Given constant soil moisture and temperature effects, negative precipitation anomalies are associ-

[1]The partial dose-response functions of the meteorological variables are depicted for the range between - 2 and + 2 standard deviations (SD). The upper row represents those models considering SMI, whilst the lower row neglects SMI. A solid line is used for those variables which are significant in both the first and second degree polynomials. A dashed line is employed if only one of the first two polynomials is significant. The vertical axis represents the change in silage maize converted into % approximated by the formula $100(\exp(\sum_{j=1}^{3} \beta_j (\mathrm{x_{ikm}})^j) - 1)$, where x_{ikm} is either precipitation or temperature. Under the assumption that the variables are normally distributed, the range depicted accounts for about 95 % of the observations. The dark gray areas denote the interval between the 0.023 % (- 2 SD) and the 10 % as well as the 90 % and 97.7 % (+ 2 SD) quantile. Similar, in medium gray the range between either the 10 % and the 20 % and the 80 % and 90 % quantiles is marked. The light gray quantifies the impact between the between either the 20 % and the 30 % and the 70 % and 80 % quantiles.

Figure 2.3: Partial dose-response functions of the meteorological variables.



ated with reduced yield in these months. The largest effect is observed for June (- 5 % at - 1 SD) and July (- 6.5 % at - 1 SD). These are the overall most significant months, but with different patterns compared to the remaining two. In June and July, more than average precipitation is associated with comparatively higher yield (at 1 SD: + 2.2 % in June and + 2.1 % in July), whilst the opposite is the case for May and August.

The results indicate the importance of sufficient water supply provided to plants by precipitation, especially in June and July. In Germany, the begin of flowering is usually in July and extends into August (based on data provided by the German Weather Service - Deutscher Wetterdienst, 2019). Maize plants are susceptible to water stress during this growing phase (Barnabás et al., 2008; Fageria et al., 2006; Grant et al., 1989; Bolaños and Edmeades, 1996). Despite the necessity to control for intra-seasonal variability of precipitation effects, explicitly controlling for this sensitive phase is not very common in recent reduced form studies (Carleton and Hsiang, 2016). Notable exceptions are Lobell et al. (2011a), who used precipitation centered around flowering (anthesis) in statistical models based on historical data of trials in Africa, and Ortiz-Bobea and Just (2013), who controlled for the vegetative, flowering, and grain-filling stages. Instead, many approaches employ total precipitation over the growing season (Annan and Schlenker, 2015; Burke and Emerick, 2016; Roberts et al., 2013; Schlenker and Roberts, 2006, 2009), monthly mean growing season precipitation (Urban et al., 2012) or the average of a subset of the season (Urban et al., 2015a). Studies for Germany commonly separate the season into the periods May to July and August to October (Gornott and Wechsung, 2015, 2016; Conradt et al., 2016), thus dividing exactly the time interval most susceptible to water stress and averaging over periods with diverse effects (e.g. May and June in Fig. 2.3a). This may hide water related effects. Other studies neglect precipitation entirely and only rely on temperature measures (Butler and Huybers, 2013, 2015; Schlenker et al., 2013). According to their results, the explanatory power is not improved when adding precipitation. This is contradictory to our observations that precipitation is particularly relevant (see also Section 2.4.1 & 2.4.2).

The models employed here do not explicitly account for interactions between the meteorological and the soil moisture terms. Nevertheless, soil moisture is a function of the meteorological variables and all effects are correlated to each other (see Table 2.2). The overall pattern in the effects of the meteorological variables only changes to a small extent when estimating the standard model configuration without the term for soil moisture anomalies (Fig. 2.3b). One of the most pronounced differences is that the positive effect of precipitation in June diminishes when not accounting for soil moisture. The coefficients in June are also less significant. The effects in September become significant in the second and third polynomial degree when not considering SMI (blue dashed line in Fig. 2.3b). On the contrary, May is less significant and thus not included in this panel. SMI improves the model fit but only slightly affects the functional form of precipitation, which highlights that soil moisture adds relevant but different information as those entailed in precipitation. The next section presents an analogue analysis for temperature.

2.4.3.2 Partial effects of temperature

The significant partial temperature effects are depicted in Fig. 2.3c. A significant effect in all polynomials is only estimated for July, whilst in May and June, no significant coefficients can be found at all. In all months but September, higher than average temperatures are associated with reduced crop yield. The extent of the effects, however, varies over time. In July, less than average temperature is associated with above-normal crop yield. The estimated function peaks at - 1.24 SD, which is 16.18 °C (mean in July is 18.34 °C). Additional 2.66 % crop yield can be expected at this temperature, all other variables hold constant. In August, elevated temperatures are associated with negative effects. September exhibits a large but not significant linear effect, whilst the second and third polynomials are significant. Because maize is maturing during this time, higher temperatures up to a threshold are favorable as shown in Fig. 2.3c. Crop yield is reduced beyond this threshold, which might be related to heat waves. Cold temperatures have a negative effect in October, which is the strongest one observed. Harvesting commonly begins at the end of September within the period from 1999 to 2015 (Deutscher Wetterdienst, 2019). Thus, low temperatures may be related to early harvesting and result in lower yield.

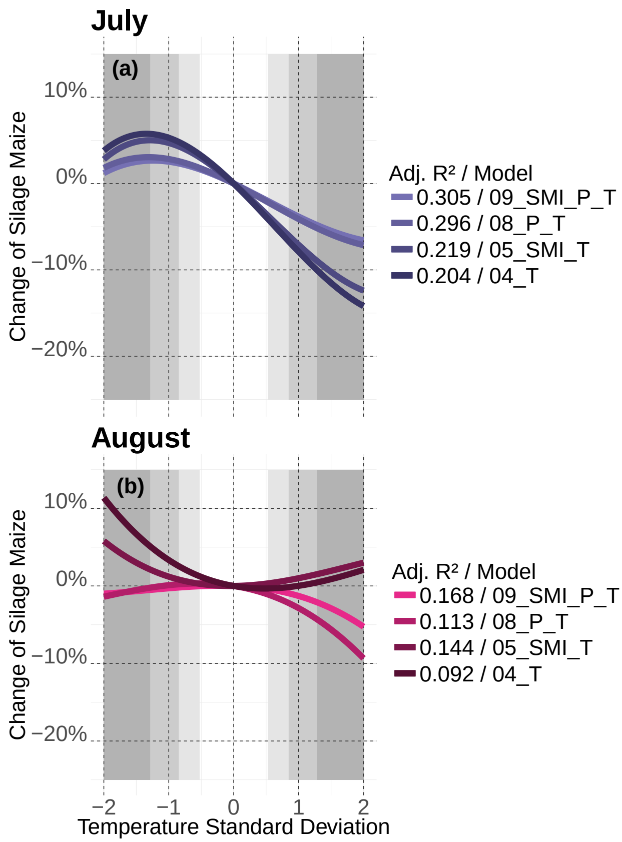
When comparing the effects of precipitation and temperature in the months most relevant for meteorology, i.e. June and July, those of precipitation clearly outweigh temperature. The largest effects can be found for negative anomalies of precipitation in July (compare Fig. 2.3a and Fig. 2.3c). The limited effect of temperature is in alignment with agricultural literature, which states that maize is tolerant to heat as long as enough water is provided (FAO, 2019). This is also the case in our study area given the fact that Germany lies in a rather temperate and marine climate zone. Additionally, sufficient provision of water is associated with prolonged grain filling and hence diminished heat sensitivity (Butler and Huybers, 2015). Recent literature often neglected precipitation and emphasized mostly extreme temperature instead (Carleton and Hsiang, 2016; Lobell and Burke, 2008; Lobell et al., 2011b; Schlenker et al., 2005; Schlenker and Lobell, 2010), which may have led to biased assessments.

The general functional form of temperature are hardly affected by neglecting SMI (Fig. 2.3d). For example, crop yield changes from one - 3.82 % with SMI to - 4.11 % without for one SD of elevated temperature in July. These effects are smaller than those seen for precipitation, which highlights again that soil moisture provides an information that is independent to the one provided by T.

As mentioned before, a substantial amount of studies employed temperature as the major explanatory variable neglecting knowledge about plant physiology and plant growth (Wahid et al., 2007; FAO, 2019). The functional form of the partial temperature effects derived from different model configurations for July and August is presented in Fig. 2.4 to evaluate the magnitude of bias between the full model (presented in Fig. 2.3) and a temperature-only model.

In both months, the in-sample explanatory power is reduced compared to the full model when only using temperature as explanatory variables. In July, the model fit is - 34.2 % lower when employing the temperature only model compared to the full model, while it is - 45.9 % in August (Fig. 2.4). In July, the in-sample goodness of fit is affected stronger by removing precipitation (- 29.0 %) than by doing so for SMI (- 3.2 %), (Table 2.3). This is not surprising because the partial effect of precipitation in July is largest, whilst soil moisture anomalies only show negligible effect. On the contrary, considering SMI in August (- 35.3 %) exceeds the losses in Adjusted R^2 compared to a model without precipitation (- 17.6 %), (Table 2.3). In July, the functional form stays qualitatively the same across all model configurations (Fig. 2.4a). The magnitude of the effects is, however, larger when precipitation is not considered. In August, the temperature effect is elevated by not considering SMI. Taking out precipitation reverses the effects found for the full models. This observation clearly demonstrates that adequate control of water supply is necessary to derive non-biased estimates of partial temperature effects. These results also indicate that the biases seen for different model configuration depend on the month considered. Overall, a model using only temperature as explanatory variable has larger partial effects and potentially even different ones with regard to the direction compared to those of the full model. In the next section, the partial effects of the soil moisture index are investigated.

Figure 2.4: Sensitivity of the functional form of temperature partial effects for various controls for water supply.

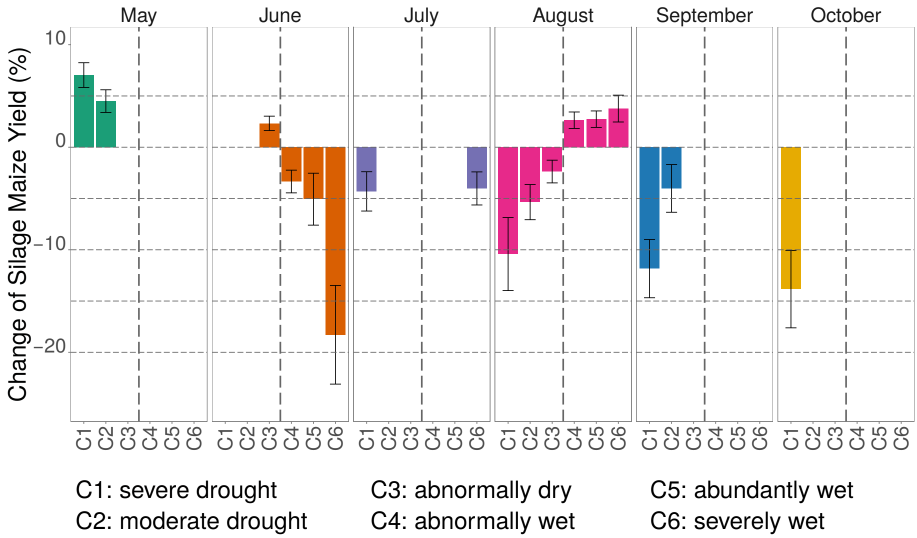


2.4.3.3 Partial effects of the soil moisture index (SMI)

Similar to the meteorological terms, the susceptibility to SMI changes over the months (Fig. 2.5). In particular, a change in the general patterns can be observed. In May and June, dry conditions are associated with positive yield (up to + 7 % in May, and + 2.3 % in June), whilst wet conditions are harmful (up to - 18.3 % under severely wet conditions in June). In July, both extremes have negative impacts of around - 4 %. In all of the following months, dry conditions are associated with reduced crop yield (up to - 10.4 % in August, - 11.8 % in September, and - 13.8 % in October), whilst only extreme wet conditions in August are positive for annual silage maize yield (up to + 3.77 %). These deviations are as high as the ones observed for the meteorological variables (Fig. 2.3).

For the interpretation of the results, the climatology of mean soil water content needs to be taken into account. The SMI of each month refers to different fractions of absolute water sat-

Figure 2.5: Percentage change of silage maize yield caused by significant soil moisture anomalies for each month. The vertical axis represents the change in silage maize converted into % approximated by the formula $100(\exp(\sum_{j=1}^{6}\alpha_j \mathrm{I}(\mathrm{SMI}_{ikm} \in \mathrm{C_j}) - 1)$, where C_j are the soil moisture classes. The standard errors are indicated by the black error bars.



uration in the soil. This seasonality is depicted in Fig. 4 in Samaniego et al. (2013) for different locations in Germany. In general, the optimal water content for plant development is defined by 60 % to 80 % of the available field capacity, whilst less than 40 % field capacity, as for instance in the year 2003, is associated with depression in crop yield (Chmielewski, 2011). In May and June, dry anomalies represent soil moisture fractions above critical water content because the soil has been replenished with water in preceding winter and spring. For silage maize, however, rather dry conditions are preferable during this time because high soil moisture saturation can induce luxury consumption and thus reduced root depths (FAO, 2019). This is particularly relevant for maize due to its capability to develop deep roots (FAO, 2019). This feature allows the plants to access deep soil water under dry conditions during the sensitive phase of flowering and grain filling. Empirical studies indicated that early wet conditions slow down the spreading of seeds and young plants can be damaged through indirect effects, such as fungus (Urban et al., 2015a). A detailed analysis indicates that the large effect of severely wet conditions in June can be partly associated to the 2013 flood in Germany (not shown), which exhibited wet soils in large parts of the country. Starting in July, the level of soil water content decreases (see Fig. 4 in Samaniego et al., 2013). As a consequence, dry anomalies represent damaging conditions because plant available soil water starts to be too low to provide enough water during the most susceptible phase. These effects are increasing over the subsequent months because of the seasonality, the particular growing stage, and the persistence of soil moisture. Lower levels in absolute soil water also explain why wet anomalies have a positive impact in August, but not in July. July exhibits the highest evapotranspiration among all months. This leads to a highly dynamic soil moisture in July which is characterized by a transition from a wet regime to a dry regime. Thus, small deviations from average soil moisture in this month have no significant effect on yield (Fig. 2.5). These are only observed for the very extreme conditions.

Additionally, the growing stage modifies the impact of soil moisture coefficients. In our sample, flowering commonly begins between mid- and end-July and milk ripening occurs in the second half of August (based on own calculation from data provided by Deutscher Wetterdienst, 2019). Plants exhibit an increased susceptibility to insufficient water supply during these development stages. As shown in section 2..3, July has the highest partial effect with respect to meteorological variables. In August, soil moisture anomalies show a significantly higher impact on annual silage maize yield than in July. Due its seasonality, absolute soil moisture values are in general lower in August than in July. Further, soil moisture in August integrates temperature and precipitation effects of the preceding months. Thus, dry soil moisture anomalies show harmful effects, while wet ones are beneficial. In September and October, soil moisture usually starts to refill (see Fig. 4 in Samaniego et al., 2013). Maize is in the less susceptible phase to dryness of ripening in September and harvesting usually starts in the second half of this month (Deutscher Wetterdienst, 2019). This implies, that severe drought anomalies in September and October might be associated with extended periods of water stress over the sensitive growing stages in the months before.

In this section, it was shown that the seasonality of soil moisture underlying the soil moisture index needs to be considered to disentangled its temporal effects on silage maize yield. Thus, it is necessary to consider seasonality in soil moisture content and silage maize growth when assessing effects caused by soil moisture anomalies.

2.5 Conclusions

In this study, the intra-seasonal effects of soil moisture on silage maize yield in Germany are investigated. It is also evaluated how approaches considering soil moisture perform compared to meteorology-only ones. A demeaned reduced form panel approach is applied, which employs polynomials of degree three for variables of average temperature, potential evapotranspiration, precipitation, and a step wise function for soil moisture anomalies to capture nonlinearities. Potential evapotranspiration and average temperature are mutually exclusive. The model selection is based on the Bayesian Information Criterion (BIC) and the adjusted coefficient of determination (R^2).

This study provides a proof of concept, that a) soil moisture improves the capability of models to predict silage maize yield compared to meteorology-only approaches and that b) temporal patterns in the seasonal effects of the explanatory variables matter. It is shown that soil moisture anomalies improve the model fit in all model configurations according to both the BIC and R^2. SMI entails the highest explanatory power in all months but May (most explained by T) and July (most explained by P). This highlights that soil moisture adds different information than meteorological variables. All time invariant variables show seasonal patterns in accordance to each particular growing stage of silage maize. Furthermore, the dynamic patterns of the SMI effects originate from the seasonality in absolute soil moisture. Those results support the supposition that it is necessary to control for intra-seasonal variability in both the index for soil moisture and meteorology to derive valid impact assessments. Also, the comparison of various meteorological effects based on BIC showed that potential evapotranspiration adds no explanatory power compared to average temperature. Further, partial effects of precipitation outweigh those of temperature when controlling for intra-seasonal variability.

The temporal resolution for the meteorological and soil moisture data is months. This might be too low to accurately resolve the stage of plant growth. Future improvements will involve the use of daily data from high resolution remote sensing campaigns which would allow to determine growing seasons more accurately.

Our results have further implications for climate change impact assessment. First, it is shown that soil moisture can improve agricultural damage assessment and enrich the climate adaptation discourse in this realm, which is mostly based on temperature measures as major explanatory variable (Carleton and Hsiang, 2016). We recommend to control for at least those seasonal dependent pathways that affect plant growth presented in our study. Measures of soil moisture should be considered to derive evidence about climate impacts and adaptation possibilities. This particularly concerns climate econometrics, where frequently used reduced form approaches and dose-response functions should also control for soil moisture. For example, Butler and Huybers (2013) derived from a dose-response function only relying on temperature measures that the sensitivity to extreme degree days is lower in southern rather than northern U.S. counties. Based on these estimates they concluded that the south is better adapted to hot condition compared to the north. Transferring those adaptation potential to future impacts diminishes the estimated losses. However, various issues need to be considered when employing such an approach, such as the costs of adaptation and wrong institutional incentives (Schlenker et al., 2013; Annan and Schlenker, 2015). Also, Schlenker et al. (2013) argued that higher average humidity levels in the south diminish the correlation between heat and measures based on evapotranspirative demand. Accordingly, it is recommended to directly control for evapotranspirative demand by vapour pressure deficit (VPD). As shown in section 2.4.1, no superior effect of potential evapotranspiration over temperature was found when controlling for either precipitation or both precipitation and SMI. Potential evapotranspiration and VPD both account for the water demand of the atmosphere. Instead, the results of this study show that controlling for water supply by measures of either soil moisture and precipitation avoids biased effects in a humid climate. This study further indicates, that it is necessary to account for the seasonal dynamics in both the meteorological and soil moisture effects that constitute the variation in crop yield to employ spatial adaptation as surrogate for future adaptation.

Second, the definition of an index as anomaly has general implications for climate econometrics. Such an index is less prone to systematic errors (Lobell, 2013; Gornott and Wechsung, 2015, 2016), because any bias associated to the spatial processing and the meteorological or climatological modeling is minimized (Auffhammer et al., 2013; Conradt et al., 2016; Lobell, 2013). Also, the persistence in soil moisture and the resulting smoother distribution in comparison to the meteorological variables might deliver more reliable estimates than climate assessment based on meteorological variables because climate simulations only show robust trends at coarse temporal resolutions (Gornott and Wechsung, 2015). An index can also be interpreted as inter-annual variability beyond the demeaning framework. Any linear model employing a categorical variable for each spatial unit is equivalent to joint demeaning of both the dependent and the independent variables and thus the source of variation is the deviation from the mean. For instance, anomalies are used within the adaptation discourse to derive implications for short-term measures (Moore and Lobell, 2014). Again, in such a setting soil moisture can serve as more comprehensive measure than the commonly used temperature.

Finally, this study has also several implications for the design of adaptation measures on weather realizations to reduce current welfare losses of climate events (UNISDR, 2015; Kunreuther et al., 2009). First, indexes derived from soil moisture can be used in risk transfer mechanism. For instance, insurance schemes based on a particular weather indexes can be enhanced in both developed and developing countries (Agriculture Risk Management Team, 2011). Second, the detrimental effects of wet soil moisture anomalies might allow to extent the risk portfolio of multi-peril crop insurance and thus foster the advancement and implementation of those schemes in Germany (Keller, 2010). Third, the installation of agricultural infrastructure should be investigated because negative effects of soil moisture anomalies can be mitigated by irrigation and drainage. In 2010, only 2,34 % of the agricultural area used for silage maize is irrigated (own calculation from data provided by Statistisches Bundesamt (Destatis) (2011)) and the latest numbers about drainage systems in Germany date back to 1993 (ICID, 2015).

Overall, an index of soil moisture considering intra-seasonal variability has relevant implications for current and future damage assessment and adaptation evaluation, which are supposed to gain importance in the course of climate change.

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Chapter 3

Climate impacts on long-term silage maize yield in Germany

3.1 Introduction

There is growing evidence that all areas of daily life will be affected by climate change and that, in addition to existing initiatives for climate change prevention, adaptation measures are becoming increasingly necessary. One of the sectors exposed to the greatest risk of climate change is agriculture, as changes in meteorology and trace gas concentrations have direct impacts on crop yields and agricultural ecosystems (Gömann et al., 2017). While higher CO_2 concentrations, higher average temperatures and longer growing seasons can have positive effects on crop yields, drought, heat stress, heavy rainfall and high ozone concentrations can reduce these yields (Gömann et al., 2017). A higher variability of individual weather events is expected (Gömann et al., 2017) because climate change not only increases temperature but also changes in precipitation patterns in space and time (Jacob et al., 2017). Data from this study show that the time under drought conditions in Germany will increase by approximately 50% with a global warming of 3 °C. This variability is particularly relevant for agricultural production, as the sensitivity of plant growth to meteorological variations is time-dependent (Peichl et al., 2018). In this study, the impact of climate change on rainfed silage maize in Germany is examined, which is becoming increasingly important in the wake of the German *Energiewende* (energy transition) due to the increased demand for biomass.

It is necessary to know the impacts of climate change and what is causing these to provide sound recommendations for action. Within this context, there are two research communities that employ different tools to estimate crop yield, namely, process-based and statistical models. An explanation for the occurring differences in the results of the approaches are, among others, the factors used in the individual modelling approaches (Ciscar et al., 2018). In this context, a particular problem with statistical models is proneness to collinearity. Apparently causal associations of weather determinants with yield variations can obscure underlying physiological mechanisms

(Roberts et al., 2017). For example, the influence of heat on crop yields has not been fully clarified. This topic is important because the measure of extreme temperature over the entire growing season is often used as the main determinant of yield variation in statistical approaches while neglecting proper control for water supply. Accounting for plant water availability in a statistical approach leads to a reduced temperature sensitivity for silage maize yields in Germany (Peichl et al., 2018). A recent study (Ciscar et al., 2018) concluded that harnessing the best features of both approaches can improve predictive power. Sub-seasonal patterns of precipitation, vapor pressure deficit, and solar radiation are implemented in process-based models but are often simplified or neglected in statistical approaches (Roberts et al., 2017). It is likely that aggregated measures of water supply commonly used in statistical models, such as precipitation averaged over the entire growing season, have lower sensitivities than those found in process-based models because seasonal effects and extremes can be averaged out (Lobell and Asseng, 2017).

Recently, a meta-analysis on climate impacts for central Europe projected a change in average maize yield of −9% for the 2020s and −15% for the 2080s (Knox et al., 2016). Literature on impact assessments for parts of Germany based on aggregated time series models with estimates at the district level under the A1B scenario show moderately negative effects on maize for East Germany by the middle of the 21st century, moderately negative to positive effects on maize for Saxony-Anhalt, and positive effects on maize for North Rhine-Westphalia (Wechsung et al., 2008; Kropp et al., 2009b,a). Negative impacts on silage maize are mainly found with a global increase in temperature of 3 °C for the East German plains (Lüttger et al., 2011). No consistent assessment for entire Germany is currently available.

In this study, we examine the impacts of climate change on variations in the long-term mean of silage maize yield for all counties in Germany. A reduced-form model is developed and fitted for the period 1999–2015 for which yield records on county level are available. We explicitly use the most relevant factors of a statistical model, which considers sub-seasonal variations of meteorological variables and soil moisture anomalies to predict silage maize yields (hereafter PTMS (Peichl et al., 2018)). Those are dry and wet soil moisture anomalies for June and August and temperature and precipitation for July. The soil moisture anomalies are calculated as an index (Samaniego et al., 2013) and are based on the output of the mesoscale Hydrologic Model (mHM) (Samaniego et al., 2010). Climate simulations only show robust trends with rough temporal resolutions. Therefore, we argue that the persistence of soil moisture and the resulting smoother distribution compared to the meteorological variables can provide a more reliable climate assessment compared to those based only on meteorological variables (see Supplementary Fig. S1 for more information) (Peichl et al., 2018). Extreme annual yield variations, e.g., due to drought, are not explicitly considered in this study. Five hydro-meteorological simulations are used to force the statistical crop model. Changes in the long-term average crop yield are evaluated for two climate periods (2021–2050 and 2070–2099) compared to the reference period 1971–2000.

3.2 Results and discussion

3.2.1 Estimated coefficients of the regression model

Table 3.1: Table of Regression

Variable	Month	Specification	Silage Maize Anomaly Standard Errors: (Standard) / (Driscoll-Kraay) / (Bootstrap)
Precipitation	July	Polynom (degree 1)	0.264^{***} (0.028) / (0.033) / (0.110)
	July	Polynom (degree 2)	0.001 (0.0003) / (0.001) / (0.001)
	July	Polynom (degree 3)	-0.00001^{**} (0.00000) / (0.00000) / (0.000)
Temperature	July	Polynom (degree 1)	-6.443^{***} (0.634) / (1.001) / (5.840)
	July	Polynom (degree 2)	-4.050^{***} (0.305) / (0.291) / (3.664)
	July	Polynom (degree 3)	0.703^{***} (0.078) / (0.104) / (0.976)
Soil Moisture Index	June	severe drought	10.622^{***} (2.196) / (2.880) / (7.150)
	June	moderate drought	8.723^{***} (1.988) / (2.303) / (3.960)
	June	dry	3.198^{*} (1.722) / (1.763) / (2.561)
	June	wet	-6.155^{**} (2.203) / (2.462) / (4.311)
	June	abundantly wet	-12.173^{***} (2.660) / (3.813) / (5.767)
	June	severely wet	-52.091^{***} (3.618) / (5.850) / (21.034)
Soil Moisture Index	August	severe drought	-47.447^{***} (2.609) / (3.820) / (12.549)
	August	moderate drought	-21.952^{***} (2.066) / (2.837) / (5.985)
	August	dry	-8.200^{***} (1.771) / (2.495) / (2.716)
	August	wet	0.656 (2.084) / (1.800) / (4.000)
	August	abundantly wet	−3.447 (2.428) / (2.431) / (5.881)
	August	severely wet	-10.703^{***} (3.548) / (3.755) / (10.706)
Constant			18.905^{***} (1.155) / (1.527) / (4.710)
In-sample:	R^2: 0.389	Adj. R^2: 0.387	Adj. R^2 - full variation: 0.705
LOCV (10-folds, 20 repeats):	R^2: 0.385	RMSE: 37.014	MAE: 28.288
LOCV (annual blocks):	R^2: 0.083	RMSE: 39.145	MAE: 30.589
LOCV (state blocks):	R^2: 0.378	RMSE: 37.637	MAE: 29.169
Observations	4,625		

The coefficients estimated by the reduced-form model combining the major hydro-meteorological predictors closely match those found in PTMS (Peichl et al., 2018). The largest effects estimated for soil moisture are −52 decitonnes/hectare (dt ha^{-1} = 100 kg ha^{-1}), which is about −11.6% for severely wet soil moisture conditions in June and 47 dt ha^{-1} (−10.5%) for severe drought conditions in August, all other determinants being equal (Table 3.1). We would like to stress that the SMI is monthly percentile based index. The SMI in June and August corresponds to different soil water saturation fractions (for various locations in Germany, the annual development of soil moisture fractions are shown in Fig. 4 in Samaniego et al. (2013) (Samaniego et al., 2013)). In June, wet anomalies represent potentially harmful soil moisture above optimal conditions. The soil has been replenished in the past seasons, and a high level of moisture saturation in the soil can, for example, lead to water logging or luxury consumption and thus to lower root depth. From July, the soil water content decreases below the optimal conditions (60-80% of the available field capacity (Chmielewski, 2011)). As a result, dry anomalies represent harmful conditions because the available soil water is too low to provide enough water in the most drought-susceptible phases of flowering, pollination and grain filling (Gömann et al., 2017). These results highlight that the availability of water is key for the successful cultivation of arable crops in Germany. Soil moisture is considered a major limiting factor to simulated crop yields, in particular during sensitive phenological stages (Andresen et al., 2001).

The in-sample adjusted coefficient of determination is 0.38 (Table 3.1[1]). However, when comparing this estimate with the results of other studies, it should be noted that the model used here only accounts for inter-annual variation. A model that uses the full crop yield variation and fixed effects has an adjusted R^2 of 0.71 (Table 3.1). The out-of-sample fit measures, which were derived from leave-out cross validation, are comparable to the in-sample measure, except for when annual blocks were omitted. For the latter resampling approach, the coefficient of determination decreases, while other out-of-sample measures such as root mean squared error (RMSE) and mean absolute error (MAE) only slightly increase. The reason for this result is assumed to be the higher sensitivity to outliers of the coefficient of determination than of the RMSE and MAE, which may be due to the relatively short silage maize yield record of 17 years.

3.2.2 Model evaluation against historical observations

There is a large difference between the observed and predicted yield anomaly data (Fig. 3.1a). The range of the observed anomalies is between −200 and 144 $\mathrm{dt\,ha^{-1}}$, and the range of the predicted anomalies is between −120 and 55 $\mathrm{dt\,ha^{-1}}$. As the density contour lines show, the data around the mode are better predicted than the extreme values (Fig. 3.1b). In general, the variability of the data is underestimated by the model, mostly because positive yield deviations are not captured by the model. However, the model is able to predict the observed values over the entire period. The long-term difference between the predicted and actual yield anomalies for the period 1999-2015 is between −13 and 10 $\mathrm{dt\,ha^{-1}}$ (Fig. 3.2). The relative deviation is at most 2.36% for each county (Fig. 3.2b).

[1]Standard errors are derived from three configurations. The first is the standard parametric configuration, and the second is the Driscoll-Kraay standard error, which parametrically accounts for serial and cross-sectoral autocorrelation and heteroscedasticity. The third configuration is based on a bootstrap approach resampling the years in the sample. The smallest standard errors are reported by the standard configuration, and the largest standard errors are reported by the bootstrap configuration.
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; based on Driscoll-Kraay Standard Errors.

Figure 3.1: Scatterplot and density plots of the observed maize yield anomaly data against the simulated data. In panel a) the observed data (Y-axis) are plotted against the predicted yield anomaly data (X-axis) for the period 1999-2015. The blue contour lines show the density of the point cloud, and the blue line shows the linear fit. Panel b) shows the marginal density of the observed and the predicted data (derived from observed meteorological forcings) for the period 1999-2015. In panel c), the observed data are compared against the projected data with input data derived from the 5 different regional climate models for the period 1999-2015. The dashed lines in the density plots represent the median of each distribution.

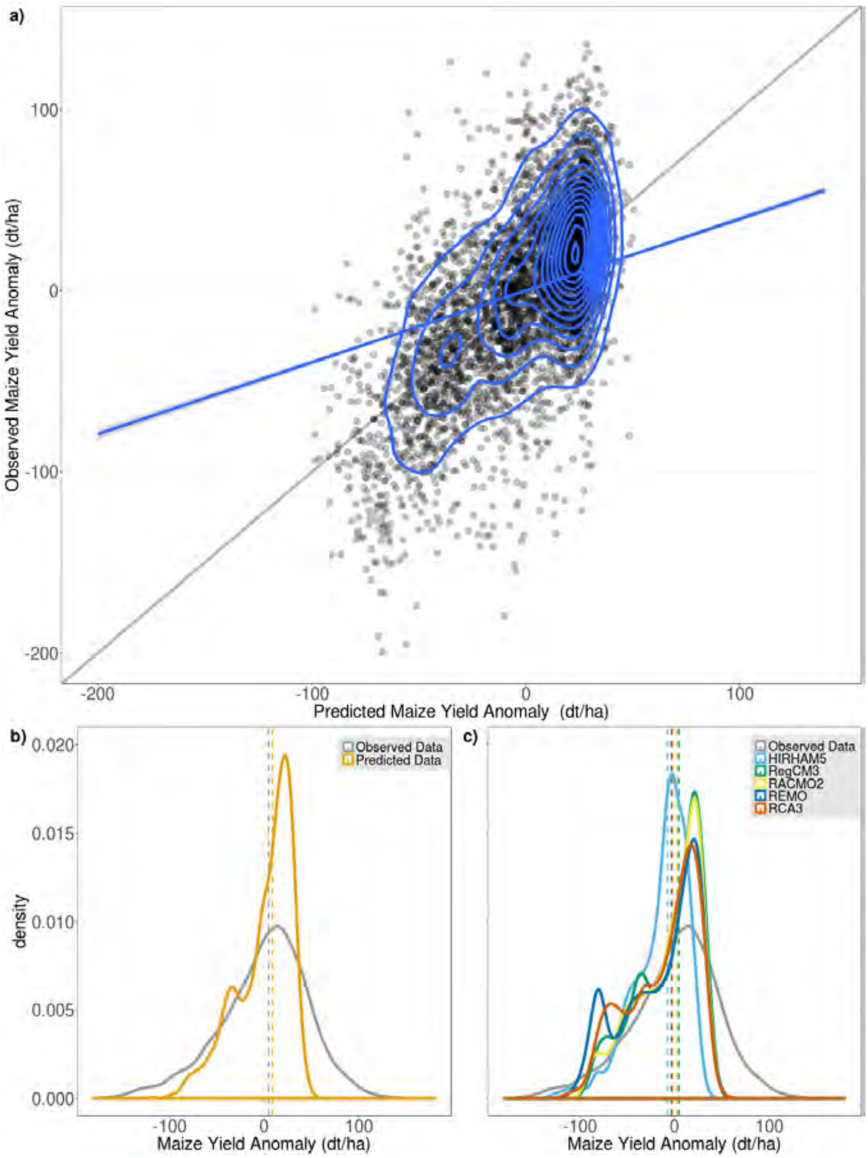
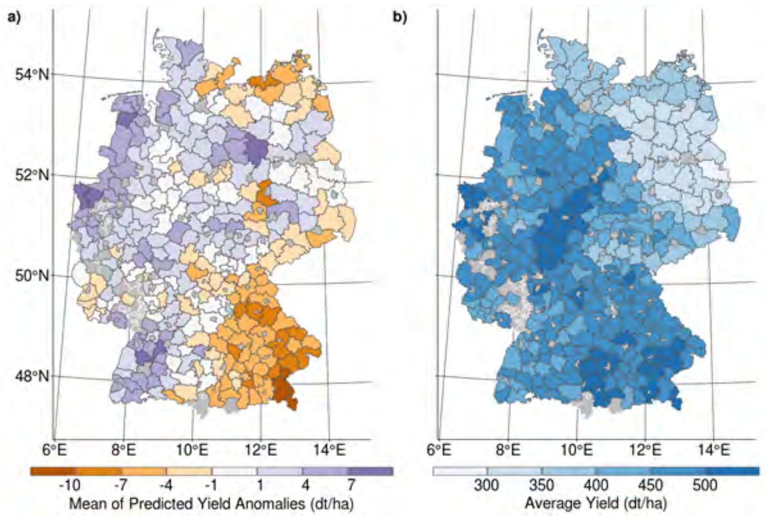


Figure 3.2: The map in panel a) shows the difference between the average predicted and actual yield anomalies at the county level for the period 1999-2015. Panel b) shows the average yield of each county for this period. Grey areas indicate the counties neglected in the model due to insufficient sample sizes. See Supplementary Fig. S2 and S3 for further information.

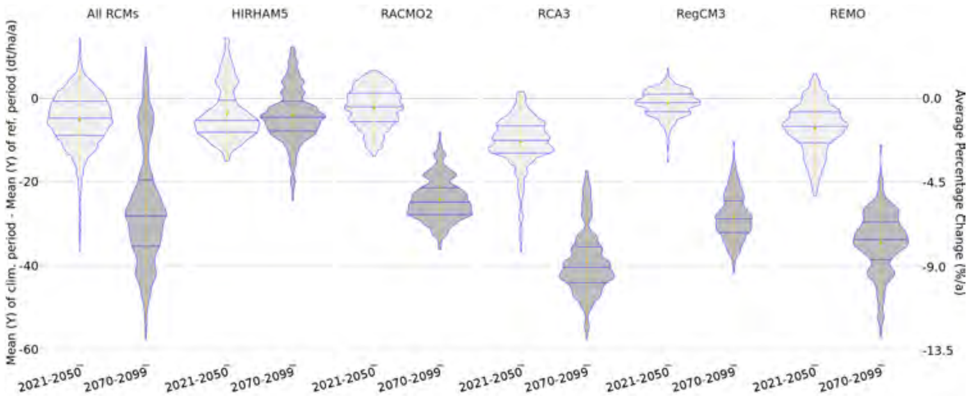


We also evaluated the model using the hydro-meteorological data derived from the regional climate models (RCMs) for the period 1999–2015. The model overall underestimates the observed values over Germany for the individual RCMs in similar ways as this is the case with historical data as input (Fig. 3.1c). The median values of the simulations using input data derived from the RCMs (dashed lines) are slightly below the median of the observations. The shape of the distributions of the simulations differ from the distribution of the observations mainly in the negative range. However, the negative estimates reflect the bandwidth of the observed data better than that of the positive range. This result indicates that the approach is not able to capture positive extremes and overestimates negative climate impacts. The long-term district averages for near- and far-future periods in comparison to averages of the reference period 1971–2000 are compared in the following subsection.

3.2.3 Climate projections

The variation in the average yield anomalies of silage maize was estimated for the reference period (1971–2000) and two climate periods (near future: 2021–2050 and far future: 2070–2099). Five RCMs (HIRHAM5, RegCM3, RACMO2, REMO, RCA3) were used to drive the mHM and the statistical crop model. All RCMs project decreases in silage maize yield. The average projections for all five multi-model simulations are -5 dt ha^{-1}a^{-1} (≈ -1.1 % a^{-1}) for the near future period and -25 dt ha^{-1}a^{-1} (≈ -5.6 % a^{-1}) for the far-future climate period (Fig. 3.3). There is a consensus

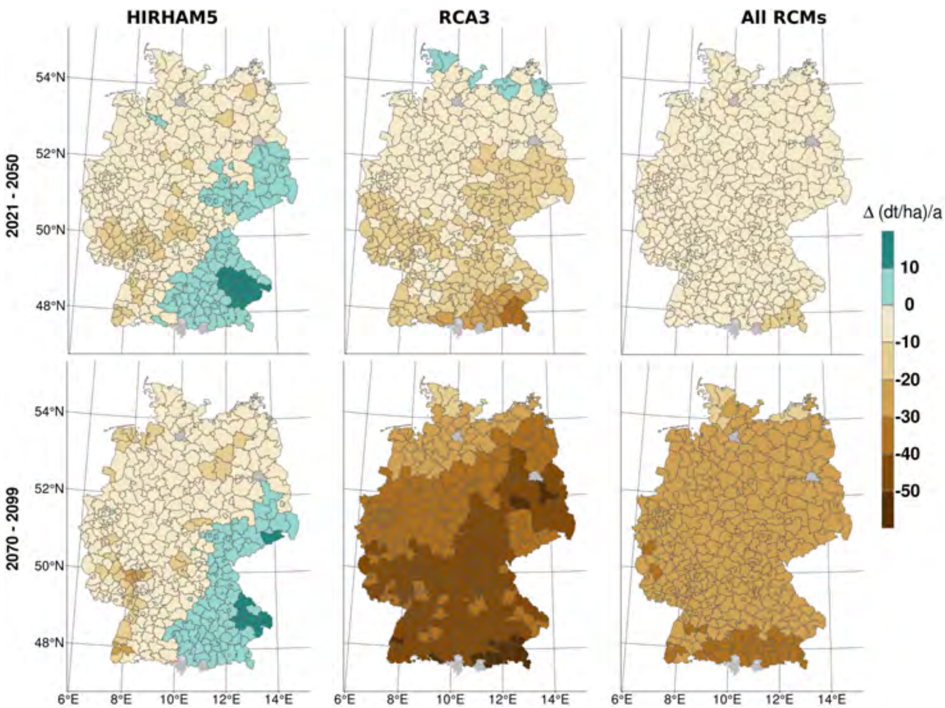
Figure 3.3: Violin plot of the projected average yield anomalies at the county level for the periods 2021-2050 and 2070-2099 compared to the reference period 1971-2000. The first panel shows the cumulated results for all RCMs, and the other five panels show the results for each RCM separately. The blue lines represent the quantiles 0.25, 0.5, and 0.75. The orange dots show the mean values, and the vertical lines emanating from each dot represent the standard error times 2.



that decreases in yield will be larger in the second half of the 21st century than in the near future, with less severe damages in regions with temperate climates (Challinor et al., 2014; Moore et al., 2017a). These results are confirmed by the changes in average yield presented in Fig. 3.3 because all RCMs exhibit a lower magnitude of change in the near future period than in the far-future period.

In this study, the biophysical processes in the statistical models are approximated by incorporating measures of sub-seasonal soil moisture anomalies, which are assumed to support the convergence in the outcomes between the statistical models and process-based models (Fishman, 2016; Lobell and Asseng, 2017; Peichl et al., 2018). Other factors reflected in process-based models that are usually neglected in statistical models are the effects of adaptation, CO_2 fertilization, and ozone (Lobell and Asseng, 2017). The impact of the first two factors will be discussed here, while the last factor will not be considered because there is a lack of scientific understanding of the effects of ozone. First, adaptation in process-based models is sometimes referred to as 'adaptation illusion' (Lobell, 2014) because it usually only represents on-farm or within-crop adaptation that provides benefits unconditional on climate development (Moore et al., 2017b). For instance, global computable general equilibrium models specifically designed for the agricultural sector could contribute to truly account for economic adaptation (Moore et al., 2017b). Second, CO_2 fertilisation can explain more variability in the agricultural sector as for instance adaptation (Moore et al., 2017b; Ciscar et al., 2018). For this reason, it should be taken into account when the impact assessment using statistical approaches is evaluated (Lobell and Asseng, 2017; Moore et al., 2017b; Gömann et al., 2017). The CO_2 fertilization effect can, among other ways, be considered using a yield correction model (Wechsung et al., 2008). Since Maize is a C4 plant it mainly benefits from the increase in CO_2 under drought conditions through reduced transpiration as long as nitrogen supply is not limited (Leakey et al., 2009; Manderscheid et al., 2014). The correction factors therefore consider both the rather negligible direct yield effect through stimulated photosynthesis and the more important compensation of yield losses from drought stress through increased water use efficiency by reducing the stomatal conductance (Long, 2006; Tubiello et al., 2007). Both are a function of CO_2 change and translate yield projections without CO_2 fertilization into estimates with CO_2 fertilization. Accordingly, an estimated yield change without CO_2 fertilization of −10% can be transformed to an estimated yield change of +5% by 2056 and +11% by 2086 for the CO_2 levels in the A1B scenario (Kropp et al., 2009b). In the study presented here, the highest projected average yield loss (RCA3 in the second climate period) is less than -10% in magnitude. As explained later for the five regional climate models considered here, factors related to dry conditions such as temperature in July and soil moisture deficit in August usually correlate with yield variability. Thus, when assuming that rising CO_2 will benefit maize growth under drought conditions (Leakey et al., 2009; Manderscheid et al., 2014), slightly positive yield changes may be expected on average even without taking into account potential adaptation. The approach in this study has several limitations. It is assumed that the currently known connections will continue in the future because the impact model is trained with historical data. Thus, the approach is not able to take into account future developments not reflected in the past (Lüttger et al., 2011). Extreme climate anomalies are scientifically accepted to be a consequence of climate change and are known to have significant impacts that pose elementary adaptation and economic challenges to farmers (Urban et al., 2012; Hansen et al., 2012; Challinor et al., 2014). These effects are, for instance, linked to the duration, area and frequency of droughts (Samaniego et al., 2018). Simultaneous production shocks related to silage maize caused worldwide by climate change are also not taken into account (Tigchelaar et al., 2018). The analysis in this study is focused on mean yield changes and does not assess the climate-induced year-to-year variability of crop yields, e.g., large losses caused by droughts from which farmers are not able to recover. This increases the uncertainty in our results, especially for the second half of the century (Gömann et al., 2017). Here, only the variance in the long-term means of climate periods is assessed. The projected variance of the mean yield losses is between $-36.7\,\mathrm{dt\,ha^{-1}a^{-1}}$ and $14.5\,\mathrm{dt\,ha^{-1}a^{-1}}$ for the first period and between $-57.6\,\mathrm{dt\,ha^{-1}a^{-1}}$ and $12.4\,\mathrm{dt\,ha^{-1}a^{-1}}$ for the second period. The upper boundaries of the variations are marked in both climate periods by HIRHAM5, and the lower boundaries are marked by RCA3. There are high inter-model variabilities in the projected averages of the mean yield losses. The smallest values in the mean yield losses are generally projected by RegCM3 ($-1.2\,\mathrm{dt\,ha^{-1}a^{-1}}$) in the first period and by HIRHAM5 ($-3.7\,\mathrm{dt\,ha^{-1}a^{-1}}$) in the second period. In both climate periods, RCA3 generally projects the highest mean yield losses (-10.5 and $-39.1\,\mathrm{dt\,ha^{-1}a^{-1}}$). This variability, however, mainly reflects the spatial heterogeneity of the projected mean yield losses.

Figure 3.4: Selected maps of county-specific yield anomaly deviations (climate period-reference period) for both climate periods. The first column represents the lowest average yield anomaly deviations (derived by HIRHAM5), the second column the highest average yield deviations (RCA3), and the third column shows the county-specific mean of all yield anomaly deviations projected by the five RCMs for each county. The first row represents the climate period 2021-2050, and the second row represents the climate period 2070-2099.



3.2.4 Influence/spatial analysis of individual regional climate models

The spatial patterns in the mean yield anomaly differ among the RCMs (Fig. 3.4). There are also differences in the mean yield anomaly spatial patterns between the climate periods. Projected yields based on the HIRHAM5 model (column 1 of Fig. 3.4) increase in south-east Germany, while small decreases are projected by the other RCMs in this region. This model predicts the lowest mean losses overall. Decreasing yields are projected by the RCA3 model during both future periods along a gradient from north-west to south-east Germany. These decrements are larger for the second climate period than the first climate period. This trend also applies to estimates derived from all other models except for HIRHAM5 (Fig. 3.3). As shown previously, other projections for the east of Germany show a negative future yield development, while a positive future yield development is predicted for the west of Germany (Wechsung et al., 2008; Kropp et al., 2009b,a; Lüttger et al., 2011). These studies use time series approaches for each district, allowing more flexible yield sensitivities to external meteorological and soil variations. However, there are several reasons in support of a panel approach. First, this approach is less susceptible than other approaches to coefficient bias caused by omission of time-invariant factors. Second, we can only evaluate the reported yield data for each district for a 17-year time period. A panel approach increases the data set by considering the time series and spatial information from counties.

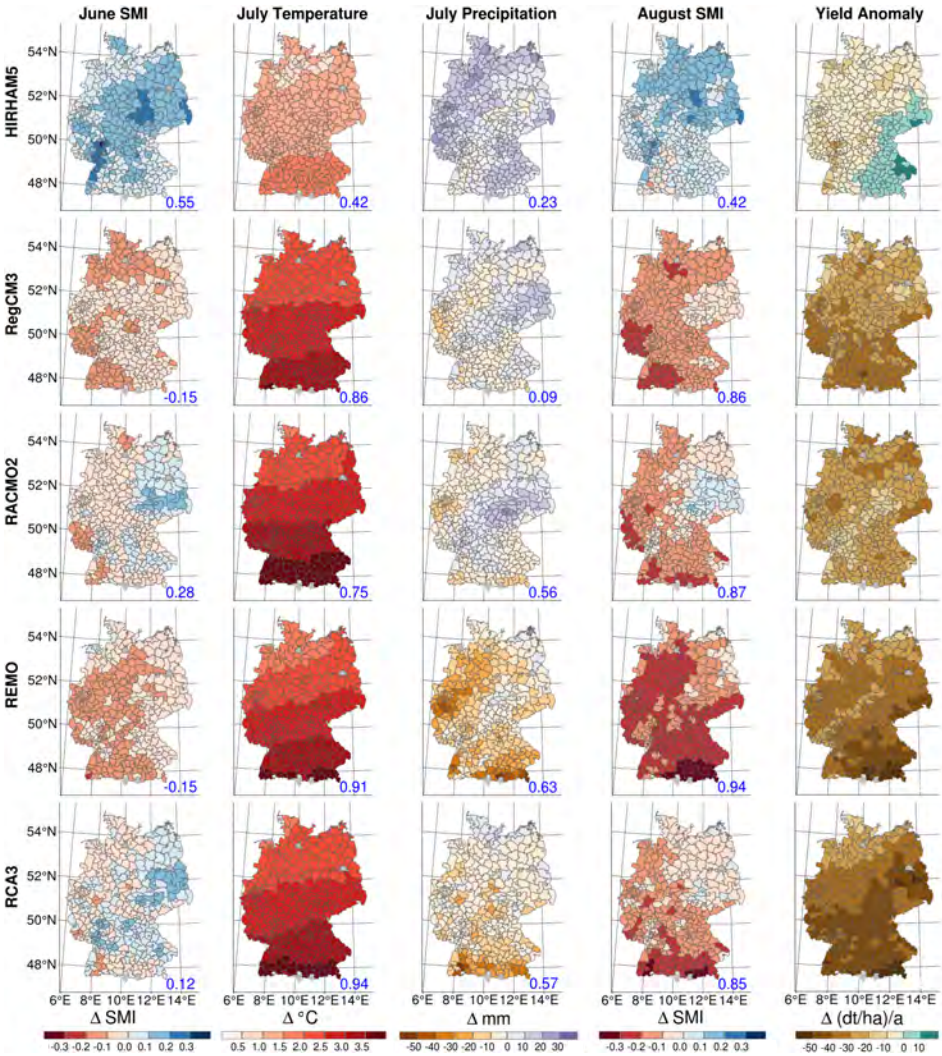
The multi-model ensemble mean exhibits very little spatial heterogeneity, with slightly higher losses in the south of Germany than in other areas (Fig. 3.4, column 3). Since the impact model takes into account different sensitivities to different factors over the season, it responds to certain patterns reproduced by the RCMs. Thus, the projected yield estimates cancel each other out when averaged in a multi-model ensemble.

Figure 3.5 shows maps of the mean changes for the second climate period (2070–2099) within each county, for both the predictors and the yield anomalies (descriptive statistics can be found in the Supplementary Table S1). Different patterns in SMI and meteorological changes can be observed among the individual RCMs, with HIRHAM5 exhibiting the most distinct patterns. For example, in June, the SMI shows a broad range of changes in all five RCMs (first column). HIRHAM-driven simulations show that the soil moisture index increases comparatively over time, while RegCM3 and REMO show a decrease in future soil moisture represented by the index. For the other RCMs, a mixed development is shown. Overall, the long-term mean changes in SMI are between −0.19 (RCA3 and RegCM3) and 0.31 (HIRHAM5) in June.

As expected, the maps in the second column of Figure 3.5 show an increase in temperature in July for all RCMs. In addition, the spatial temperature trends show greater increases in the south than in the north. For HIRHAM5, the model with the lowest temperature increase, the maximum increase is 2 °C. For REMO, the model with the second lowest temperature rise, the maximum increases are between 1.7 °C and 3.7 °C; for the other RCMs, the maximum increases range between 2 °C and 4 °C.

Notably, annual temperature fluctuations are not sufficient to explain the development of crops. In fact, the temperature changes in the periods in which plant development is particularly

Figure 3.5: All panels show maps with the mean value changes within individual counties, with either explanatory variables or yield anomalies derived from the various RCMs for the second climate period (2070-2099). The columns represent the different variables, and the rows represent the RCMs (HIRHAM5, RegCM3, RACMO2, REMO, RCA3). The explanatory variables are normalized by the procedure used for yield anomalies. The blue numbers indicate the Spearman correlation coefficients of the mean data. A more detailed description can be found in the Supplementary Information.



susceptible to heat, such as the reproductive, flowering, and grain-filling stages, are most important (de Bruyn and de Jager, 1978; Sinclair and Seligman, 1996; Tubiello et al., 2007; Wahid et al., 2007). Heat can, for example, shorten the grain-filling phase and thus lead to a reduction in yield and quality. However, the susceptibility of plants to heat, especially silage maize, is reduced by an adequate water supply (FAO, 2019). For maize, only temperatures above 35 °C interfere with fertilization and fruit formation and thereby reduce yield (Gömann et al., 2017). The amount of soil water available to the plants during this time therefore plays an essential role. The projected change in precipitation in July is between −52.5 mm ((≈ −67%, REMO) and 36.9 mm (≈ 47%, HIRHAM5) across all RCMs (Fig. 3.5, column 3). In the central and north-eastern regions of Germany, the precipitation spatial patterns of different RCMs are similar, while in the north-west and south-east, these patterns differ among RCMs. REMO and RCA3 project a precipitation decrease in almost all regions, although the effect is more pronounced for REMO than for RCA3. RCA3 projects slight increases in precipitation along the German coast, while the pre-Alpine areas face precipitation reductions. RegCM3 and RACMO2 show mixed results.

In all but a few regions, the HIRHAM5-driven mHM simulations show moister conditions in the second climate period, as can be inferred from the soil moisture anomalies in August (Fig. 3.5, column 4). RegCM3 projects drier soils across the whole country. This trend is also shown by REMO in all areas of Germany, except for the most north-eastern part of the country. RACMO2 and RCA3 show mixed effects in the hydro-meteorological simulations, with more regions expected to become drier. Overall, the model that projects the driest conditions is REMO. For all models, the projected change in the SMI ranges between −0.36 (REMO) and 0.25 (HIRHAM5).

As described above, different spatial patterns and seasonal dynamics are predicted by the RCMs. These patterns can also be seen in the resulting yield changes for the far-future period (Fig. 3.5, column 5). The blue numbers in the lower right corner of the maps in Fig. 3.5 show the Spearman rank correlation coefficients of each predictor with the yield anomalies (see here for the mean changes; the coefficients for the respective counties can be found in the Supplementary Fig. S4). We use these correlation coefficients to approximate the effect of the summands from the regression model on the projected yield variability. The summands are the mathematical product of the estimated coefficients for a predictor and the corresponding input data provided by each RCM. As previously described, HIRHAM5 is an exception in regard to changes in yield anomalies and is the only model that projects positive changes (for south-east Germany). For the rest of Germany, low losses of less than −20 dt $ha^{-1}a^{-1}$ (≈ −4.5%/a) are projected. There, the SMI has the highest correlation coefficient in June. The projections are different for the other RCMs, where losses of up to −57.6 dt $ha^{-1}a^{-1}$ (≈ −12.8%/a) are projected. The influence of soil moisture anomalies in June on crop yields seems to be comparatively small. Instead, the temperature in July and soil moisture anomalies in August seem to be the main factors underlying yield anomalies.

Overall, REMO projects the lowest soil moisture anomalies in June and August and the least precipitation in July. However, this model does not represent the greatest loss potential (see

Supplementary Table S1). Instead, the greatest loss potential is predicted by RCA3, for which some regions in the east of Central Germany also show high water losses, despite the fact that, compared to other regions, there are no exceptionally extreme temperature, precipitation and soil moisture developments in August (see county-specific correlation coefficients in the Supplementary Fig. S4). The soil moisture factor, in particular, represents a comparatively low soil dryness pressure in this region. However, the losses in this area overlap with regions that become relatively wet in June. This emphasizes that considering soil moisture in multiple months is helpful because wet conditions in June affect yields (Table 3.1). From this analysis, we conclude that no single driver, such as high temperatures or soil moisture anomalies, defines the total harvest losses; rather, a combination of these sub-seasonal factors must be considered. However, outliers in the projection of yield, as with HIRHAM5, can be traced consistently by evaluating the projected RCM outputs.

3.3 Summary and conclusion

To our knowledge, this is the first climate impact assessment based on a statistical approach for silage maize yield in Germany as a whole to appear in a peer-reviewed journal. A reduced-form model that considers sub-seasonal soil moisture and meteorological effects was applied. The model is able to explain long-term average changes in yield but is not designed to simulate extreme crop losses in single years. Climate data were derived for two climate periods from five different RCMs for scenario A1B. The maximum projected long-term mean yield loss of silage maize in Germany was estimated to be less than 10% of the average yield between the past and future 30-year periods based on the multi-model RCM simulations driving the mHM and the statistical crop model. Considering adaptation and CO_2 fertilization, positive yields are expected.

The convergence of process-based and statistical approaches should be further promoted in the near future; the present study took the first step in this process by considering sub-seasonal soil moisture patterns. Further key determinants of plant development need to be integrated into statistical approaches, always based on scientifically sound agronomic knowledge, to address potential multicollinearity problems. An impact assessment of spatial clusters, which better takes the spatial heterogeneity of soils and meteorological dynamics into account, would enable a more precise approach for covering extremes.

Further attention should be paid to improving the precipitation distribution in global climate models. The simulated temperature changes of different global models show the same trends, but precipitation projections, especially the projected seasonal distribution of precipitation, are very different (Jacob et al., 2017; Tigchelaar et al., 2018). The five RCMs used in the present study have high inter-model variability. For this reason, it is advisable that future research will address such issues through larger RCM ensembles.

3.4 Methods and data

3.4.1 Methods

The statistical model developed here is a reduced-form panel approach that exploits the exogenous variation in key explanatory variables (Timmins and Schlenker, 2009). Endogenous variables are not included because they are considered bad control (Angrist and Pischke, 2008). It incorporates the most influential variables identified in PTMS (Peichl et al., 2018). The model relates silage maize yield anomalies (Y) to a step-wise function of soil moisture anomalies (SMI) for June and August and polynomials of the demeaned meteorological variables precipitation (P) and temperature (T) for July. The model can be written as:

$$
\begin{aligned}
Y_{ik} &= \sum_{n=1}^{6} \alpha_n \mathrm{I}(SMI_{ik}^{June} \in \mathrm{C_n}) \\
&+ \sum_{j=1}^{3} \beta_j (\mathrm{P}_{ik}^{July})^j + \sum_{j=1}^{3} \gamma_j (\mathrm{T}_{ik}^{July})^j \\
&+ \sum_{n=1}^{6} \delta_n \mathrm{I}(SMI_{ik}^{August} \in \mathrm{C_n}) \\
&+ c + \epsilon_{ik}
\end{aligned}
\tag{3.1}
$$

The observation-specific zero-mean random-error is referred to as ϵ, and c is a constant. The i index represents the counties within Germany, k represents the years, and the superscript j represents the degree of the respective polynomial. Polynomials with a degree of three are used according to the results of PTMS (Peichl et al., 2018). $\mathrm{I}(\cdot)$ is the indicator function of the soil moisture categories $\mathrm{C_n}$, where this value is 1 if the SMI belongs to class n and 0 otherwise (more details are given below).

As only annual weather deviations from the average of the reference period 1951–2015 are considered by the predictors, the coefficients of the exogenous variables are determined on the basis of inter-annual fluctuations. Farmers are expected to optimize the entire production process at their site based on their experience of local weather conditions. By restricting the coefficients to the same values in all districts, it is implicitly assumed that the response of plants to these inter-annual stressors is the same at all sites. Differences in sensitivity to exogenous weather and soil moisture variations caused by the use of different silage maize varieties or particular soil characteristics are thus ignored by this modelling approach.

3.4.2 Historical observations

Annual yield data for silage maize are available since 1999 from the Federal Statistical Office of Germany for different district levels (Statistische Ämter des Bundes und der Länder, 2019).

The yield data are not detrended for the period 1999–2015 because no significant linear trend is observed. To obtain anomalies, the mean of each county is subtracted.

The mesoscale Hydrologic Model (mHM) has been used to estimate soil moisture (Samaniego et al., 2010; Kumar et al., 2013). Since silage maize is able to develop a root system that uses the entire root zone depth, a three-layer soil scheme was used to model the soil moisture dynamics over the entire root zone depth (i.e. approximately up to 2 m below ground level) (Samaniego et al., 2013). The soil moisture index (*SMI*) is calculated as a non-parametric and location-specific cumulative distribution function of soil moisture for the period 1951–2015. This procedure enables a comparison across locations (Samaniego et al., 2013). The index ranges between 0 and 1 and quantifies the probability of occurrence of the monthly soil moisture values. For example, a SMI of 0.2 indicates that the soil water saturation fraction is not exceeded during 20% of the time. A median soil moisture value obtains a SMI of 0.5. The advantages of using an index include the relatively low probability of measurement errors and that the estimated coefficients should be less susceptible to attenuation bias (Fisher et al., 2012; Auffhammer and Schlenker, 2014; Hsiang, 2016). In addition, an index minimizes systematic errors associated with spatial data processing and meteorological and climatological modelling (Auffhammer et al., 2013; Lobell, 2013; Conradt et al., 2016; Gornott and Wechsung, 2015, 2016).

The monthly SMI values are divided into seven classes, following the approach of PTMS (Peichl et al., 2018). The interval between $0.3 < SMI \leq 0.7$ characterizes normal situations, which are not used in equation 3.1 to avoid perfect multicollinearity in the explaining variables. The lower quantile intervals ($SMI \leq 0.1$, $0.1 < SMI \leq 0.2$ and $0.2 < SMI \leq 0.3$) are defined as severe drought, moderate drought and abnormally dry, respectively. Correspondingly, $0.7 < SMI \leq 0.8$, $0.8 < SMI \leq 0.9$ and $0.9 < SMI$ are defined as abnormally wet, abundantly wet, and severely wet, respectively. All explanatory variables are averaged from their original resolution to the district level to match the spatial scale of the yield data. This averaging weights the explanatory variables according to the area of the non-irrigated agriculture within each grid cell (Peichl et al., 2018).

Daily precipitation and temperature data are obtained from a station network of the German Weather Service (Deutscher Wetterdienst, 2019). Interpolation details can be found in Zink et al. (2017) (Zink et al., 2017). All daily values are aggregated to monthly values. By subtracting the county-specific averages, the variables P and T are demeaned. The selected time horizon for P and T is 1951–2015 because this period serves as a basis for generating the SMI. Considering anomalies by either demeaning or employing an index potentially reduces the bias of the coefficients caused by the time-invariant confounding variables specific to each spatial unit for a given period. This approach is not the same as employing fixed effects. However, Lagrange multiplier tests (Honda test for unbalanced panels and F test) show that the remaining fixed effects are insignificant.

3.4.3 Climate data

The climate data are taken from five RCMs of the EU ENSEMBLES Project for the period 1951–2099 (Van Der Linden and Mitchell, 2009). The A1B SRES scenario, which represents a 1.75 °C warming for the period 2046–2065 and a warming of 2.65 °C for the period 2080–2099 compared to the period 1980–1999, is employed (Nakicenovic et al., 2000; Meehl et al., 2007). The RCMs are forced by the same global model, i.e., the ECHAM5 model of the Max-Planck-Institute for Meteorology in Germany. An earlier meta-analysis showed that impact assessments of crop yields based on ECHAM5 showed lower but positive yield changes than other global models (Knox et al., 2016). The applied RCMs are HIRHAM5 by the Danish Meteorological Institute (HIRHAM5), RegCM3 by the Abdus Salam International Center for Theoretical Physics (RegCM3), RACMO2 by the Royal Netherlands Meteorological Institute (RACMO2), REMO by the Max-Planck-Institute for Meteorology (REMO), and RCA3 by the Swedish Meteorological and Hydrological Institute (RCA3). The RCM outputs (i.e., P and T) for the period 1951–2099 are used within this study. The data obtained from these RCMs are also used to drive mHM to simulate soil moisture data. The reference period 1971–2000 is chosen for the climate data. The SMI is thus generated on the basis of the cumulative distribution function of each RCM for this period. Accordingly, the mean value for the period 1971–2000 is subtracted from the meteorological data. Only indices and demeaned input data are used in equation 3.1 to create yield projections. Thus, projections are corrected for bias in the means while preserving the trend. Notably, by using 1971–2000 as the reference period, soil moisture extremes during the periods used for climate projections may lie outside the reference period spectrum. An evaluation showed that this potential effect plays a subordinate role in the analysis. For these extreme values, the SMI is within its bounds (i.e., 0 for dry extremes and 1 for wet ones). The effects of these extreme classes can then be used in the estimation of projected yields.

3.5 Supplementary information

Figure 3.6 shows the correlation of soil moisture indices for the months April to October. This indicates the persistence of soil moisture (memory) and the resulting smoother distribution compared to meteorological variables. The SMI in June is strongly correlated with the SMI in the preceding spring. Conversely, August SMI is strongly correlated with the later part of the season, i.e. September and October. This affirms, besides the analysis in Peichl et al. (2018), the choice of SMI for June and August in the statistical model.

The regression model is fitted on a spatiotemporal data set that contains 410 counties and 17 years. All districts with less than nine years of reported yields are excluded from the analysis because the influence of individual observation points is too strong in these cases (see Figure 3.7). The threshold of 9 was chosen after Cooks' distance Cook (1977, 1979), and the systematic omission of yield data from the 410 counties was evaluated (not shown). There were a total of 286 remaining districts. To allow the evaluation of spatial differences in model performance the county specific quadratic Pearson correlation coefficients between the yield variability of silage maize predicted by the regression model and the observed historical values from the regional statistics for the fitting period 1999–2015 are shown in Fig. 3.8. It can be stated that the variability is relatively well predicted in the most important maize growing areas in Germany, which are located in the north-western and south-eastern parts of Germany. For regions with high data availability and low correlations, it is worth mentioning that the relative bias between predicted and actual yield is rather small (Fig. 3.2).

Figure 3.6: Correlations of soil moisture indexes for the month April to October.

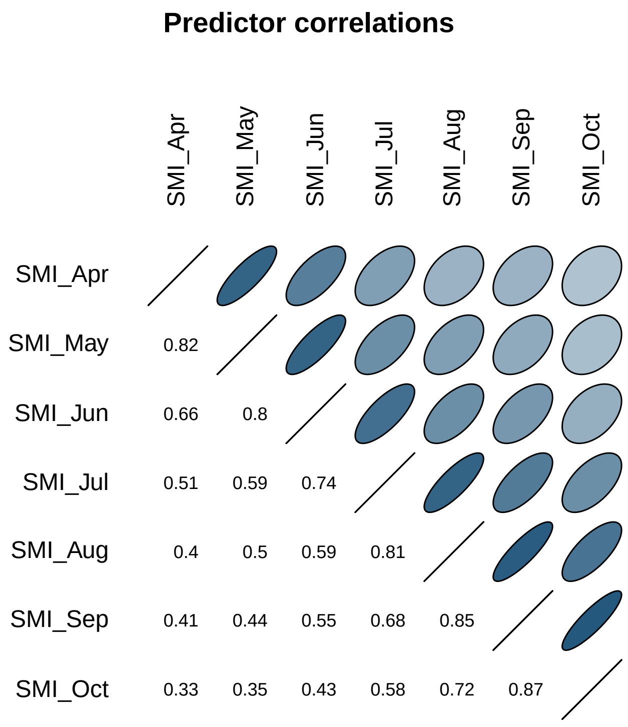


Figure 3.7: Map showing the number of silage maize yield observations available for each county.

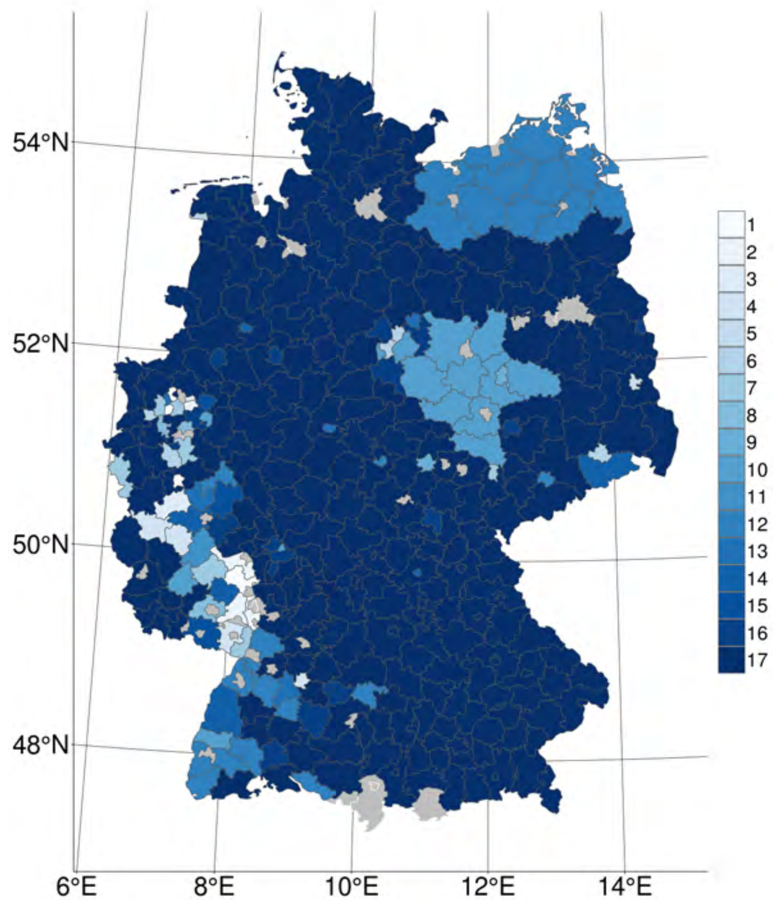


Figure 3.8: Map showing the county specific quadratic Pearson correlation coefficients between the yield variability of silage maize predicted by the regression model and the observed historical values for the fitting period 1999–2015.

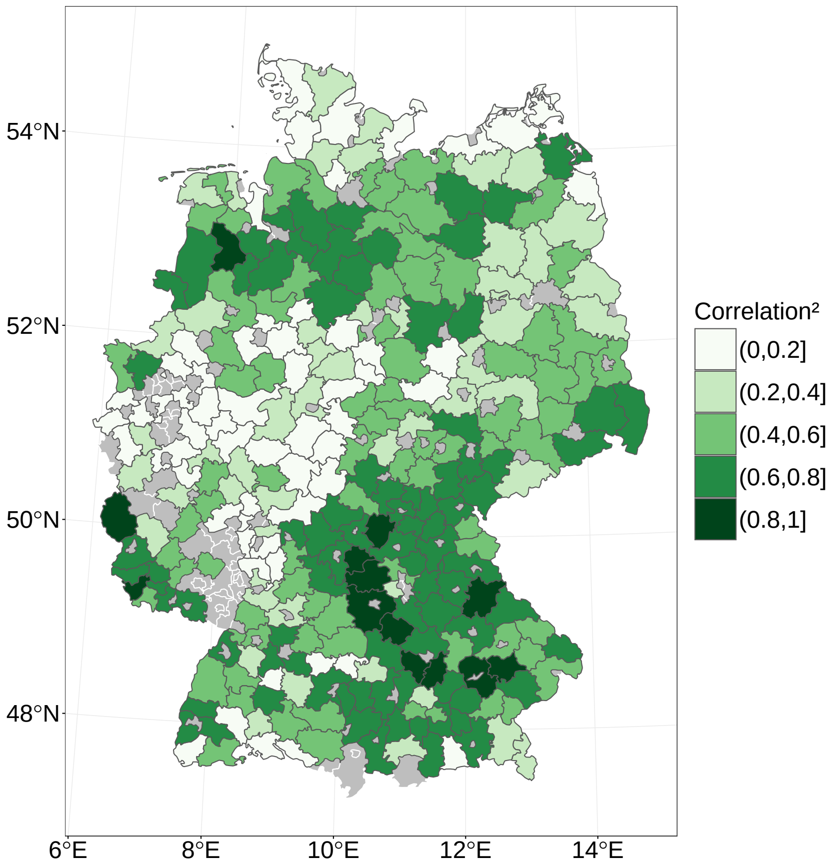
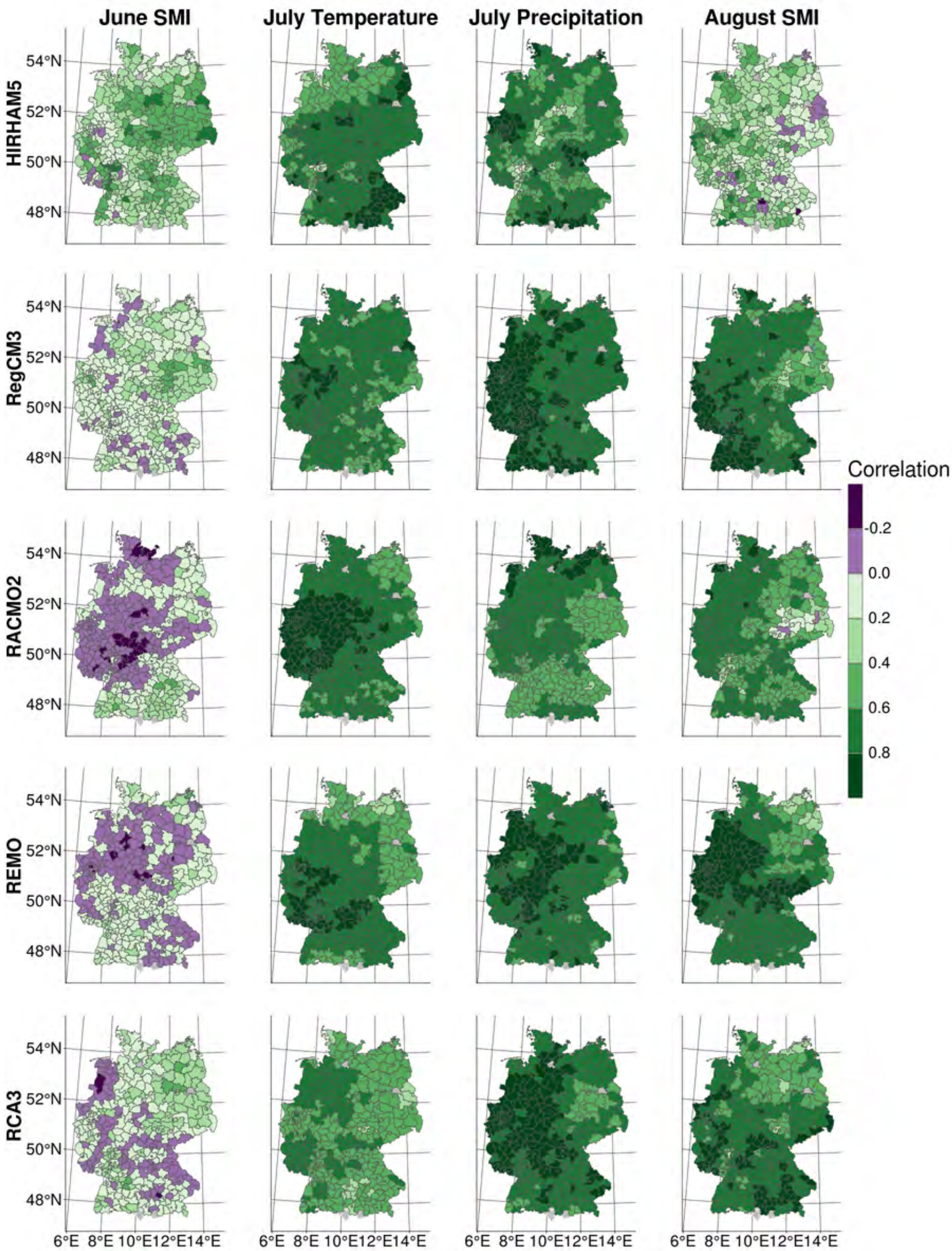


Table 3.2 shows descriptive statistics of the mean changes in the late climate period 2070–2099 in comparison with the reference period 1971-2000. The data are used in detail in the maps in Fig. 3.5 (main article). The Spearman correlation coefficients used are those derived from the mean values of each county. The maps in Figure 3.9 show the Spearman correlation coefficients between the time series of each explanatory variable in the late climate period with the respective time series of the annual yields in each district.

Table 3.2: Descriptive statistics of the mean changes in the five RCMs for the climate period 2070-2099 and the climate period 1971-2000. Absolute historical observations are provided for the period 1971-2000 for all RCMs, except for yield (last row). The absolute observed values for the period 1999-2015 are presented in the last row.

	Statistic	HIRHAM5	RegCM3	RACMO2	REMO	RCA3	historical
June SMI	Mean	0.16	−0.09	−0.02	−0.10	0.02	0.51
	St. Dev.	0.05	0.04	0.06	0.04	0.06	0.27
	Min	0.01	−0.19	−0.18	−0.21	−0.19	0.02
	Max	0.33	−0.01	0.16	0.03	0.18	0.99
Aug. SMI	Mean	0.08	−0.15	−0.11	−0.22	−0.13	0.47
	St. Dev.	0.06	0.05	0.08	0.07	0.08	0.26
	Min	−0.10	−0.29	−0.25	−0.36	−0.33	0.02
	Max	0.25	−0.01	0.12	0.10	0.05	0.99
July P. (mm)	Mean	9.82	0.01	−0.65	−16.56	−8.77	77.80
	St. Dev.	6.79	6.13	7.51	11.10	9.03	39.00
	Min	−9.47	−17.08	−19.54	−52.53	−50.69	1.19
	Max	36.96	19.73	21.54	24.24	11.27	341.00
July T. (°C)	Mean	1.34	2.69	2.98	2.65	2.79	17.70
	St. Dev.	0.26	0.38	0.51	0.50	0.45	1.83
	Min	0.92	1.97	1.91	1.71	1.88	12.60
	Max	1.96	3.51	3.98	3.68	3.76	23.60
Yield ($dt\,dt^{-1}a^{-1}$)	Mean	−4.05	−8.28	−24.26	−34.38	−39.13	447.50
	St. Dev.	6.30	5.35	4.90	7.26	7.52	71.94
	Min	−24.50	−41.75	−36.09	−57.12	−57.62	35.00
	Max	12.37	−10.31	−8.18	−11.17	−17.39	830.00

Figure 3.9: All panels show maps of the Spearman correlation of the summands for each variable (the coefficients used in the model times the input data), with the yield predicted by the model. Data from the climate projections for the period 2070-2099 are used for this purpose. The data are normalized by a procedure that subtracts the mean of the period 1970–2000 from each value. The columns represent the different variables, and the rows represent the RCMs (HIRHAM5, RegCM3, RACMO2, REMO, RCA3).



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Chapter 4

Machine learning methods for predicting winter wheat yield in Germany

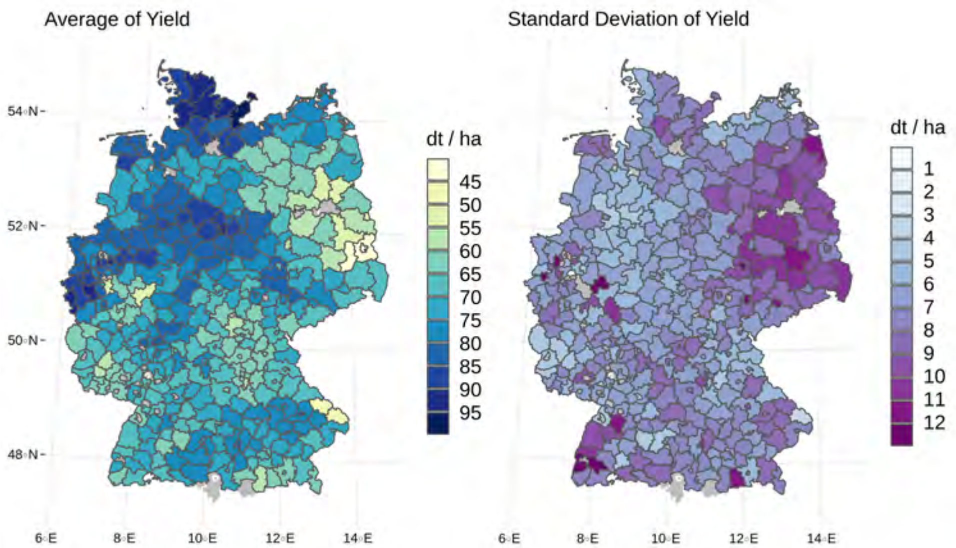
4.1 Introduction

Extreme weather conditions have increased over the last two decades over Germany, leading to an amplification of inter-annual crop variations in the agricultural sector. These include years with above-average wet years (2002, 2007, 2010), but also the droughts of 2003, 2015 and 2018 and the year 2012 with a longer period of bare frost (Gömann, 2018). Models that accurately map weather conditions to crop yields allow a better understanding of the damage mechanism and can thus support management and adaptation (Albers et al., 2017; Peichl et al., 2018) as well as be used for decision support systems and seasonal forecasts (van der Velde et al., 2019; Lecerf et al., 2019; Sutanto et al., 2019; Guimarães Nobre et al., 2019). Furthermore, such damage functions form the basis for projections of the social and economic effects of climate change (Carleton and Hsiang, 2016; Diaz and Moore, 2017; Hsiang et al., 2017). It has been shown that classical statistical models outperform process-based models in predictive power, especially on a large scale (Lobell and Asseng, 2017). Statistical models, unlike process-based models, which are based on detailed representations of plant physiology (Rosenzweig et al., 2014), usually reduce the processes that affect plant development to the main features (Timmins and Schlenker, 2009; Kolstad and Moore, 2020). According to the seminal work of Schlenker and Roberts (2009), statistical crop models routinely include extreme heat as the main variable (Carleton and Hsiang, 2016). However, we consider inference, based on these often aggregated measures of meteorological variables, to be critical, as they can be confounded by missing or only roughly represented variables (Peichl et al., 2018; Roberts et al., 2017). A global study based on process-based models for maize and wheat, for example, found that for most countries water stress is a major source of the observed yield variations (Frieler et al., 2017). Furthermore, it has been shown that it is necessary to account for multiple adverse environmental conditions such as frost, heat, drought and excessive soil moisture during sensitive growth phases (Trnka et al., 2014; Albers et al., 2017; Schauberger et al., 2017;

Mäkinen et al., 2018; Peichl et al., 2018, 2019). In previous studies we have tried to approximate this non-linear and complex damage spectrum by considering the sub-seasonal effects of hydro-meteorological variables such as temperature and soil moisture, however, applying a linear model neglecting sub-seasonal interaction of the features. This approach was very well able to project long-term mean yield changes, but not the inter-annual variations caused by extreme conditions (Peichl et al., 2019). A first approach employing a semi-parametric machine learning approach to explain crop yields in the mid-western USA and thus taking into account the complexity of the underlying reaction mechanism, surpasses classical parametric statistical methods (Crane-Droesch, 2018). Moreover, the projected climate impacts were less severe than those found by linear models that rely mainly on heat as the main predictor variable. Similar, this study applies a statistical framework that does not rely on a key predictive variable, but takes into account a range of potentially harmful factors. The goal is allow a better prediction of inter-annual crop yield variation by a higher predictive capacity of the model, while at the same time allowing for a representation and thus an interpretation of the damage mechanisms. Usually, the latter is conducted through a parametric approach, as the parameters are easy to interpret. Machine learning, on the other hand, focuses largely on maximizing predictive capacity by generating high-dimensional and highly non-linear functions, at the sacrifice of interpretability (Breiman, 2001b; Zhao and Hastie, 2019). Here, we use model agnostics, which compromises various methods that allow the interpretation of machine learning approaches (Ribeiro et al., 2016). We use those methods to disentangle the nonlinear spectrum of damage patterns that determine plant growth. In doing so, we can rely on machine learning algorithms that usually exceed the classical statistical model in predictive power whilst allowing interpretability. For this purpose we map various sub-seasonal hydro-meteorological extremes and their interaction with yield variation of winter wheat using random forests. Winter wheat has the largest share in cultivated area (2018: 46 %) and total production (2018: 51 % of quantity harvested) (Statistisches Bundesamt (Destatis), 2018) amongst all crops in Germany. Predictors used (see Table 4.1) are meteorological extreme indicators for frost, heat and precipitation extremes as well as soil moisture, which is the main water source for plant growth. This allows for sub-seasonality in the model and the quasi-consideration of plant growth and different phenological stages. In our framework, we consider plant growth as non-linear system, as time of occurrence and the different features themselves interact. Because of that, we use random forest, which are particular suitable for non-linear systems (James et al., 2013; Breiman et al., 1984). Neural networks are not considered, because model agnostics is not fully suited to reveal the structures in the hidden layers of those models (Molnar, 2020). To further refine the model, we rely on spatial clustering, which accounts for regional differences in climate, soil moisture and soil properties and thus helps to increase the predictive power (Conradt et al., 2016) of the models as well as to reveal spatially dependent damage mechanisms.

The paper describes the data (Section 4.2), methods (Section 4.3) and results (Section 4.4). Most results are discussed in the results section. A short conclusion is given at the end.

Figure 4.1: 20-year winter wheat yield average (1999-2018, left) and standard deviation (right) of the yields for counties over Germany. Data source: Federal Statistical Office DESTATIS



4.2 Data

The annual yield data for winter wheat are provided by the Federal Statistical Office for the counties from 1999 to 2018 (Statistische Ämter des Bundes und der Länder, 2019). Figure 4.1 shows a map of the average yield and the standard deviation for the period 1999 - 2018. On average, the highest yields are recorded in the extreme north of Germany, while the lowest yields and the highest inter-annual variation are found in the eastern part of Germany. For each county, the data is converted into yield anomalies in percent by subtracting the average yield and dividing the resulting difference by this average. Anomalies potentially reduce the bias of the coefficients caused by the time-invariant confounding variables. In this way, we mimic the fixed effects approach in panel econometric regression methods. Since the mid-1990s, annual increases in yields have ceased and no trend in yields has been observed since then (Gömann, 2018). A trend correction is therefore not required. All counties with yield data of less than ten years of observations are removed from the analysis, which results in 350 remaining districts (figure 4.6 in the appendix shows a map of the numbers of observations available for each county).

The daily temperature and precipitation data are obtained from a network of stations of the German Weather Service (Deutscher Wetterdienst, 2019). For the interpolation method to gridded data see Zink et al. (2017). Daily meteorological data are converted into monthly aggregates by counting the days above or below a defined threshold based on Gömann et al. (2015). Table 4.1 shows the seven meteorological extreme indicators, the underlying meteorological variables and

Table 4.1: Indicators of seven extreme weather conditions (first column) are generated by counting the days above or below the thresholds of certain meteorological variables for specific months (second column). The variable names of the resulting features are displayed in the last column. The number indicates the month. For example, Frost10 represents the number of days with black frost in October of the previous year, and Heat6 the number of days with heat in June. T reflects temperature, P precipitation.

Ext. weather conditions	Meteorological variables	Variable Names
Black Frost	min. T < −20°C: Dec. - Feb.	Frost12, Frost1, Frost2
	min. T < −10°C: Mar. & Nov.	Frost3, Frost11
	min. T < −5°C: Oct.	Frost10
Late Frost	min. T < 0°C: May	Frost5
Alternating Frost	min. T < −3°C min. T > 3°C: Jan. - May	AF1, AF2, AF3, AF4, AF5
Heat	max. T > 30°C: Apr. - Aug.	Heat4, Heat5, Heat6, Heat7, Heat8
Heavy rain season	P > 30 mm/d: Oct. - Jun.	Rain10, Rain11, Rain12, Rain1, Rain2, Rain3, Rain4, Rain5, Rain6
Rain harvest	P > 5 mm/d: Jul. & Aug.	Rain7, Rain8
Precipitation scarcity	P = 0 mm/d: Oct. - Aug.	PS10, PS11, PS12, PS1, PS2, PS3, PS4, PS5, PS6, PS7, PS8

considered months as well as the corresponding variable names in the model.

The soil moisture simulation was obtained from the German Drought Monitor (Zink et al., 2016) using the mesoscale Hydrologic Model (mHM) (Samaniego et al., 2010; Kumar et al., 2013). The soil moisture index (SMI, Samaniego et al. (2013)) is derived from a non-parametric and site-specific cumulative distribution function of soil moisture for the period 1951-2018. The percentile-based index quantifies the likelihood of occurrence of the monthly absolute soil moisture. Consequently, seasonal effects due to drought and wet conditions during different agrophenological stages are taken into account. Furthermore, the SMI reduces systematic errors in simulated soil moisture such as a bias (Auffhammer et al., 2013; Lobell, 2013). Here, we include two variables denoting soil moisture at two depths, namely the uppermost 25cm (SMI) and the total soil column (SMIa) with variable depth depending on the soil map BUEK1000 (BGR, 2013). Due to the high positive time correlation of SMIa to its first and second order neighbours, only the months October, January, April and July are considered (figure 4.7, Appendix). The meteorological indices and SMI fields have a spatial resolution of 4×4 km^2. See Peichl et al. (2018) for a detailed description of the spatial processing to the county level.

4.3 Method

The goal of this study is to maximize predictive power while allowing interpretabiliy of the model. To achieve the latter, we use model agnostics, which includes various flexible methods that allow the interpretation of black box models. Accordingly, the same method can be used for any kind of machine learning algorithm, different types of explanations and different types of features can be presented (Ribeiro et al., 2016). The particular method considered here is accumulated local effects (ALE), which is a visualization of the average effect of features on prediction using black box supervised learning models (Apley and Zhu, 2016; Molnar, 2020). It is an unbiased alternative to the popular approach of Partial Dependence Plots (Friedman, 2001). For a domain covering the whole of Germany, random forest (RF) proved to be superior to other machine learning algorithms that are particularly suitable for nonlinear systems, such as support vector machines and gradient boosting (not shown). RFs have also been widely used in related disciplines such as drought impact assessment (Bachmair et al., 2016) and forecasting (Sutanto et al., 2019). Within these applications, it has proven to be more powerful for classification than other data-science methods (Bachmair et al., 2017). RF randomly produces numerous independent trees as an ensemble to avoid over-fitting and sensitivity in the configuration of training data, while being very efficient (Sutanto et al., 2019). The trained model is Breiman's RF (Breiman, 2001a) based on 500 trees. It is tuned to the number of variables available for splitting at each tree node (based on out-of-bag error estimation).

The crop yield potential varies regionally in Germany due to differences in climate and soils among other factors. Consequently, a spatial clustering was performed. The clustering methods used are representatives of centroid-based ones, such as KMEANS and partitioning around medoids (PAM), which is less sensitive to outliers, as well as the connectivity-based hierarchical clustering (HIERARCHICAL). Standard internal validation such as Connectivity, Average Silhouette Width, Dunn index for cluster numbers between 2 and 16 were tested for the evaluation. However, the results show no clear outcome on which algorithm and size combination to use (figure 4.8). Instead, we chose the clusters so that the average predictive capacity of the machine learning algorithm is maximized. The data used for clustering are monthly averages and daily observations of the meteorological data for the entire year. SMI is included for both the upper layer and the entire soil column. Average yields are also taken into account in the data for cluster formation. This is based on the intuition of taking into account time-invariant factors of each cluster that affect yields such as soil quality and average farm size. These factors are not considered in the random forest due to use of yield anomalies. This approach is inspired by fixed effect econometric models. There, the group means are fixed, thus taking into account the time-invariant heterogeneity of these groups (for econometric literature see for instance Wooldridge (2012)).

4.4 Results

4.4.1 Evaluation of spatial clustering

To evaluate the cluster algorithm and the number of clusters the out-of-sample R-squared for each cluster and number of cluster combination is generated. The model is trained on 80 percent of the data and predicted for the rest. Table 4.2 shows results for three different soil moisture

Table 4.2: Table with the average R-square (test) for the three best combinations of cluster algorithm and cluster size (in parentheses) for three soil moisture configurations.

Soil moisture configuration	Algorithm size combination	Avg. R-square (test)
SMI for uppermost 25cm	KMEANS (8), PAM (8)	0.70
	PAM (3)	0.69
	PAM (2)	0.69
	non-cluster	0.65
SMI for entire soil column	KMEANS (10), PAM (8)	0.68
	PAM (8)	0.67
	HIERARCHICAL (6), KMEANS (6)	0.67
	non-cluster	0.64
SMI for both uppermost 25cm and entire soil column	KMEANS (8), PAM (8)	0.69
	PAM (2)	0.69
	KMEANS (10)	0.68
	non-cluster	0.65

Figure 4.2: Spatial structure of clusters derived from the PAM algorithm with 8 clusters (a) and with 2 clusters (b).

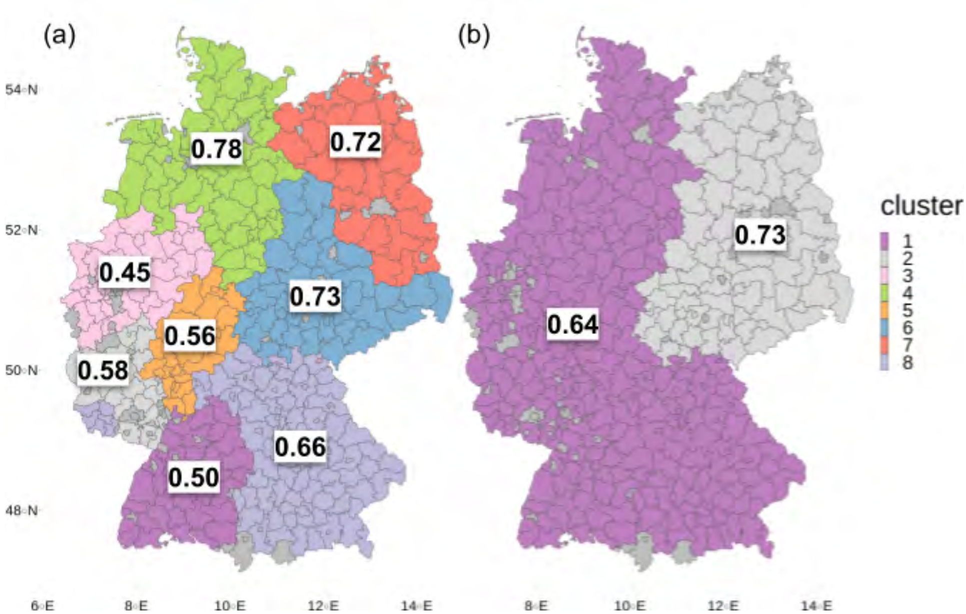
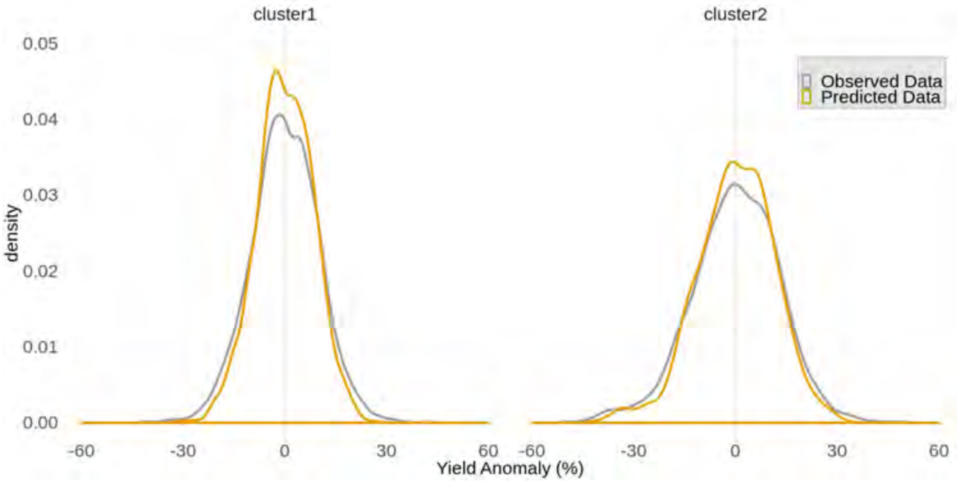


Figure 4.3: Density plots of observed and predicted data for the two clusters derived by the PAM algorithm with size 2.



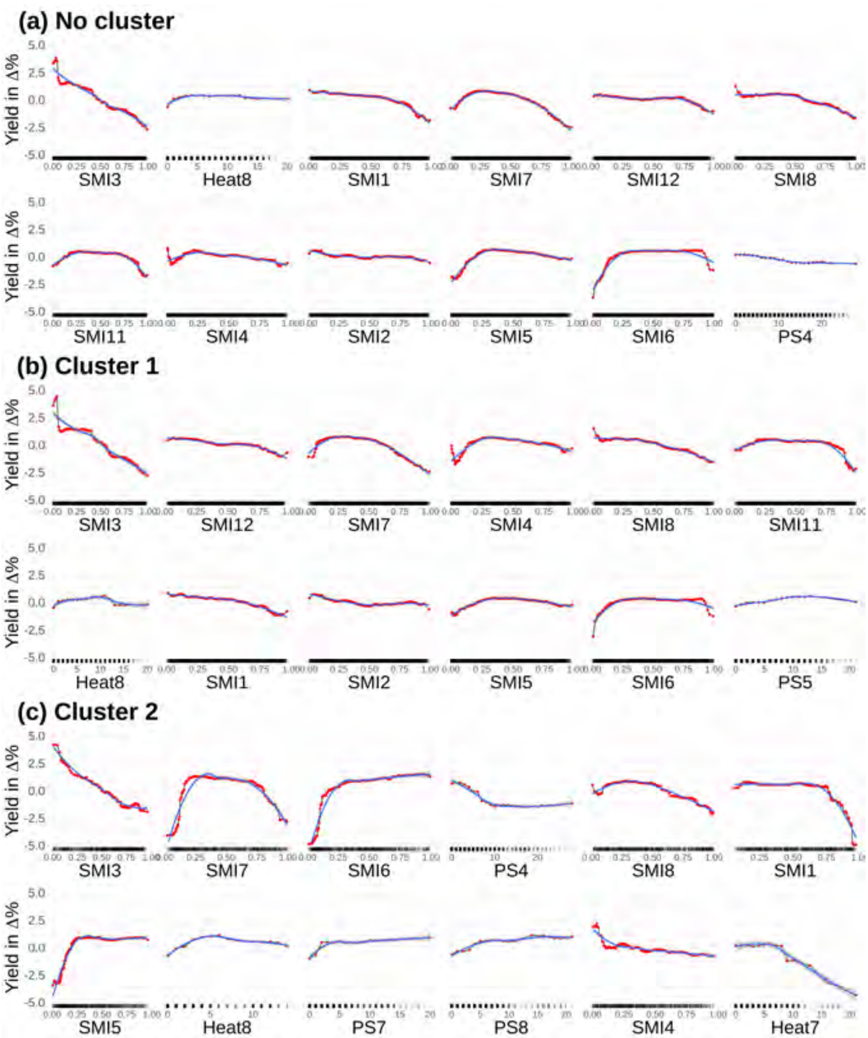
configurations, i.e. one each for the upper layer as well as the entire soil column and one that takes both into account. For each of these soil moisture configurations the three combinations of algorithms and cluster sizes with the highest R-square are shown. The validation criterion for non-cluster formation is also shown as a reference. Overall, the best results can be achieved if only SMI for the uppermost 25 cm is considered. The best results explain more than 70% of the wheat yield anomaly variation. A regression model with similar variables and time-invariant variables is able to explain a maximum of 32% of the variation (Gömann et al., 2015). A large fraction of the variability is usually explained by time-invariant factors, which are largely not considered here due to the demeaned yield data. For example, Peichl et al. (2018) using a regression model for silage maize showed that up to 32% of the variation explained by the model is explained by time-invariant factors. An approach modelling relative year-to-year yield changes has similar results (Conradt et al., 2016). The results are comparable when considering the spatial distribution of the explanatory power, because the best explanatory power is found for northern and eastern Germany with comparable coefficients of determination. However, for the rest of Germany the model presented here performs better as it is doing well in regions with rather low yield variability such as in the south of cluster 4 or in Bavaria (figure 4.2a). We choose to further explore the results of PAM with two clusters because it provides a compromise between a high predictive power and reduced complexity. The clusters are divided along the former border between western and eastern Germany (see figure 4.2b). This division along administrative borders is also supported by other cluster (figure 4.2a). Generally, higher variability in yields can be observed for most parts of eastern Germany (figure 4.1). This indicates structural differences between western and eastern Germany (Albers et al., 2017). Those might be for instance different data reporting practices as well as different business structures. The R-square of cluster 1 is 0.64 and of cluster 2 is 0.73. For both clusters, the tails are slightly underestimated (figure 4.3). The higher explanatory power for cluster 2 might be related to the higher variation in yield anomaly there (see figure 4.1). Furthermore, different impact mechanisms might work within each cluster. Those are disentangled in the following.

4.4.2 Model agnostics

In the following, model agnostics is used to unravel the spectrum of effects on winter wheat yield variation for each cluster. To generate variable importance and ALE plots, no split is made between test and training data. The non-cluster results are compared with the spatial clusters generated with the PAM clustering algorithm for a cluster size of 2 (PAM (2)). The detailed ALE plots for the overall best algorithm cluster size combination (PAM (8)) can be found in the appendix (figure 4.9). In general, the ALE visualization there is more wiggly, which indicates an over-fit of the model. The effects shown here are additive as the they are cleared off the correlation to other features. However, an assessment of the interaction effects does not show stable results and varies from run to run due to the lack of available data. Therefore, these results are not discussed here.

The ALE plots in figure 4.4 are ranked in accordance to their variable importance (for further information see the variable importance section in the appendix). In general, soil moisture supports best the performance of the model. This is valid in particular for the non-cluster approach and cluster 1, since in cluster 2 more meteorological variables are critical. Figure 4.4a shows the ALE plots for the non-cluster approach. Cluster 1 (figure 4.4b) shows almost similar sensitivities to those observed for the non-cluster approach. Besides the importance ranking, basically only the amplitudes of the effects change. Only the least important variable is PS5 instead of PS4 in cluster 1. In both clusters, for most of the ten soil moisture variables more than normal water is comparatively more harmful than water shortage in the soil. Topsoil SMI in February and March as well as in August show a positive signal for shortage in soil moisture. This indicates a preference for drier than normal conditions during those months. For December and January, no negative impact of soil water scarcity can be found. SMI shows a negative drought signal for the months April to July with the one in June being the largest. For July a drop in yield can be observed for small values of SMI. However, the negative effects of soil water abundance are much larger in this case. For cluster 1, in May and June, the drought signal by soil moisture is comparatively smaller than the one found in the non-cluster setting. For April the signal is stronger but still ambiguous. Overall, the signals associated with water deficit stress are rather weak in both cluster approaches, but particularly in cluster 1. This is consistent with the results of a statistical model for North Rhine-Westphalia, which compromises a large part in the west of cluster 1, according to which water stress has no limiting effect on wheat yield there, not even due to climate change (Kropp et al., 2009). For cluster 2, this pattern changes (figure 4.4c). There, a stronger negative water shortage signal is visualized for the months April to July, which are typically associated

Figure 4.4: Accumulated local effects plots of the twelve most important features for for no cluster (a), cluster 1 (b), and cluster 2 (c). The red dots are estimated by the ALE plot algorithm (Feature-Effect of the iml-package in R). We have chosen a rather large interval size of 100, which allows us to reveal the true complexity of the model at the expense of shakiness. Therefore a nonlinear smoothing function (LOESS - locally estimated scatterplot smoothing) is added in blue (with confidence interval in grey). SMI represents the soil moisture index for the uppermost 25 cm of the soil column, PS stands for days without rain in a given month and Heat for days with a maximum temperature of more than 30 degrees. The number indicates the month, 10, 11, and 12 refers to the year before. For example, SMI10 represents SMI in October, i.e. the start of the growing season.

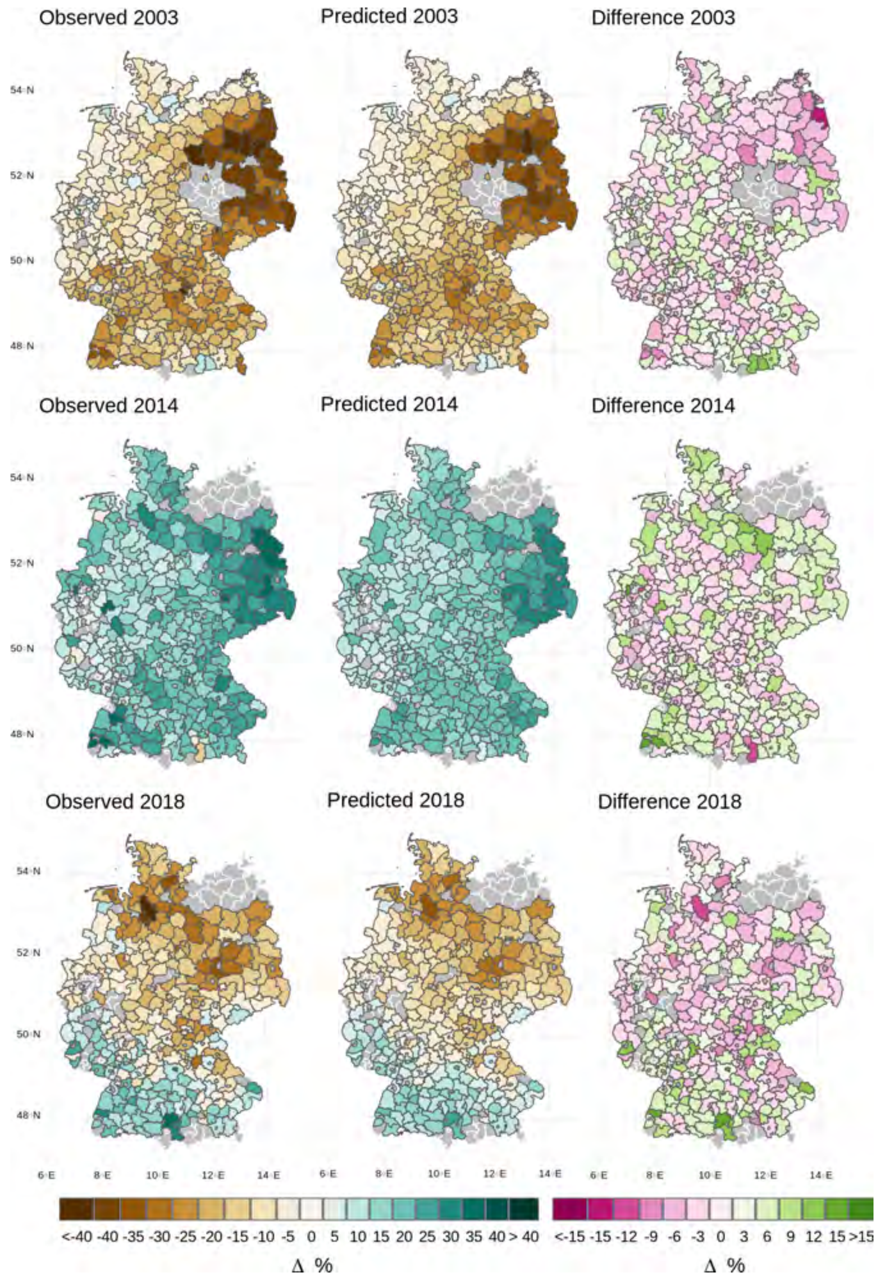


with the drought sensitive vegetative and generative phase of winter wheat (Lüttger and Feike, 2018). For the SMI features, a pivotal transition in the patterns takes place between April and May, as the negative effects of drought are evident first in May. Counter-intuitive effects can be observed for April: fewer days without rain are advantageous (PS4), but a positive effect of soil moisture drought can be observed (SMI4). Opposed to the other clusters, June shows a minor positive effect of higher than normal soil water on crop yield, but no negative effect for high SMI values. For July and August, those effects are similar to the other clusters. However, unlike in the other clusters, in cluster 2 the negative effect of water scarcity this time is larger than the one of water excess.

An earlier study showed for Germany a higher sensitivity of wheat yields to excess water compared to drought (Zampieri et al., 2017). In our study, the most important variable for all three cluster considerations is the same, i.e. soil moisture in March. The relationship between SMI3 and yield anomalies is generally negative for the entire range of the SMI. However, a strong drought signal can be found in the data if the model is applied to a specific cluster for eastern Germany. In a non-cluster approach, those signals are mostly confused. The observation that the absence of water govern crop production in this region is in alignment with recent studies (Conradt et al., 2016; Vinet and Zhedanov, 2010). There, lack of precipitation together with sandy soils, which have a lower water holding capacity, may result in water shortage for winter wheat growth (Rezaei et al., 2018). For the rest of Germany for most growing stages, extensive wet periods with water-saturated soil represent an extreme weather situation for agriculture (Gömann, 2018). The most sensitive growth phase for waterlogging is after germination, but before emergence (Barber et al., 2017; Grotjahn, 2020). Oxygen deficiency can cause damage to the plant that result in yield losses (Cannell et al., 1980). In addition, excessive soil water fosters pathogens (Grotjahn, 2020) and complicates plant treatment operations (Urban et al., 2015; Gömann, 2018).

Generally, it is difficult to disentangle the correlated effects of heat and water supply on plant growth (Gourdji et al., 2013; Roberts et al., 2013, 2017; Lobell and Asseng, 2017; Schauberger et al., 2017; Siebert et al., 2017; Mäkinen et al., 2018; Peichl et al., 2018). However, for Germany studies show that heat was more harmful than drought during sensitive growing stages in Germany in the past (Lüttger and Feike, 2018; Trnka et al., 2014). Here, however, neither for cluster 1 nor cluster 2, a heat signal is observed for June, which is associated with the most heat sensitive phase of anthesis (Barber et al., 2017; Rezaei et al., 2018). In cluster 2, more than 8 days of heat above 30 degrees in July show adverse effects, a period that could be linked to grain filling (Lobell et al., 2012; Lüttger and Feike, 2018; Mäkinen et al., 2018). In both clusters, heat in August, a period generally associated with ripening, has positive effects for each additional day and from day 11 onward negative effects. Our approach, which explicitly controls for the water supply of plants by soil moisture, shows more water-related effects compared to heat effects.

Figure 4.5: Maps of observed, the predicted and the difference between those two for winter wheat yield anomalies for the years 2003, 2014 and 2018 on county level.



4.4.3 Predictions of years with extreme yield anomalies

Figure 4.5 shows the maps of observed, the predicted and the difference between those two for winter wheat yield anomalies for the years 2003, 2014 and 2018. These are the years with both the largest losses and gains during the period considered. For 2003, the year with the highest overall losses, losses are observed throughout Germany. The highest losses were recorded in the eastern part of Germany. The year 2018 shows a spatially different loss pattern than 2003. There the losses are more likely to be in the northernmost parts of Germany, while the south of Germany shows positive yield anomalies. 2014 is a particularly good year with higher than expected yields, especially in the easternmost parts of Germany. The general spatial patterns of losses and gains of the observed data are represented by the simulated data for all three years. However, as can be seen from the differences, the model tends to slightly underestimate the extent of both extremes. For example, the largest negative differences between observed and projected data for 2003 are found for Vorpommern-Greifswald, a county in the north-east of Germany. The region around this county also shows the largest contiguous area of negative differences, i.e. an underestimation of the losses. The largest positive difference is found in the very south. For 2018 the picture is comparable and the positive yield anomalies in the south and the negative anomalies in the north are underestimated. For both years, however, there is no clear pattern of over- and underestimation for estimating values between the two extremes. For 2014, the very positive results in the easternmost districts are underestimated. However, the highest positive differences are not consistent with the highest positive anomalies observed. The highest differences in the positive anomalies are those for the high yield anomalies in the extreme southwest. The negative differences are for the underestimated losses in southern Bavaria. In summary, the model is very well able to predict district yield anomalies, but does not represent the full extent of the anomaly variation in the extremes. With less variation in the observed yield data, no clear pattern of under- or overestimation can be observed.

4.5 Conclusion

Here, for the first time a machine learning algorithm was used to predict crop yield in Germany. To our knowledge, it is the statistical model, which is not relying on time-invariant factors, with the highest predictive capacity for entire Germany. In comparison to other models, this approach performs better in regions with low crop yield variance. Furthermore, it is the first time model agnostics has been applied in such a context. Different clustering algorithms and cluster sizes have been applied to improve the predictive capacity of the model from 65% in average test R-squared to 70%. In general, it is able to explain the general pattern of losses and gains of the counties, also those in particular extreme years such as the years 2003, 2014, and 2018. However, it slightly underestimates the extremes on both ends. Because of its predictive capacity, we consider the model suitable to be applied for instance for annual yield forecasting. In addition, in Germany, yield data are reported more than half a year later than the actual time of harvesting. The predictions generated by this model can support the design of tailor-made and, above all, prompt support mechanisms for large losses caused by extremes. Our approach also helps to disentangle the damage spectrum for clustered regions in Germany. Soil moisture dominates the variable importance ranking, in particular in western Germany (cluster 1 in figure 4.4). Thereby, it is preferred to account for the upper 25 cm of the soil moisture column compared to the entire column or a combination of both. Whereas the northeastern part of Germany is rather driven by damages related to water shortages, water abundance is problematic for winter wheat growth in the other parts of Germany. Those water shortage effects for the smaller cluster remain undetected in a non-cluster approach. Heat related measures are underrepresented in explaining the effects on winter wheat yield anomalies. Those information are helpful to tailor management and adaptation measures. For example, it is particularly suitable for the insurance industry to provide index-based insurance policies, as they help to identify harmful features and visualize thresholds in those features that cause damage (Albers et al., 2017). Furthermore, such an approach, which explicitly captures the complexity of the underlying reaction mechanism rather than relying on one major determinant, is suitable for the projection of climate impacts, since GCMs explicitly capture the dynamics of several hydro-meteorological variables (Crane-Droesch, 2018). More research is needed, however, to better take into account small-scale incidents such as hail and thunderstorms and to better approximate region-specific seasons. Furthermore, the use of deep learning instead of classical machine learning can help to further increase prediction skills. Similarly, a sensitivity analysis of the expert thresholds used to define the extremes could help to improve the model.

4.6 Appendix

Data

We use a spatio-temporal data set containing 410 counties and 20 years. All counties with less than ten years of reported yields are excluded from the analysis (figure 4.6). There were 350 remaining counties in total.

Figure 4.7 shows the correlation of soil moisture indices for total root zone depth for the season of winter wheat in Germany from October to August. This correlation shows the persistence of soil moisture and the smoother distribution resulting from it compared to meteorological variables. The Pearson correlation coefficient between the neighbouring SMIa is between 0.62 and 0.95. For the second order neighbours it is still between 0.42 and 0.88. In general, the largest correlation coefficients are found for the first half of the season. For this reason, within the Random Forests, we consider only the months of October, January, April and July.

Figure 4.6: Map showing the number of winter wheat yield observations available for each counties.

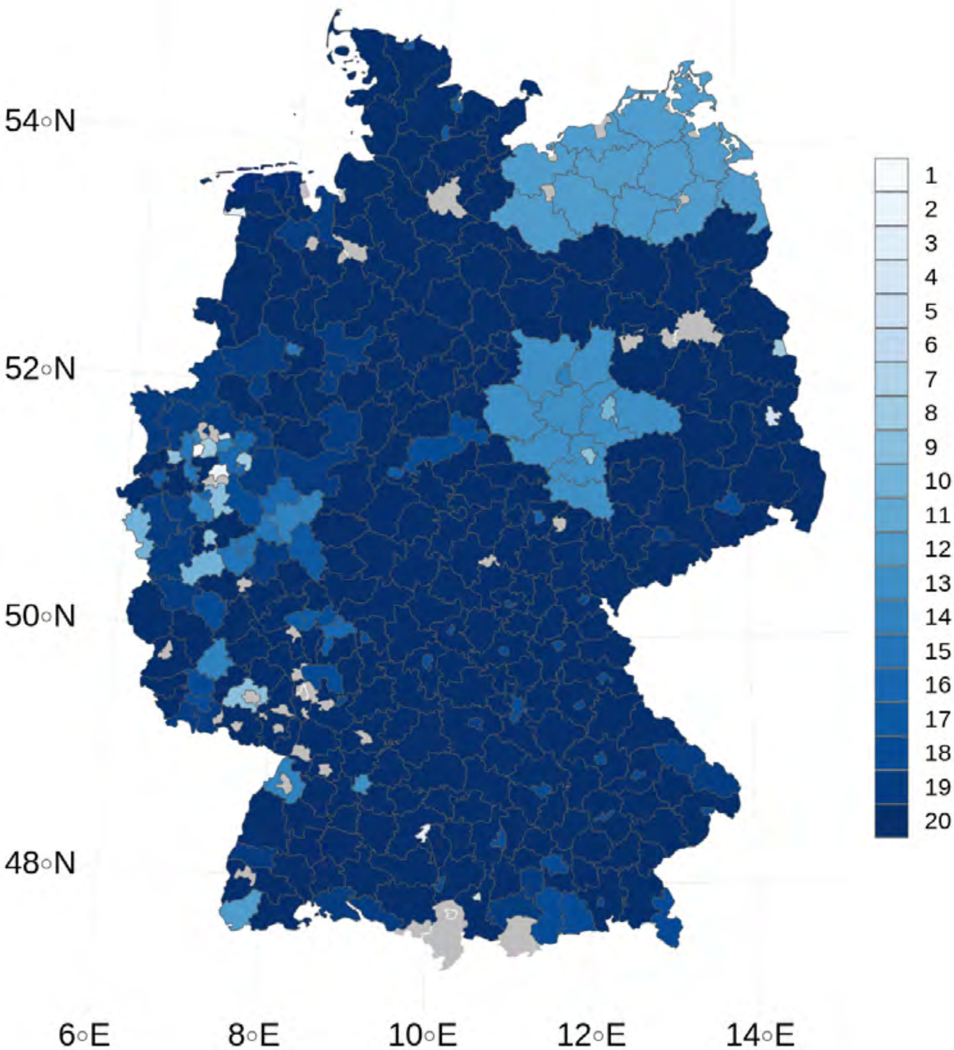


Figure 4.7: Correlation plot (Pearson correlation coefficient) of the soil moisture index for the entire root zone for all months of the season of winter wheat.

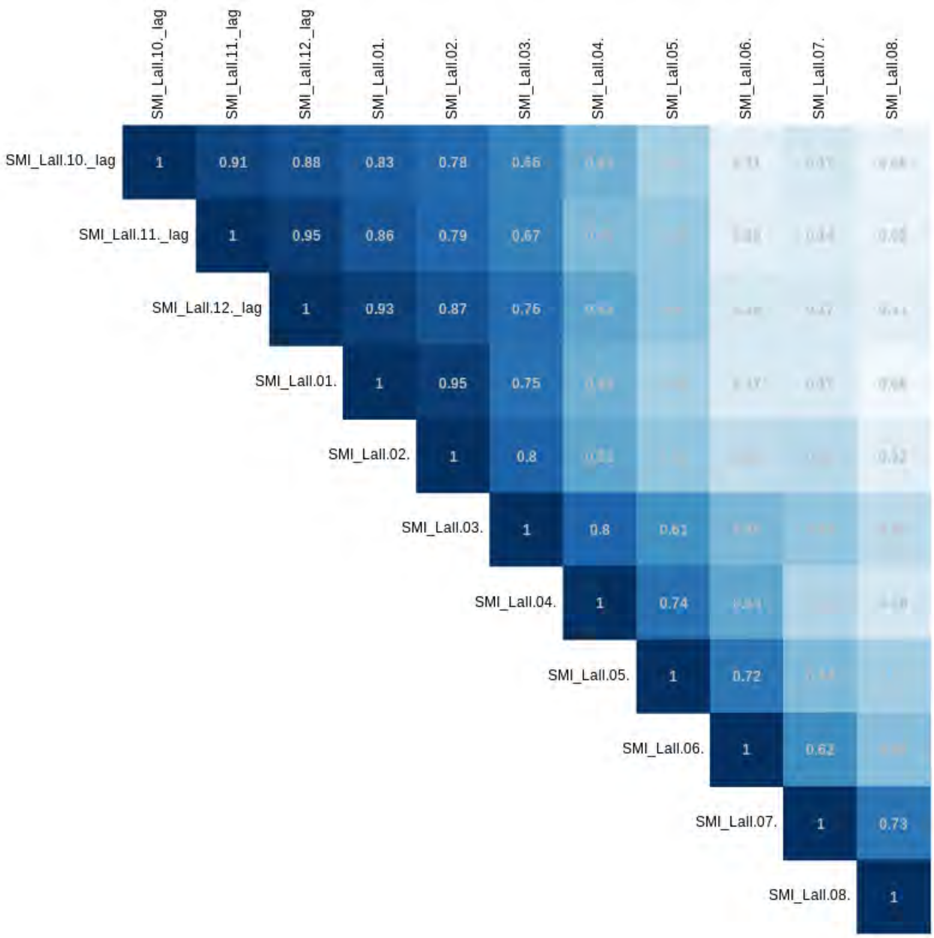
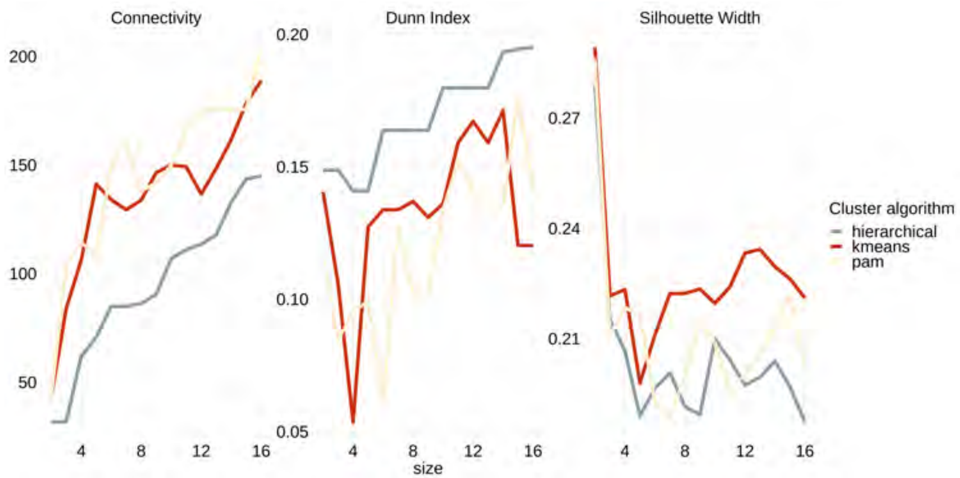


Figure 4.8: Internal validation measures for clusters with different sizes between 2 and 16. The measures depicted are Connectivity, Dunn Index, and Silhouette Width.



Cluster validation

Here, we use internal validation measures to assess the quality of the clustering, which employ only the data set and the clustering partition for the assessment (Subbaswamy, 1977). The specified measures are connectivity, silhouette width, and Dunn index. Connectivity refers to the degree of connectivity of the clusters (Handl et al., 2005). It has a value between 0 and infinity and should be minimized. Both the silhouette width and the Dunn index represent linear combinations of compactness and separation of the clusters. The Dunn index has a value between 0 and infinity and should be maximized (Dunn, 1974). The silhouette width ranges between -1 and 1 and well clustered observations have a value close to 1 (Rousseeuw, 1987). The connectivity mainly indicates the use of small number of clusters, Dunn, at the other end, rather large number. Silhoutte Width, on contrast, prefers a rather small number of clusters. In all three approaches the HIERARCHICAL algorithm is preferred. As a consequence of this ambiguity, we decided to evaluate the cluster algorithm and the number of clusters by the R-square outside the sample, which is generated for each cluster and the number of cluster combinations for the separate soil moisture configuration.

The ALE plots for the best combination of cluster algorithm, size, and SMI for the corresponding eight clusters are shown in Figure 4.9. The spatial arrangement of the clusters can be seen in Figure 4.2. The six most important features are shown for each cluster. As shown above, this ranking of importance is associated with a large uncertainty (not shown). These ALE plots give a more detailed description of the damage mechanism for subregions in Germany. However, they are more erratic than those shown before, which could indicate an over-fit.

Figure 4.9: Accumulated local effects (ALE) plots for the best combination of cluster algorithm, cluster size and SMI, i.e. PAM with 8 clusters and soil moisture for the uppermost 25 cm. For each cluster ((a) - (h)) the six ALE plots with the highest feature importance are shown. The importance ranking is established with 50 reputations. We have chosen a rather large interval size of 50 to estimate the ALE plots, which allows us to reveal the true complexity of the model at the expense of shakiness. Therefore a nonlinear smoothing function (LOESS - locally estimated scatterplot smoothing) is added in blue (with confidence interval in grey).

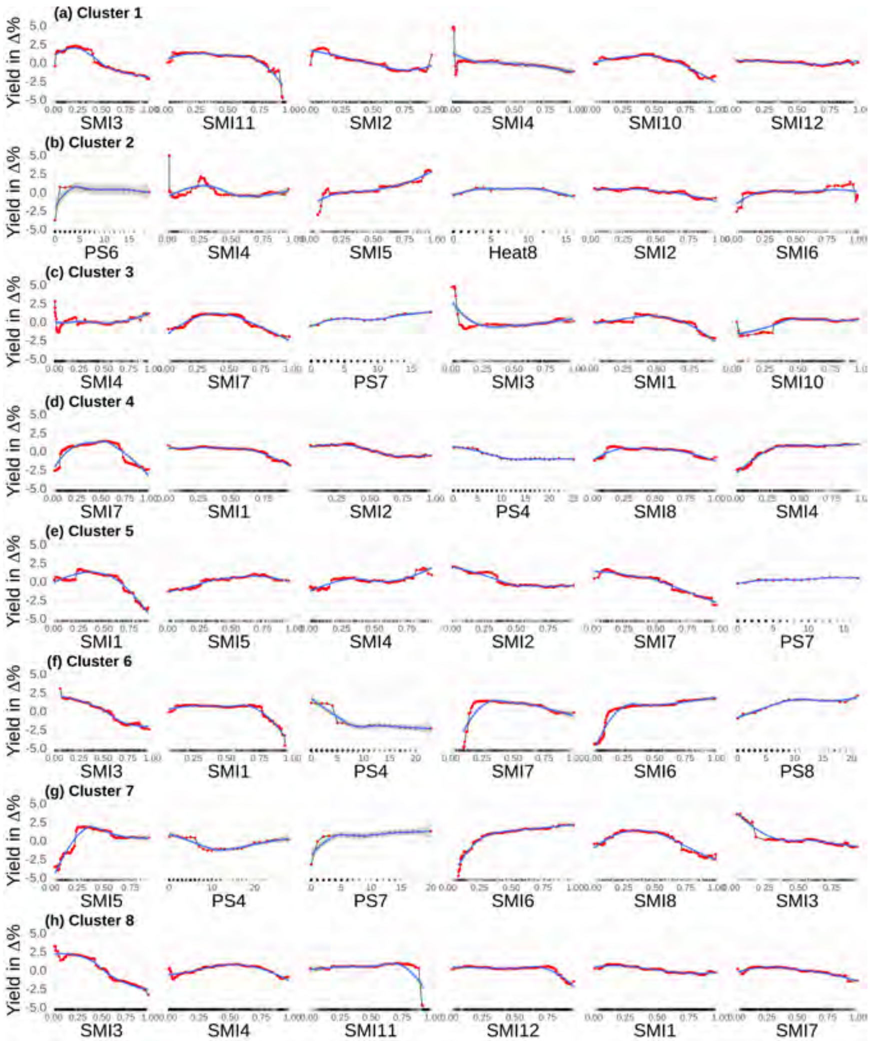
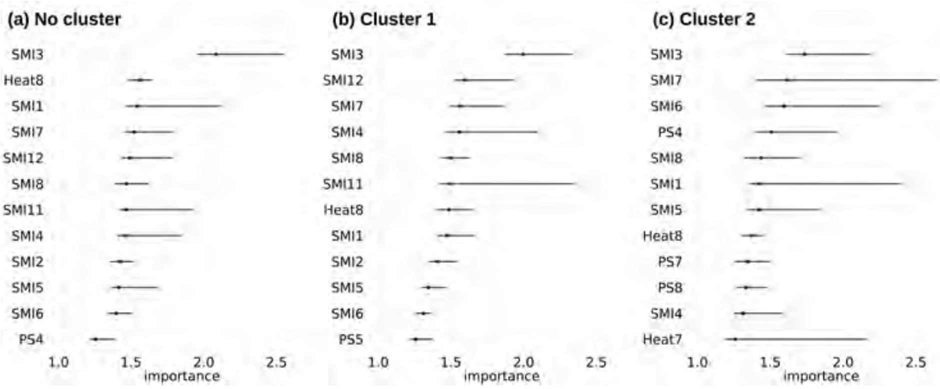


Figure 4.10: Variable importance of the twelve most important features for no cluster (a), cluster 1 (b), and cluster 2 (c). SMI represents the soil moisture index for the uppermost 25 cm of the soil column, PS stands for days without rain in a given month and Heat for days with a maximum temperature of more than 30 degrees. The number between the two points indicates the month, refers to the year before. For example, Frost10 represents black frost in October.



Variable importance

Here, importance is defined as the factor by which the model's mean average error (mae), a measure of model performance, changes when the feature is shuffled (Molnar, 2020). To overcome the randomness added by this shuffling, the permutation is repeated 50 times and the results are averaged. Hence, the results show a large variability, especially in the most important features (figure 4.10). Moreover, the less data are available, the greater is the variability of the results. Cluster 2 has the smallest number of counties compared to cluster 1 and the non-cluster approach. As figure 4.10a shows for a non-cluster approach ten out of the twelve most important variables are soil moisture in the uppermost 25cm during different times within the growing season and March being the most important month. The most important meteorological variable is Heat for August. Cluster 1 represents almost the same variables as those found in the non-cluster configuration (figure 4.10b). Only PS5 is considered instead of PS4. However, the order of the variables changes. In particular the most important meteorological variable Heat8 is less important in cluster 1. Overall, SMI of March is still the most important variable. Also, the two lagged soil moisture variables gain relevance. For one of those two, i.e. SMI in November(Heat8), the largest variability can be found. For cluster 2, a new picture evolves as four different variables are considered here (figure 4.10c). In particular lagged soil moisture values of the year before are not considered as well as February soil moisture. Also, PS5 is not represented in the data there. Instead, precipitation scarcity of April, July, and August is considered now. This indicates, that the meteorological variables are more important in the regions considered here. Also, the late spring and summer seasons are more pronounced as precipitation scarcity in April as well as soil moisture from May to July are amongst the most important variables. However, soil moisture in

March is still the most relevant variable. In general soil moisture supports the performance of the model for all three considerations the most. This is particular true for the non-cluster approach and cluster 1 as in cluster 2 more meteorological variables are critical. The most important variable for all three cluster considerations is the same. The only meteorological variable listed for all three clusters is Heat8. It can be observed that the non-cluster approach particularly reflects cluster 1 whereas cluster 2 is underrepresented.

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