

We thank the reviewers and the editor for their comments, which helped us to further improve our manuscript. We provide a marked-up manuscript with highlighted changes in blue additional to the final manuscript.

A point-by-point response to the reviewer can be found below. Comments are in *italic* font; answers are in **bold** font. The pages and lines of the changes are included and refer to the pdf file with highlighted changes.

The most relevant changes are as follows:

- We expanded the method section and clarified the use of fixed effect terms (page 8, lines 1 to 15 in the manuscript with highlighted changes).
- We included a paragraph discussing the use of seasonal cumulates of precipitation (page 11, line 32 to page 12, line 4 in the manuscript with highlighted changes).

Reviewer #1

The paper has in general excellent quality. Methods and analysis of results are well developed and sound. The only comment is that according to the underlying data bases (as well as indirect influence of spatial variability of soil conditions and soil+crop management) some more information should be provided regarding related uncertainties and limitations. For example, the potential influence of various maize cultivars used over Germany (on results) -through their different sensitivity to drought and heat stress - and related limitations as well as suggestions for future potential improvements of the demonstrated method in that context should be addressed, i.e. by application of high resolution Remote sensing data (Sentinel etc..).

We would like to thank the reviewer for her/his comments on our manuscript that helped to further improve it. In detail we addressed the comments as follows. Regarding the maize cultivars, the basic assumptions and limitations of the models is elaborated in greater detail. This includes mentioning two major assumptions. First, that the farmers optimized their production process, given their experience about a particular site, which also covers the choice of the variety. Second, it is assumed that the response of plants to inter-annual stressors is the same across all locations. Future potential improvements include the expansion of the model to different varieties to alleviate the second assumption mentioned above (changes are implemented on page 8, lines 1 - 15 in the marked-up manuscript). Another improvement that we refer to is using remote sensing data. With regard to future improvements, we include this in the discussion section, as this note relates mainly to the underlying data. Here we point out that improvements can be achieved through data with higher temporal resolution, which better take into account certain growth stages (changes are implemented page 21, lines 7 - 9 in the marked-up manuscript).

Reviewer #2

The manuscript "The effect of soil moisture anomalies on maize yield in Germany" by Peichl et al. describes the intra-seasonal impact of meteorological drivers and soil moisture on silage maize yields in Germany. Reduced form fixed effect models are employed to perform the analysis.

The results are revealing the important meteorological factors driving inter-annual maize yield variability, and therefore provide important step towards development of seasonal forecasting framework (which can be used to advise farmers/policy makers). The results are interesting and scientifically sound. Nevertheless, I would suggest to revise the clarity of the methods used as well as several discussion aspects before the manuscript is accepted for publication.

We would like to thank the reviewer for her/his comments on our manuscript that helped to further improve it. We revised the methods section and take into account several discussion aspects as outlined below in more detail.

[1]Page 1, line 21: instead of yield, I would mention maize yield variation.

Corrected accordingly on page 1, line 21 in the marked-up manuscript.

[2] Page 2, line 18: temperature above which threshold? Do you mean the Heat degree days (i.e. above 30 deg. C) or base temperature? Moreover, is temperature accumulation above that threshold considered or number of days with temperature above that threshold?

Thank you for this comment. In this paragraph we cite the results of Schlenker and Roberts (2009). Regarding the threshold: it is estimated to be 29° Celsius and is explicitly mentioned in the text. To clarify the applied method, the original sentence of the seminal paper is included here: "The new weather data include the length of time each crop is exposed to each one-degree Celsius temperature interval in each day, summed across all days of the growing season, all estimated for the specific locations within each county where crops are grown" (Schlenker and Roberts, 2009). In other words, the authors considered the exposure of the plants to all one degree temperature intervals between 0 and 42 degrees at hourly time steps. They report substantial reductions in yield above 29 degrees. We clarified this point in the corresponding paragraph in the introduction (page 2, lines 18 - 24 in the marked-up manuscript) .

[3] Page 2, line 20: I propose better reasoning before nonlinearity is mentioned; only stating the threshold is not sufficient. A reference to non-linear response of processes would be better.

Thank you for this comment. We would like to highlight here that, as seen in Schlenker and Roberts (2009), these thresholds generally describe that the relationship between yield variability and temperature is non-linear, in the sense that it is initially increasing and then decreasing. This reflects the assumption that optimal conditions exist for plant growth in each growth stage (Thompson, 1969). In the seminal paper, to which we refer here mostly, no processes are described explicitly to underpin nonlinearity (Schlenker and Roberts, 2009). When it comes to "dynamic physiological process of plant growth, seed formation, and yield" (Schlenker and Roberts, 2009), the authors refer to agronomic studies, that "use a rich theoretical model to simulate yields given daily and subdaily weather inputs, nutrient applications, and initial soil conditions" (Schlenker and Roberts, 2009). "A strength of simulation models is that they fully incorporate plant-growth theory. These models also incorporate the whole distribution of weather outcomes over the growing season. This differs markedly from earlier regression-based approaches that typically use average weather outcomes or averages from particular months and thus give biased estimates of nonlinear temperature effects" (Schlenker and Roberts, 2009). The goal of this study is to test for and then introduce nonlinear effects of key determinants into regression models. These regression models are often used to estimate climate impact as they have the advantage of good predictive power (Timmins and Schlenker, 2009). In such a context, however, "[a]ccurate estimation of nonlinear

effects is particularly important when considering large, nonmarginal changes in temperatures, now expected with climate change” (Schlenker and Roberts, 2009). We clarified the application context and why nonlinearity matter in such a context in the revised text (page 2, lines 18 - 24 & page 10, lines 9 - 14 in the marked-up manuscript).

[4]Page 3, lines 1-5: Authors state that the temperature sensitivity is the highest during the flowering period. Nevertheless, high temperatures during the reproductive period affect maize as well, causing increased senescence rates, shortened duration of grain filling period and therefore reduced yields.

We thank the reviewer for this comment. In this section we try to show that the sensitivity to stressors such as temperature above 29 degrees is not the same for all growing periods, but strongly depends on the stage of growth. We use the flowering period as an example of such an increased susceptibility, amongst others. We included the reproductive period as an example in the revised version, since it is also mentioned in the literature cited (see for instance Wahid et al. (2007)) (changes are implemented on page 3, lines 4 - 5 in the marked-up manuscript).

[5] Page 5, line 15: rephrase (i.e. E is calculated based on empirical estimate, it is not measured). We agree with the reviewer on this comment. We rephrased it in the revised section: ” E is calculated by the equation of Hargreaves and Samani (1985) based upon extraterrestrial radiation and temperature and is estimated in millimeter per day” (page 5, lines 19 - 20 in the marked-up manuscript).

[6] Page 5, lines 28-30: Are crop yield data normalized as well? Moreover, you mention the normalization of meteorological data, followed by mentioning that their mean and standard deviation are 0 and 1, respectively. Does this mean that you have standardized rather than normalized the data? With this respect, the SMI ranges between 0 and 1, and is not standardized. How does this affect the regression coefficients? Better explanation would be welcomed.

Thank you for that comment. Harvest yields are not normalized. However, it is logarithmized and adjusted linearly to the time trend (see section 2.1.). In addition, the fixed effects on the right-hand side of the equation 2 also take into account the mean yield for each administrative district. This means that the data for each district is mean-centered. However, the spread of returns remains unchanged. We agree on the terminology and now use standardization instead of normalization in the revised version (page 5, line 30 in the final version; page 6, line 1 in the marked-up manuscript). Regarding the standardization of SMI. SMI is already defined as a measure of an anomaly. An alternative would be to standardize soil moisture. However, it is unclear how drought can be defined in such a case. Here, we use SMI because it is a standard approach for quantifying soil moisture drought. See for example the German Drought Monitor and the US Drought Monitor. In addition, we use index functions and standardization would take no effects because the intervals would be adjusted accordingly. In other words the index functions would give the same results irrespective of the usage of SMI or Soil Moisture. The index functions are used to map soil moisture to six classes of dryness and wetness. This mapping uses location depended percentiles to guarantee a spatial consistency (lines 11 - 12 in the marked-up manuscript).

[7]Page 7, line 1: absence instead of absent.

Corrected on page 7, line 4 in the marked-up manuscript.

[8] Page 7, Eq. 3: Index j in the first term indicates drought class, in the second term it indicates exponent and is therefore misleading. Moreover, three numberings are provided for the same equation.

Thanks for the remark. This is now corrected on page 7 (equation 2) and page 7, line 21 in the marked-up manuscript. We use the index n for classes. In addition, the numbering is corrected and we use only one for the same equation.

[9] Page 7, line 20: Why are coefficients constrained to be the same? Should they not reflect also the impact of non-climatic factors (such as agro-management, which can differ among different regions under consideration) on yield variability?

Thank you for your comment on our modeling approach. In general, we rely on methods that are widely used for studies in the United States and other parts of the world and are based on econometric theory, especially in the evolving field of climate econometrics. One of the basic assumptions is that we do not explicitly control for endogenous processes such as management. Instead, only exogenous variation within the sample is used (Timmins and Schlenker, 2009). Instead, we control for time-variant differences between the districts through constants. These are the mean values of the explained and explanatory variables specific to each district and add up to the fixed effects (c_{im}). Fixed effects are a common term in econometrics. Since fixed effects represent the means of a predictor such as meteorology and soil moisture for a certain period, it may be interpreted as the long-term conditions for farming (Schlenker and Roberts, 2006). Those are usually known by the farmer. For instance, it is assumed that the farmer does not only know the average weather conditions but also the water holding capacity of the soil and adapts the management accordingly. The source of identification of the coefficients is thus year-to-year variation of weather and soil moisture. This interpretation is enhanced by the use of anomaly categories for soil moisture. This is clarified in more detail in section 3 (page 7, line 24 - 25, and page 8, lines 1 - 15, in the marked-up manuscript).

[10] Page 7, lines 28-30: Better explanation is needed: - are fixed effect terms included in C_i ? - how is C_i calculated? - this substantially increases the number of variables for regression model trained on the relatively small sample sizes. It is worthwhile mentioning that standardization of predictors avoids problems with multi-collinearity arising from structure of regression models.

Thanks you for this valuable comment which helps to clarify important aspects of the model. The fixed effects (c_{im}) are constants that are generated for each district and are composed of the administrative district specific means of the left and right variables of the model. It is possible to take these explicitly into account by using dummy variables for each district, here referred to as the least square dummy variable approach (lsdv). Alternatively, each variable can be demeaned for each district, here referred to as the demeaning framework. The demeaning framework therefore has fewer variables to be estimated. However, both approaches provide the same estimates for the coefficients. Also, the fixed effects are functions of the means and the coefficients and thus add no degrees of freedom to the dimensionality of the parameter space. We plan to clarify the meaning of fixed effects in the revised text. For instance we plan to include: "Time-invariant differences between administrative districts are taken into account by the fixed effects. These consist of the districts specific mean values of the individual variables on the right and left side of the equation" (page 7, lines 24 -25 in the marked-up manuscript. We also deleted a half sentence on page 9, line 3 in the marked-up manuscript).

Some clarifications are implemented also in the sections, in which we compare least

square dummy variable approaches and the demeaning framework (page 9, lines 14 - 15 & page 13, lines 1 - 16 in the marked-up manuscript).

With regard to the standardization recommendation, we have not been able to find any evidence of it. We only found literature suggesting that centered means play a role in dealing with problems of multicollinearity caused by polynomial concepts. However, we found no differences in the standard errors between those estimated by the demeaning framework, where the administrative specific mean for each spatial unit is subtracted, and the least squares dummy variable approach. Thus, centering by demeaning has no influence on the standard errors.

[11] Page 8, line 1: *what is natural experiment?*

In social science, where experiments are very difficult to implement, it describes a study design which allows to reveal causal effects. A typical example in econometrics is, that a "natural experiment occurs when some exogenous event - often a change in government policy - changes the environment in which individuals, families, firms, or cities operate. A natural experiment always has a control group, which is not affected by the policy change, and a treatment group, which is thought to be affected by the policy change. Unlike a true experiment, in which treatment and control groups are randomly and explicitly chosen, the control and treatment groups in natural experiments arise from the particular policy change" (Wooldridge, 2012). In our case, in which we rely only on exogenous variations of period-to-period effects, the farmer cannot choose which group they belong to, as the weather conditions are stochastic. This is clarified in more detail in section 3 (page 8, lines 10 - 13 in the marked-up manuscript).

[12] Page 9, line 1: *what is demeaning? Short description might help.*

Demeaning is subtracting the mean, here the administrative specific mean of all variables. Description is included in the revised text (page 9, lines 14 - 15 in the marked-up manuscript).

[13] Page 10, line 14: *Is BIC related to explanatory power? Or is it referred to table 2?*

The Bayesian information criterion is chosen by us as a measure to achieve a good balance between the explanatory power (i.e. goodness of fit in the sample) and model complexity (i.e. number of parameters). It is not referring to table 2. This table show the comparison of the Pearson Correlation Coefficients of the exogenous variables, in particular to show that E and T are highly correlated (e.g. as a measure of multicollinearity).

[14] Page 10, lines 20-25: *In this analysis you have applied separately for each month the regression models and evaluated their capability to predict yields. You argue that soil moisture during the grain filling is a variable with memory from previous months and is therefore explaining more variability. Wouldnt that be the case also if you would take seasonal cumulates of precipitation and/or evapotranspiration, or climatic water balance (as their difference)? In that sense I agree that soil moisture is more relevant variable, however the comparison is not fair towards the monthly meteorological cumulates.*

We performed additional analysis to investigate the relationship between seasonal cumulates of precipitation and soil moisture (figure 1 in this document). As expected longer cumulates of precipitation show a higher correlation with soil moisture as compared to one month precipitation. Soil moisture provides different information as compared to seasonal cumulates of precipitation, which becomes apparent from the following two observations. First, there is strong spatial variability of the Pearson

May

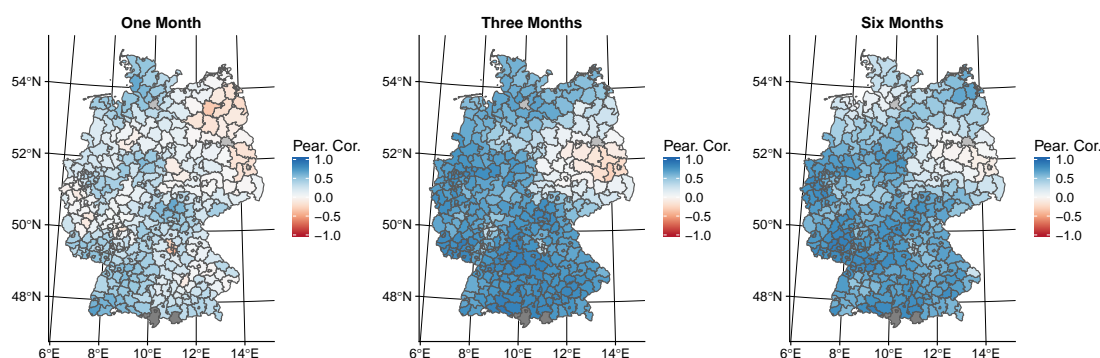


Figure 1: Figure of the Pearson Correlation Coefficients of soil moisture of May and accumulated precipitation for one month (left panel: May), three months (middle panel: March to May), and six months (right panel: December to May)

Correlation Coefficient with relatively lower values in Eastern Germany and higher values in the Southern Germany. Second, the mean coefficient of determination is at most 50 %. This implies that a substantial part of the soil moisture variability cannot be explained by precipitation, even at the seasonal time scale. This stems from the fact that soil moisture persistence is not only determined by precipitation but also by evapotranspiration and soil hydraulic properties. Therefore, soil moisture has a qualitatively different memory as precipitation and we think it is fair to state that the model profits from the persistence of soil moisture. However, we will acknowledge in the revised manuscript that seasonal cumulates of precipitation do exhibit longer memory than one month precipitation (implemented on page 11, line 32 - page 12, line 4 in the marked-up manuscript).

[15] Page 11, lines 5-10: see previous comment could seasonally cumulated precipitation and evaporation give similar results? Can you comment on this?

Please see answer to previous comment.

[16] Page 11, lines 9-20: The study doesnt really show what is the role of soil information (i.e. soil water holding properties). Are there regions where SMI plays more/less (spatially variable) role with respect to meteorological counterpart? In the case where soils are able to retain water, the climatic water balance, integrated from the beginning of the season or for specific period during the season (i.e. flowering-maturity), could perform equally well. I think this might be important message of this study, which is not adequately shown in results.

Thanks for that valuable comment. As can be seen in figure 1 in this document, spatially heterogeneity exist in the correlation between SMI and different measures of cumulated weather measures such as precipitation. To incorporate the same information as those used by soil moisture it would be necessary to take into account different accumulates of precipitation for different locations. For example, Southern Germany exhibits higher water retaining capacities and also higher correlation with three month precipitation as compared to Eastern Germany. However, a substantial

share of the variability of soil moisture is not explained by precipitation (see also comment above). One advantage of using soil moisture in such a study is that we can restrict the coefficients to be the same at all locations, whilst assuming that the water retaining is not the same everywhere. We added this point to the discussion of the results (page 11, line 32 - page 12, line 4 in the marked-up manuscript).

[17] Page 12, line 8: 409 % with respect to what?

In this context, 409.1 % refers to the relative difference of the adjusted R-square derived least squared dummy variable regression with respect to the one derived by the demeaning framework. In other words, it is the explanatory power 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 variations as explanatory variables. We clarified this in the revised text on page 13, lines 1 - 16.

[18] Page 13, line 15: Predictive power or explanatory power? This study does not assess the out-of-sample prediction performance; therefore, I would characterize adj. R² as explanatory power. Can these models be used for silage maize yield seasonal forecasting? Out-of-sample validation would be necessary to determine the predictive power, especially due to the fact that relatively short time series are used to construct the regression model. Can you comment on that?

We agree with the reviewer that we only assessed the explanatory power of the model in this study and adjusted the test accordingly (page 14, line 4 in the marked-up manuscript). It is planned to use the models of these studies for seasonal forecasting and climate projections in follow-up studies. Part two: In this study here, we used BIC to benchmark the model configurations, because it penalizes model over-fitting which hampers the out-of-samples predictability. However, follow up studies should perform an out-of-sample validation to determine the predictive power.

[19] Page 16, lines 5-11: What could be the biophysical meaning behind the second and third terms being significant?

We want to highlight here that it is very challenging to relate biophysical process to the coefficients of the statistical model used in this study. An approach using a processed-based crop model would be required to uncover these relationships. The main objective of considering non-linearities is to represent large and non marginal changes in the weather system (due to climate change) that are outside of the optimal plant growth conditions (changed in Section 1 & 4.1 (page 2, lines 18 - 23 & page 10, lines 9 - 14 in the marked-up manuscript). Therefore, non-linear dose-response functions are implemented. Furthermore, in this setting the terms of the polynomials are not orthogonal to each other. Thus, the non-significance of a term cannot be equated with a test for non-linearity. On the basis of the study design, the common significance of all polynomials rather implies a causal effect.

References

- Schlenker, W. and Roberts, M. J.: Nonlinear Effects of Weather on Corn Yields, *Review of Agricultural Economics*, 28, 391–398, doi:10.1111/j.1467-9353.2006.00304.x, 2006.
- Schlenker, W. and Roberts, M. J.: Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change, *Proceedings of the National Academy of Sciences*, 106, 15 594–15 598, doi:10.1073/pnas.0906865106, 2009.
- Thompson, L. M.: Weather and Technology in the Production of Corn in the U. S. Corn Belt, *Agronomy Journal*, doi:10.2134/agronj1969.00021962006100030037x, 1969.
- Timmins, C. and Schlenker, W.: Reduced-Form Versus Structural Modeling in Environmental and Resource Economics, *Annual Review of Resource Economics*, 1, 351–380, doi:10.1146/annurev.resource.050708.144119, 2009.
- Wahid, A., Gelani, S., Ashraf, M., and Foolad, M. R.: Heat tolerance in plants: An overview, *Environmental and Experimental Botany*, 61, 199–223, doi:10.1016/j.envexpbot.2007.05.011, 2007.
- Wooldridge, J.: *Introductory econometrics: A modern approach*, South-Western Cengage Learning, fourth edn., 2012.

The Effect of Soil Moisture Anomalies on Maize Yield in Germany

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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.

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, 2011, 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 Ernährung 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 et al., 2008, 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 ~~is able to~~ during each day of the growing season can explain almost half of its ~~variation in yields~~ yield variations. For corn, this threshold is estimated to be 29 °Celsius. Thus, it is highly recommended to account for nonlinearity ~~Extreme degrees 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 ~~as 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). Extreme 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 additive 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). ~~These show, that~~ For example, the susceptibility to high temperatures is ~~elevated~~ 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 Water, 2016). 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 Data

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, 2017). 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 heteroscedasticity 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 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 (Samani et al., 2013). A similar procedure has been applied for the
5 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 $SMI \leq 0.1$, $0.1 < SMI \leq 0.2$, and $0.2 < SMI \leq 0.3$ are denoted as severe drought, moderate drought and abnormally dry, respectively. The wet quantile intervals between $0.7 < SMI \leq 0.8$, $0.8 < SMI \leq 0.9$, and $0.9 < SMI$ are labeled
10 as abnormally wet, abundantly wet and severely wet, respectively. The interval between $0.3 < SMI \leq 0.7$ serves as reference and characterizes normal situations. [This classification uses location depend 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
15 (Deutscher Wetterdienst, 2017). 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 ~~measured in water evaporation~~
20 ~~(mm d⁻¹)~~[estimated in millimeter per day](#):

$$E = \kappa R \sqrt{T_{\delta}} (T + 17.8), \quad (1)$$

where κ is a free parameter ($^{\circ}\text{C}^{-1.5}$) 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 ($^{\circ}\text{C}$). The term $T+17.8$ is an approximation of saturated vapour pressure, whereas the term T_{δ} is an approximation
25 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 Deficit, which has been introduced as effective crop yield predictor (Roberts et al., 2013; Lobell, 2013), potential
30 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.

Table 1. Mean and Standard Deviation of the Meteorological Variables, averaged over Germany. Data are obtained by the Germany Weather Service.

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

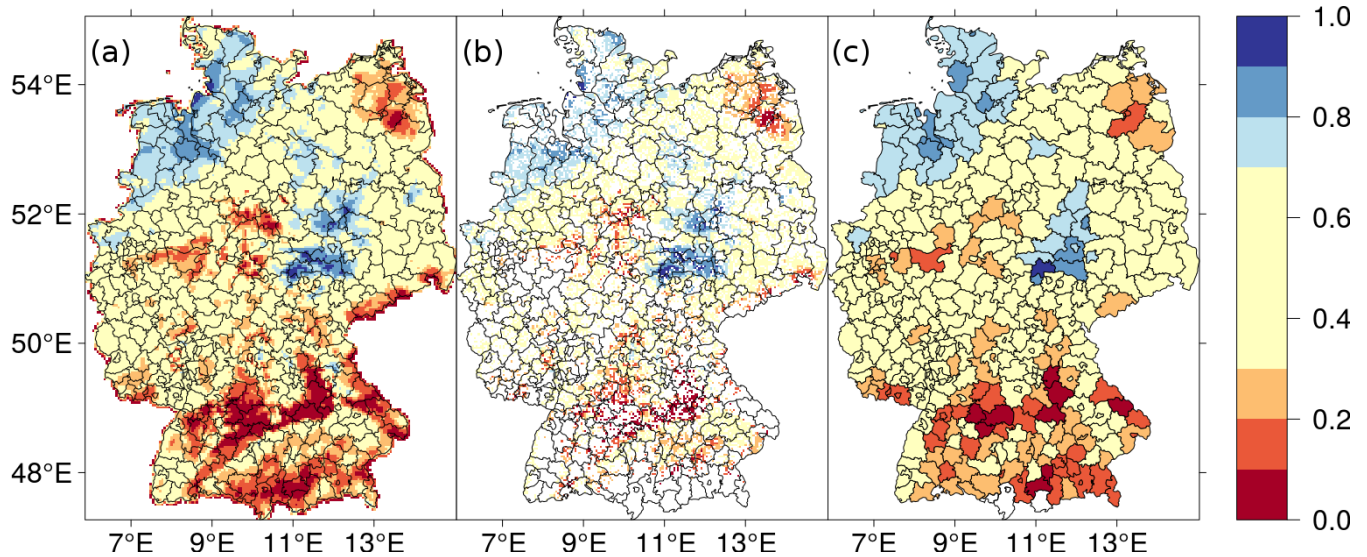


Figure 1. Illustration of the spatial processing of the SMI data of May 2003. On the left side, one can see the SMI with the $4 \times 4 \text{ km}^2$ grids. In the middle, the data are masked with the $0.1 \times 0.1 \text{ km}^2$ *non-irrigated arable land*-class of the CORINE Land Cover. Those data are then 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.

All meteorological variables are **normalized-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 1 for completeness.

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 at the different processing steps are shown in Fig. 1. Figure 1a depicts the $4 \times 4 \text{ km}^2$

grid. These absolute soil moisture fractions are masked for *non-irrigated arable land*-class of the CORINE Land Cover (2006) at a $0.1 \times 0.1 \text{ km}^2$ resolution to account for the variability due to heterogeneous land use within the administrative districts (Fig. 1b). The 0.1 km values are then averaged for each of the administrative district to obtain district level values (Fig. 1c). Blank administrative districts occur because of the absent-absence of *non-irrigated arable land* grid cells. These processing

5 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).

10 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

15 vary over time (ϵ). Each monthly model can be written as:

$$\begin{aligned}
 Y_{ik} = & \sum_{\underline{j=1} \underline{n=1}}^6 \alpha_{\underline{j} \underline{n}} I(SMI_{ikm} \in \underline{C}_j \underline{C}_n) \\
 & + \sum_{j=1}^3 \beta_j (P_{ikm})^j + \sum_{j=1}^3 \gamma_j (T_{ikm})^j + \sum_{j=1}^3 \delta_j (E_{ikm})^j \\
 & + c_{im} + \epsilon_{ikm}.
 \end{aligned} \tag{2}$$

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. $I(\cdot)$ is the indicator function of the soil moisture categories C_j , being 1 if the SMI belong to class $\underline{j} \underline{n}$ and 0 otherwise. The six classes are defined as severe drought ($SMI \leq 0.1$), moderate drought ($0.1 < SMI \leq 0.2$), abnormally dry ($0.2 < SMI \leq 0.3$), abnormally wet ($0.7 < SMI \leq 0.8$), abundantly wet ($0.8 < SMI \leq 0.9$) and severely wet ($0.9 < SMI$), 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.

25 These consist of the districts specific mean values of the individual variables on the right and left side of the equation.

The explanatory variables are correlated to each other (Table 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

30 T (Table 2). The coefficients γ or δ are set to 0, accordingly.

Table 2. Comparison of Pearson Correlation Coefficients of the Exogenous Variables.

	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

Annotation: Absolute values of the Pearson Correlation Coefficients are employed to calculate the averages presented in the last two columns.

In addition to soil moisture, a meteorological and ~~the a~~ fixed effect term ~~are included to reduce omitted variable bias~~ included. The fixed effects ~~account for the time-invariant~~ potentially reduce omitted variable bias, because they take into account the time-variant confounding factors specific to each spatial unit ~~as for instance~~, 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 identified based on determined on the basis of year-to-year variations ~~and the analysis in this study can be considered as~~. By restricting the coefficients to be same 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 could 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). ~~This interpretation~~ The outlined interpretation of the coefficients is particularly suitable for SMI, because this index, which describes deviations from ~~them the~~ median, is per definition an anomaly. ~~The meteorological term is included to account for important time-variant weather related factors.~~

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, excluding those of the fixed effects.~~ 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 ($\text{adj. } R^2$, Section 4.2). Ordinary least squares using the *lm* function (R Core Team, 2015) are employed with a dummy variable for each administrative districts 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 heteroskedasticity 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.

4 Results and Discussion

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., 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

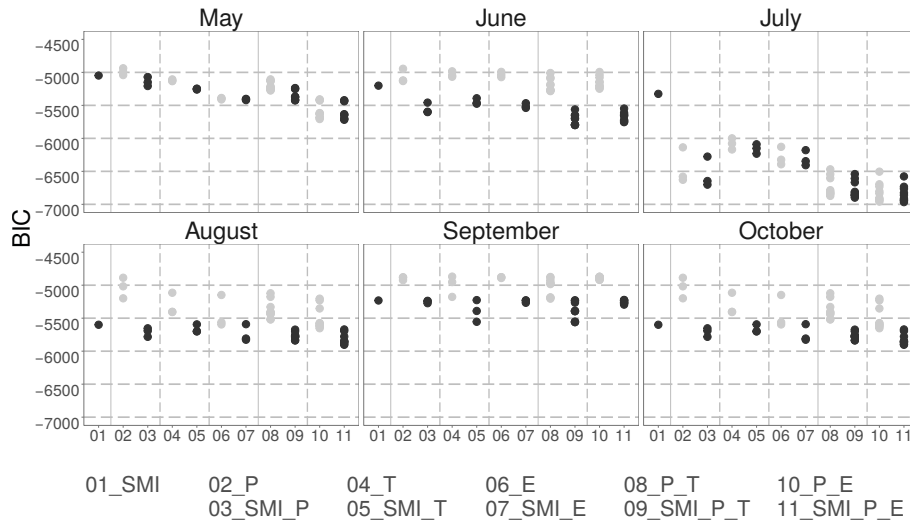


Figure 2. Each panel shows the BIC distribution of one month. Within the panels various models are compared, whilst the lowest marker is preferred. Each column represents a particular selection of variables. The markers represent different degrees of the polynomials in the meteorological term. The gray markers denote those models that neglect the SMI, whilst the black include it.

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. ~~Those observations are evident from an agronomic perspective, as for instance already early research employs curvilinear~~ These observations are consistent with agronomic studies. Curvilinear relationships between maize yield and meteorological variables (Thompson, 1969) 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. It is possible to assess 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 A2). 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. 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). 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

Table 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

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.

5 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.

10 4.2 Quantitative Assessment: Coefficient of determination for models using different explanatory variables

In this and the next section (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 meteorological 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
15 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 ~~exogenous variation~~ variation in the exogenous explanatory variables, which is derived by the demeaning framework (row (a) in Table 3); second, the least squared dummy variable model that ~~explicitly~~ accounts for both the ~~exogenous variation and the fixed effect~~ variation in the exogenous explanatory variables and the administrative district specific average yield (row (b1) in Table 3). The ratio of the coefficient of determination derived by these two model setups is investigated (row (b2) in Table 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 ~~explicitly~~ additionally accounting for the ~~fixed effects~~ share of variation explained by the average crop yield of each administrative district is July (+ 112.9 %), ~~indicating~~. ~~This suggests~~ that a large ~~share of the variation in yield is explained by the exogenous part of the yield variation is explained only by exogenous explanatory variables~~. The month with the ~~largest share of the variation explained by only fixed effects is May, where~~ 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 ~~when explicitly accounting for the mean effect of the administrative districts~~ 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 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 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 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 ~~predictive~~ 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.

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 4.3.3. Those functional forms, which are significant at least in the first or second order, are presented for individual months in Fig. 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 uncertainties in the estimated crop yield. A table with the estimated coefficients and standard errors of all models can be found in Table 4.

4.3.1 Partial Effects of Precipitation

The partial precipitation effects for the months May to August are shown in Panel a) of Fig. 3. Given constant soil moisture and temperature effects, negative precipitation anomalies are associated 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, 2017). 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. 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).

Table 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 (0.011)	0.036*** (0.014)	0.039*** (0.013)	-0.014 (0.011)	-0.011 (0.013)	-0.003 (0.010)
Precipitation ²	-0.023* (0.014)	-0.014* (0.007)	-0.023*** (0.004)	-0.019*** (0.006)	-0.005 (0.005)	0.002 (0.008)
Precipitation ³	0.004 (0.002)	0.001 (0.001)	0.005*** (0.002)	0.004*** (0.002)	0.002 (0.001)	-0.0001 (0.002)
Temperature ¹	0.024 (0.021)	-0.006 (0.015)	-0.036* (0.021)	-0.003 (0.014)	0.038 (0.024)	-0.002 (0.018)
Temperature ²	-0.005 (0.007)	-0.006 (0.006)	-0.007*** (0.002)	-0.008** (0.003)	-0.009* (0.005)	-0.016** (0.008)
Temperature ³	0.0004 (0.003)	-0.002 (0.003)	0.004* (0.003)	-0.002 (0.002)	-0.013* (0.006)	0.005 (0.003)
SMI: severe drought	0.068*** (0.012)	0.024 (0.020)	-0.044** (0.019)	-0.110*** (0.035)	-0.126*** (0.028)	-0.149*** (0.037)
SMI: moderate drought	0.044*** (0.011)	0.016 (0.017)	-0.007 (0.011)	-0.055*** (0.017)	-0.041* (0.023)	-0.024 (0.030)
SMI: abnormal dry	0.011 (0.011)	0.023*** (0.007)	-0.005 (0.007)	-0.024** (0.011)	-0.017 (0.015)	-0.005 (0.017)
SMI: abnormal wet	-0.007 (0.014)	-0.034*** (0.011)	-0.011 (0.007)	0.026*** (0.008)	0.007 (0.011)	-0.006 (0.019)
SMI: abundant wet	-0.014 (0.020)	-0.052** (0.025)	-0.004 (0.009)	0.027*** (0.008)	0.012 (0.017)	-0.001 (0.015)
SMI: severe wet	-0.009 (0.019)	-0.202*** (0.047)	-0.041*** (0.016)	0.037*** (0.013)	0.030 (0.027)	0.025 (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

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 4.1 & 4.2).

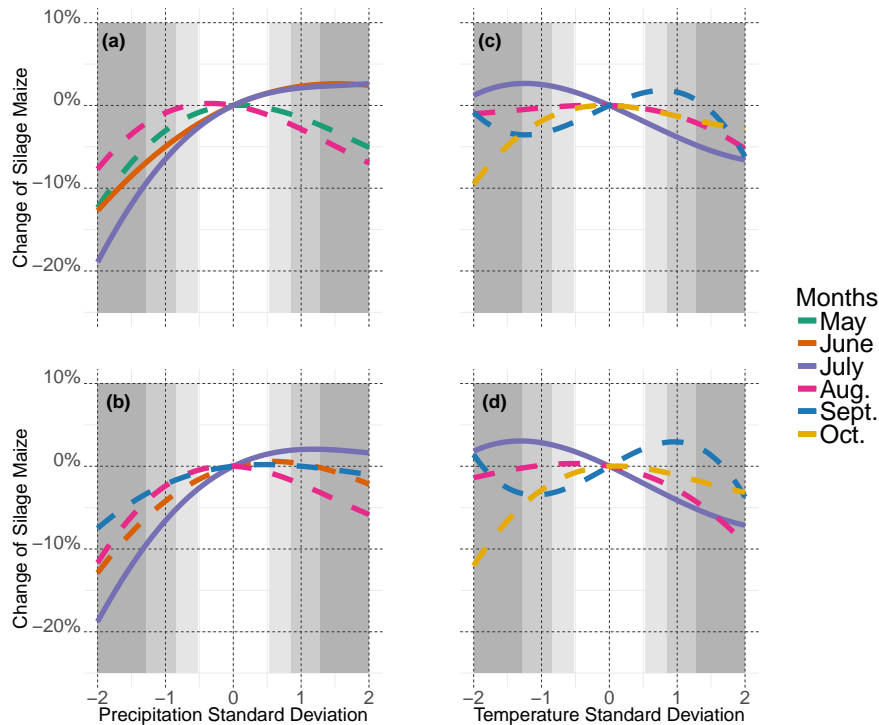


Figure 3. The partial dose-response functions of the meteorological variables are depicted for the range between - 2 and + 2 standard deviations (SD). The upper row represents those models considering SMI, whilst the lower row neglects SMI. A solid line is used for those variables which are significant 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 $100(\exp(\sum_{j=1}^3 \beta_j (x_{ikm})^j) - 1)$, 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.

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). 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. 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. 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.

4.3.2 Partial Effects of Temperature

The significant partial temperature effects are depicted in Fig. 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. 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, 2017). 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. 3a and Fig. 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 Water, 2016). 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 et al., 2008, 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. 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 Water, 2016). The functional form of the partial temperature effects derived from different model configurations for July and August is presented in Fig. 4 to evaluate the magnitude of bias between the full model (presented in Fig. 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. 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 3). This is not surprising because the partial effect of

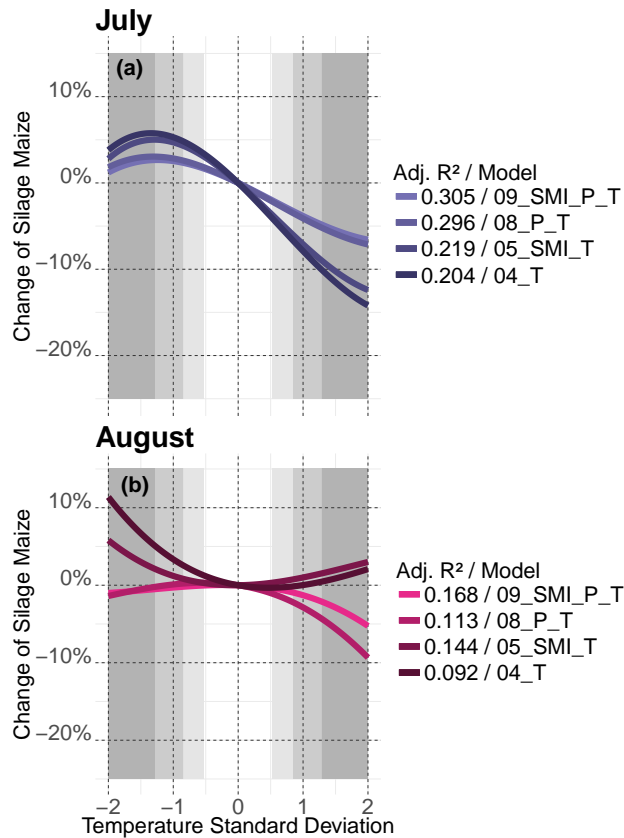


Figure 4. Sensitivity of the functional form of temperature partial effects for various controls for water supply.

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 3). In July, the functional form stays qualitatively the same across all model configurations (Fig. 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.

5 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.

10 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. 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,

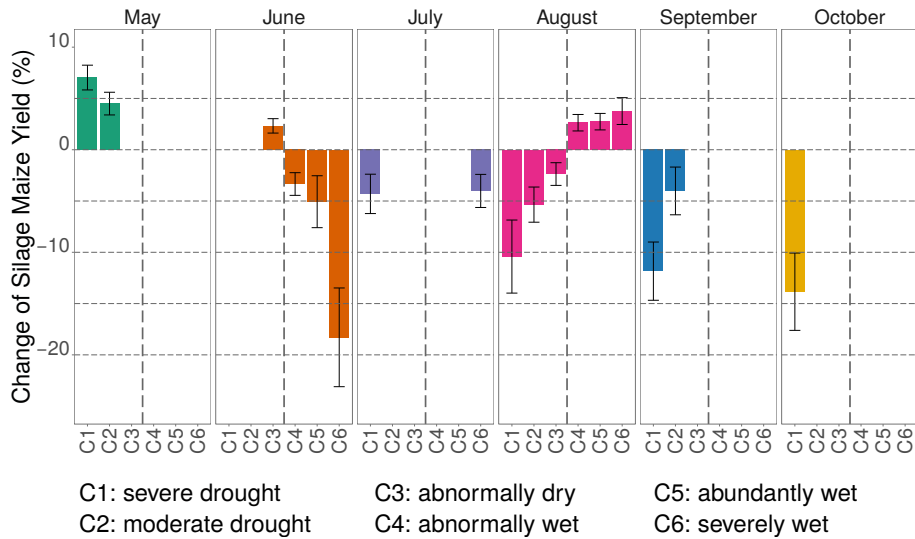


Figure 5. Percentage Change of Silage Maize Yield caused by significant Soil Moisture Anomalies for each month. The vertical axis represents the change in silage maize converted into % approximated by the formula $100(\exp(\sum_{j=1}^6 \alpha_j I(SMI_{ikm} \in C_j) - 1))$, where C_j are the soil moisture classes. The standard errors are indicated by the black error bars.

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. 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 saturation 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 Water, 2016). This is particularly relevant for maize due to its capability to develop deep roots (FAO Water, 2016). 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. 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, 2017). Plants exhibit an increased susceptibility to insufficient water supply during these development stages. As shown in section 4.3, 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, 2017). 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.

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 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 (Lobell2013, Gornott2015, Gornott2016), 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.

5 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
10 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 (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
15 damage assessment and adaptation evaluation, which are supposed to gain importance in the course of climate change.

Acknowledgements. We kindly acknowledge the German Meteorological Service (DWD), the Joint Research Center of the European Commission, the European Environmental Agency, the Federal Institute for Geosciences and Natural Resources (BGR), the Federal Agency for Cartography and Geodesy (BKG), the European Water Archiv, the Global Runoff Data Centre at the German Federal Institute of Hydrology (BfG), and the Federal Statistical Office of Germany for the provision of data. We especially thank Matthias
20 Zink (UFZ) for processing and providing the data. We also regard thanks to the authors of the R-packages used in this study (Arnold (2016); Bivand et al. (2013, 2016); Bivand and Lewin-Koh (2017); Croissant and Millo (2008); Wickham (2007, 2011, 2016); Hlavac (2015); Hijmans (2016); Neuwirth (2014); Pierce (2015); Sarkar (2008); Sarkar and Andrews (2016)). We express our thanks to Prof. Reimund Schwarze for his comments and the promotion of the project at the Helmholtz Alliance Climate Initiative REKLIM. This work is also part of the Integrated Project Water Scarcity at the UFZ - Helmholtz Centre for Environmental Research, Leipzig,
25 Germany, which served as forum to present our work. Special thanks to Dr. Andreas Marx, head of the Climate Office for Central Germany, who supported us in the final steps of this study.

References

- Agriculture Risk Management Team: Weather Index Insurance for Agriculture: Guidance for Development Practitioners, Tech. Rep. November, The World Bank, Washington, 2011.
- Akaike, H.: Information theory and an extension of the maximum likelihood principle, in: International Symposium on Information Theory, pp. 267–281, Springer New York, doi:10.1016/j.econlet.2011.12.027, 1973.
- Andresen, J. A., Alagarswamy, G., Rotz, C. A., Ritchie, J. T., and LeBaron, A. W.: Weather impacts on maize, soybean, and alfalfa production in the Great Lakes region, 1895-1996, *Agronomy Journal*, 93, 1059–1070, doi:10.2134/agronj2001.9351059x, 2001.
- Angrist, J. D. and Pischke, J.-S.: *Mostly harmless econometrics : an empiricist's companion*, March, Princeton Univers. Press, doi:10.1057/be.2009.37, 2008.
- 10 Annan, F. and Schlenker, W.: Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat, *American Economic Review: Papers and Proceedings*, 105, 262–266, doi:10.1257/aer.p20151031, 2015.
- Arellano, M.: Computing Robust Standard Errors for Within Group Estimators, doi:10.1111/j.1468-0084.1987.mp49004006.x, 1987.
- Arnold, J. B.: ggthemes: Extra Themes, Scales and Geoms for 'ggplot2' [R package ggthemes version 3.3.0], <https://cran.r-project.org/package=ggthemes>, 2016.
- 15 Auffhammer, M. and Schlenker, W.: Empirical studies on agricultural impacts and adaptation, *Energy Economics*, 46, 555–561, doi:10.1016/j.eneco.2014.09.010, 2014.
- Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A.: Using Weather Data and Climate Model Output in Economic Analyses of Climate Change, *Review of Environmental Economics and Policy*, 7, 181–198, doi:10.1093/reep/ret016, 2013.
- Barnabás, B., Jäger, K., and Fehér, A.: The effect of drought and heat stress on reproductive processes in cereals, *Plant, Cell and Environment*, 20 31, 11–38, doi:10.1111/j.1365-3040.2007.01727.x, 2008.
- Basso, B. and Ritchie, J.: Temperature and drought effects on maize yield, *Nature Climate Change*, 4, 233, doi:10.1038/nclimate2139, 2014.
- Becker, P., Imbery, F., Friedrich, K., Rauthe, M., Matzarakis, A., Grätz, A., and Janssen, W.: *Klimatologische Einschätzung des Sommer 2015*, Tech. rep., Deutscher Wetter Dienst, 2015.
- Berry, S. T., Roberts, M. J., and Schlenker, W.: Corn Production Shocks in 2012 and Beyond: Implications for Harvest Volatility, in: *The Economics of Food Price Volatility*, edited by Chavas, J.-P., Hummels, D., and Wright, B. D., pp. 59–81, University of Chicago Press, 25 2014.
- Bivand, R. and Lewin-Koh, N.: maptools: Tools for Reading and Handling Spatial Objects [R package version 0.8-41], 2017.
- Bivand, R., Pebesma, E., and Gómez-Rubio, V.: *Applied spatial data analysis with R*, Springer, <http://link.springer.com/content/pdf/10.1007/978-1-4614-7618-4.pdf>, 2013.
- 30 Bivand, R., Keitt, T., Rowlingson, B., Pebesma, E., Sumner, M., Hijmans, R., and Rouault, E.: Bindings for the Geospatial Data Abstraction Library: Package 'rgdal', <https://cran.r-project.org/package=rgdal1.2-5>, 2016.
- Bolaños, J. and Edmeades, G. O.: The importance of the anthesis-silking interval in breeding for drought tolerance in tropical maize, *Field Crops Research*, 48, 65–80, doi:10.1016/0378-4290(96)00036-6, 1996.
- Bundesministerium für Ernährung und Landwirtschaft: *Ernte 2015: Mengen und Preise*, Tech. Rep. August, BMEL, 2015.
- 35 Burke, M. and Emerick, K.: Adaptation to Climate Change: Evidence from US Agriculture, *American Economic Journal: Economic Policy*, 8, 106–140, doi:10.2139/ssrn.2144928, 2016.

- Butler, E. E. and Huybers, P.: Adaptation of US maize to temperature variations, *Nature Climate Change*, 3, 68–72, doi:10.1038/nclimate1585, 2013.
- Butler, E. E. and Huybers, P.: Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase, *Environmental Research Letters*, 10, 8, doi:10.1088/1748-9326/10/3/034009, 2015.
- 5 Carleton, T. and Hsiang, S.: Social and Economic Impacts of Climate Change, *Science*, doi:10.1126/science.aad9837, 2016.
- Chetty, R.: Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods, *Annual Review of Economics*, 1, 451–488, doi:10.1146/annurev.economics.050708.142910, 2009.
- Chmielewski, F. M.: Wasserbedarf in der Landwirtschaft, in: *WARNSIGNAL KLIMA: Genug Wasser für alle?*, pp. 149–156, Universität Hamburg, Institut f. Hydrobiologie, 3 edn., 2011.
- 10 Conradt, T., Gornott, C., and Wechsung, F.: Extending and improving regionalized winter wheat and silage maize yield regression models for Germany: Enhancing the predictive skill by panel definition through cluster analysis, *Agricultural and Forest Meteorology*, doi:10.1016/j.agrformet.2015.10.003, 2016.
- Cook, R. D.: Detection of Influential Observation in Linear Regression, *Technometrics*, 19, 15–18, doi:10.1017/CBO9781107415324.004, 1977.
- 15 Cook, R. D.: Influential Observations in Linear Regression, *Journal of the American Statistical Association*, 74, 169–174, doi:10.1080/01621459.1979.10481634, <http://www.tandfonline.com/doi/abs/10.1080/01621459.1979.10481634>, 1979.
- Croissant, Y. and Millo, G.: Panel data econometrics in R: The plm package, *Journal of Statistical Software*, 27, <http://137.122.187.16/cran/web/packages/plm/vignettes/plm.pdf>, 2008.
- de Bruyn, L. P. and de Jager, J. M.: A meteorological approach to the identification of drought sensitive periods in field crops, *Agricultural Meteorology*, 19, 35–40, doi:10.1016/0002-1571(78)90036-5, 1978.
- 20 Deschenes, O. and Greenstone, M.: The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather, *The American Economic Review*, 97, 354–385, 2007.
- Deutscher Wetterdienst: Climate Data Center, <http://www.dwd.de/>, 2017.
- Die Landwirtschaft Band 1: Landwirtschaftlicher Pflanzenbau, BLV/LVH, 2014.
- 25 Dixon, B. L., Hollinger, S. E., Garcia, P., and Tirupattur, V.: Estimating Corn Yield Response Models to Predict Impacts of Climate Change, *Journal of Agricultural and Resource Economics*, 19, 58–68, 1994.
- Driscoll, J. C. and Kraay, A. C.: Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, *Economic Systems Research*, 10, 307–324, doi:10.1016/S0099-1767(98)90076-9, 1998.
- European Environmental Agency: CORINE Land Cover 1990, 2000 and 2006, <http://www.eea.europa.eu>, 2009.
- 30 Fageria, N. K., Baligar, V. C., and Clark, R. B.: *Physiology of crop production*, CRC Press, 2006.
- FAO Water: Crop Water Information: Maize, <http://www.fao.org/nr/water/cropinfo.html>, 2016.
- Fisher, A. C., Hanemann, M. W., Roberts, M. J., and Schlenker, W.: The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment, *The American Economic Review*, 102, 3749–3760, doi:10.1257/aer.102.7.3761, 2012.
- 35 Fishman, R.: More uneven distributions overturn benefits of higher precipitation for crop yields, *Environmental Research Letters*, 11, 024 004, doi:10.1088/1748-9326/11/2/024004, 2016.
- Gornott, C. and Wechsung, F.: Niveauneutrale Modellierung der Ertragsvolatilität von Winterweizen und Silomais auf mehreren räumlichen Ebenen in Deutschland, *Journal für Kulturpflanzen*, 65, 248–254, doi:10.5073/J, 2015.

- Gornott, C. and Wechsung, F.: Statistical regression models for assessing climate impacts on crop yields: A validation study for winter wheat and silage maize in Germany, *Agricultural and Forest Meteorology*, 217, 89–100, doi:10.1016/j.agrformet.2015.10.005, 2016.
- Grant, R. F., Jackson, B. S., Kiniry, J. R., and Arkin, G. F.: Water Deficit Timing Effects on Yield Components in Maize, *Agronomy Journal*, 81, 61–65, doi:10.2134/agronj1989.00021962008100010011x, 1989.
- 5 Hargreaves, G. H. and Samani, Z. a.: Reference crop evapotranspiration from temperature, *Applied Engineering in Agriculture*, 1, 96–99, doi:10.13031/2013.26773, 1985.
- Hijmans, R. J.: Geographic Data Analysis and Modeling [R package raster version 2.5-8], <http://cran.r-project.org/package=raster>, 2016.
- Hlavac, M.: stargazer: Well-Formatted Regression and Summary Statistics Tables [R package version 5.2], <http://cran.r-project.org/package=stargazer>, 2015.
- 10 Hsiang, S. M.: Climate Econometrics, *Annual Review of Resource Economics*, doi:10.3386/w22181, 2016.
- Hsiang, S. M., Burke, M., and Miguel, E.: Quantifying the influence of climate on human conflict, *Science (New York, N.Y.)*, 341, 1235–1236, doi:10.1126/science.1235367, 2013.
- ICID: Agricultural Water Management for Sustainable Rural Development: Annual Report, Tech. rep., INTERNATIONAL COMMISSION ON IRRIGATION AND DRAINAGE, New Delhi, India, 2015.
- 15 Keller, J.: Ernteversicherungen als Risikomanagementinstrument - Eine Analyse von Versicherungstypen und Tarifierungsmodellen -, Ph.D. thesis, Justus-Liebig-Universität Giessen, 2010.
- Kumar, R., Livneh, B., and Samaniego, L.: Toward computationally efficient large-scale hydrologic predictions with a multiscale regionalization scheme, *Water Resources Research*, 49, 5700–5714, doi:10.1002/wrcr.20431, 2013.
- Kunreuther, H. C., Michel-Kerjan, E. O., Doherty, N. A., Grace, M. F., Klein, R. W., and Pauly, M. V.: At War With the Weather: Managing Large-Scale Risks in a New Era of Catastrophes, The MIT Press, Cambridge, MA, doi:10.1111/j.1539-6975.2011.01451.x, 2009.
- 20 Lobell, D. B.: Errors in climate datasets and their effects on statistical crop models, *Agricultural and Forest Meteorology*, 170, 58–66, doi:10.1016/j.agrformet.2012.05.013, 2013.
- Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., and Falcon, W. P.: Needs for Food Security in 2030 Region, *Science*, 319, 2008.
- 25 Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B.: Nonlinear heat effects on African maize as evidenced by historical yield trials, *Nature Climate Change*, 1, 42–45, doi:10.1038/nclimate1043, 2011a.
- Lobell, D. B., Schlenker, W., and Costa-Roberts, J.: Climate Trends and Global Crop Production Since 1980, *Science*, 333, 616–620, doi:10.1126/science.1204531, 2011b.
- Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W.: The critical role of extreme heat for maize production in the United States, *Nature Climate Change*, 3, 497–501, doi:10.1038/nclimate1832, 2013.
- 30 Monteith, J. L.: Evaporation and surface temperature, *Quarterly Journal of the Royal Meteorological Society*, 107, 1–27, 1981.
- Moore, F. C. and Lobell, D. B.: Adaptation potential of European agriculture in response to climate change, *Nature Climate Change*, 4, 610–614, doi:10.1038/nclimate2228, 2014.
- Moore, F. C. and Lobell, D. B.: The fingerprint of climate trends on European crop yields, *Proceedings of the National Academy of Sciences*, 112, 2670–2675, doi:10.1073/pnas.1409606112, 2015.
- 35 Mueller, B. and Seneviratne, S. I.: Hot days induced by precipitation deficits at the global scale, *Proc Natl Acad Sci U S A*, 109, 12398–12403, doi:10.1073/pnas.1204330109, 2012.
- Neuwirth, E.: RColorBrewer: ColorBrewer Palettes [R package version 1.1-2], <https://cran.r-project.org/package=RColorBrewer>, 2014.

- Orth, R. and Seneviratne, S. I.: Analysis of soil moisture memory from observations in Europe, *Journal of Geophysical Research Atmospheres*, 117, 1–19, doi:10.1029/2011JD017366, 2012.
- Ortiz-Bobea, A.: Improving Agronomic Structure in Econometric Models of Climate Change, in: Agricultural and Applied Economics Association's 2011 AAEA and NAREA Joint Annual Meeting, unpublished, 2011.
- 5 Ortiz-Bobea, A.: Is Weather Really Additive in Agricultural Production?, Working Paper, 2013.
- Ortiz-Bobea, A. and Just, R. E.: Modeling the structure of adaptation in climate change impact assessment, *American Journal of Agricultural Economics*, 95, 244–251, doi:10.1093/ajae/aas035, 2013.
- Pierce, D.: ncd4: Interface to Unidata netCDF (Version 4 or Earlier) Format Data. [R package version 1.15], <https://cran.r-project.org/package=ncdf4>, 2015.
- 10 R Core Team: R: A Language and Environment for Statistical Computing, 2015.
- Roberts, M. J., Schlenker, W., and Eyer, J.: Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change, *American Journal of Agricultural Economics*, 95, 236–243, doi:10.1093/ajae/aas047, 2013.
- Samaniego, L., Kumar, R., and Attinger, S.: Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale, *Water Resources Research*, 46, n/a–n/a, doi:10.1029/2008WR007327, 2010.
- 15 Samaniego, L., Kumar, R., and Zink, M.: Implications of Parameter Uncertainty on Soil Moisture Drought Analysis in Germany, *Journal of Hydrometeorology*, 14, 47–68, doi:10.1175/JHM-D-12-075.1, 2013.
- Sarkar, D.: Lattice: Multivariate Data Visualization with R, Springer, New York, <http://lmdvr.r-forge.r-project.org>, 2008.
- Sarkar, D. and Andrews, F.: latticeExtra: Extra Graphical Utilities Based on Lattice [R package version 0.6-28], <https://cran.r-project.org/package=latticeExtra>, 2016.
- 20 Schlenker, W. and Lobell, D. B.: Robust negative impacts of climate change on African agriculture, *Environmental Research Letters*, 5, 14010, doi:10.1088/1748-9326/5/1/014010, 2010.
- Schlenker, W. and Roberts, M. J.: Nonlinear Effects of Weather on Corn Yields, *Review of Agricultural Economics*, 28, 391–398, doi:10.1111/j.1467-9353.2006.00304.x, 2006.
- Schlenker, W. and Roberts, M. J.: Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change, *Proceedings of the National Academy of Sciences*, 106, 15 594–15 598, doi:10.1073/pnas.0906865106, 2009.
- 25 Schlenker, W., Hanemann, W. M., and Fisher, A. C.: Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach, *American Economic Review*, 95, 395–406, doi:10.1126/science.151.3712.867-a, 2005.
- Schlenker, W., Hanemann, W. M., and Fisher, A. C.: The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions, *Review of Economics and Statistics*, 88, 113–125, doi:10.1162/rest.2006.88.1.113, 2006.
- 30 Schlenker, W., Roberts, M. J., and Lobell, D. B.: US maize adaptability, *Nature Climate Change*, 3, 690–691, doi:10.1038/nclimate1959, <http://www.nature.com/doi/10.1038/nclimate1959>, 2013.
- Schwarz, G.: Estimating the dimension of a model, *The Annals of Statistics*, 6, 461–464, doi:10.1214/aos/1176344136, 1978.
- Sheffield, J. and Wood, E. F.: Drought: Past problems and future scenarios, Earthscan, 2011.
- Sinclair, T. R. and Seligman, N. G.: Crop modeling: From infancy to maturity, *Agronomy Journal*, 88, 698–704, doi:10.2134/agronj1996.00021962008800050004x, 1996.
- 35 Statistisches Bundesamt: Land- und Forstwirtschaft, Fischerei - Bodenbearbeitung, Bewässerung, Landschaftselemente - Erhebung über landwirtschaftliche Produktionsmethoden (ELPM) -, Tech. rep., Statistisches, Wiesbaden, 2011.
- Statistisches Bundesamt: Weizen und Silomais dominieren mit 45 % den Anbau auf dem Ackerland Statistisches Bundesamt, 2016.

- Statistische Ämter des Bundes und der Länder: The Regional Database Germany ("Regionaldatenbank Deutschland"), <https://www.regionalstatistik.de>, 2017.
- Teixeira, E. I., Fischer, G., van Velthuisen, H., Walter, C., and Ewert, F.: Global hot-spots of heat stress on agricultural crops due to climate change, *Agricultural and Forest Meteorology*, 170, 206–215, doi:10.1016/j.agrformet.2011.09.002, 2013.
- 5 Thober, S., Kumar, R., Sheffield, J., Mai, J., Schäfer, D., and Samaniego, L.: Seasonal Soil Moisture Drought Prediction over Europe Using the North American Multi-Model Ensemble (NMME), *Journal of Hydrometeorology*, 16, 2329–2344, doi:10.1175/JHM-D-15-0053.1, 2015.
- Thompson, L. M.: Weather and Technology in the Production of Corn in the U. S. Corn Belt, *Agronomy Journal*, doi:10.2134/agronj1969.00021962006100030037x, 1969.
- 10 Timmins, C. and Schlenker, W.: Reduced-Form Versus Structural Modeling in Environmental and Resource Economics, *Annual Review of Resource Economics*, 1, 351–380, doi:10.1146/annurev.resource.050708.144119, 2009.
- Tubiello, F. N., Soussana, J.-F., and Howden, S. M.: Crop and pasture response to climate change., *Proceedings of the National Academy of Sciences of the United States of America*, 104, 19 686–90, doi:10.1073/pnas.0701728104, 2007.
- UNISDR: Global Assessment Report on Disaster Risk Reduction - Making Development Sustainable: The Future of Disaster Risk Management -, United Nations Office for Disaster Risk Reduction (UNISDR), Geneva, Switzerland, doi:9789211320282, 2015.
- 15 Urban, D., Roberts, M. J., Schlenker, W., and Lobell, D. B.: Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields: A Letter, *Climatic Change*, 112, 525–533, doi:10.1007/s10584-012-0428-2, 2012.
- Urban, D. W., Roberts, M. J., Schlenker, W., and Lobell, D. B.: The effects of extremely wet planting conditions on maize and soybean yields, *Climatic Change*, 130, 247–260, doi:10.1007/s10584-015-1362-x, 2015a.
- 20 Urban, D. W., Sheffield, J., and Lobell, D. B.: The impacts of future climate and carbon dioxide changes on the average and variability of US maize yields under two emission scenarios, *Environmental Research Letters*, 10, 045 003, doi:10.1088/1748-9326/10/4/045003, 2015b.
- Wahid, A., Gelani, S., Ashraf, M., and Foolad, M. R.: Heat tolerance in plants: An overview, *Environmental and Experimental Botany*, 61, 199–223, doi:10.1016/j.envexpbot.2007.05.011, 2007.
- White, H.: A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity, *Econometrica*, 48, 817–838, 1980.
- 25 Wickham, H.: Reshaping Data with the reshape Package, *Journal of Statistical Software*, 21, 1–20, doi:10.18637/jss.v021.i12, 2007.
- Wickham, H.: The split-apply-combine strategy for data analysis, *Journal of Statistical Software*, 40, 1–29, doi:10.18637/jss.v040.i01, 2011.
- Wickham, H.: *ggplot2 : elegant graphics for data analysis*, Springer, New York, 2016.
- Zink, M., Samaniego, L., Kumar, R., Thober, S., Mai, J., Schäfer, D., and Marx, A.: The German drought monitor, *Environmental Research Letters*, 11, 074 002, doi:10.1088/1748-9326/11/7/074002, 2016.
- 30 Zink, M., Kumar, R., Cuntz, M., and Samaniego, L.: A High-Resolution Dataset of Water Fluxes and States for Germany Accounting for Parametric Uncertainty, *Hydrology and Earth System Sciences Discussions*, pp. 1–29, doi:10.5194/hess-2016-443, 2017.