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Impacts of hot-dry compound extremes on US soybean yields

Raed Hamed[1], Anne F. Van Loon[1], Jeroen Aerts[1,2], Dim Coumou[1,3]

[1] Department of Water and Climate Risk, Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, the Netherlands
[2] Deltares Institute, Delft, The Netherlands
[3] Royal Netherlands Meteorological Institute (KNMI), De Bilt, the Netherlands

Correspondence to: Raed Hamed (raed.hamed@vu.nl)

Abstract. The US agriculture system supplies more than one-third of globally-traded soybean and with 90% of US soybean produced under rainfed agriculture, soybean trade is particularly sensitive to weather and climate variability. Average growing season climate conditions can explain about one-third of US soybean yield variability. Additionally, crops can be sensitive to specific short-term weather extremes, occurring in isolation or compounding at key moments throughout crop development. Here, we identify the dominant within-season climate drivers that can explain soybean yield variability in the US, and explore synergistic effects between drivers that can lead to severe impacts. The study combines weather data from reanalysis, satellite-based evapotranspiration and root-zone soil moisture with sub-national crop yields using statistical methods that account for interaction effects. Our model can explain on average about half of the year-to-year yield variability (60% on all years and 40% on out-of-sample predictions). The largest negative influence on soybean yields is driven by high temperature and low soil moisture during the summer crop reproductive period. Moreover, due to synergistic effects, heat is considerably more damaging to soybean crops during dry conditions, and less so during wet conditions. Compound and interacting hot and dry August conditions (defined by the 95th and 5th percentiles of temperature and soil moisture, respectively) reduce yields by 1.25 standard deviation. This sensitivity is, respectively, 6 and 3 times larger than the sensitivity to hot or dry conditions alone. Other important drivers of negative yield responses are lower evapotranspiration early in the season and lower minimum temperature late in the season, both likely reflecting an increased risk of frost. The sensitivity to the identified drivers varies across the spatial domain with higher latitudes, and thus colder regions, being less sensitive to hot-dry August months. Historic trends in identified drivers indicates that US soybean has generally benefited from recent shifts in weather. Overall warming conditions have reduced the risk of frost in early and late-season and potentially allowed for earlier sowing dates. More importantly, summers have been getting cooler and wetter over eastern US. Still, despite these positive changes, we show that the frequency of compound hot-dry August month has remained unchanged over 1946-2016. Moreover, in the longer term, climate models project substantially warmer summers for the continental US which likely creates risks for soybean production.

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1 Introduction

Soybean is one of the most in-demand crops worldwide, with the largest increases in production-area over the last two decades when compared to all other major staple crops (Hartman et al., 2011). A recent estimate based on FAOSTAT data in 2013 reports that soybean ranks second in terms of globally-produced kilocalories (~20% of the total kcal traded on the global food market) and first among staple crops in terms of globally-aggregated trade monetary value (Torreggiani et al., 2018). The US agriculture system alone supplies more than one-third of globally-traded soybean, of which 90% is produced under rainfed agriculture (Jin et al., 2017). The recent surge in global soybean demands is expected to increase further in the future due to increasing global population and associated shifts in dietary preferences (Fehlenberg et al., 2017). At the same time, climate change is expected to increase annual mean and extreme temperature levels over the US (Dirmeyer et al., 2013; Winter et al., 2015; Wuebbles et al., 2014a). To support adaptation measures that reduce the potential impacts of these future challenges, we need a quantitative understanding of crop sensitivity to climate and weather variables.

Climate variability can strongly impact crop yields. The effects of growing season temperature and precipitation conditions can explain about one-third of US soybean year-to-year yield variability (Leng et al., 2016; Lobell et al., 2011; Ray et al., 2015; Vogel et al., 2019). In particular, heat and drought conditions are among the most limiting environmental factors affecting crops (Lesk et al., 2016). These are increasingly detrimental when coinciding with vulnerable stages of the crop growth cycle (Troy et al., 2015). Such conditions can occur separately or in combination, in the latter case, leading often to more severe impacts (Leonard et al., 2014). For instance, it is reported that US economic agricultural losses between 1980 and 2012 are four times larger during hot and dry conditions compared to drought events alone (Suzuki et al., 2014). Moreover, the response to multiple climatic stressors is complex and can be subject to interaction effects where climatic drivers create more damage in combination than the sum of each in isolation (Ben-Ari et al., 2018; Matiu et al., 2017). Interestingly, multiple climatic stressors can also result in positive interactions with beneficial effects on crop yields (Carter et al., 2016; Suzuki et al., 2014). Such features, positive or negative, are likely to have important implications on future impacts and adaptation strategies to climate change. Nevertheless, these have received little attention in current assessments so far (Matiu et al., 2017; Zscheischler et al., 2017).

A compound event framework has lately been proposed to underline the need for impact-centric approaches that identify multiple climatic drivers contributing to socio-economic risk (Leonard et al., 2014; Zscheischler et al., 2018, 2020). The types of damaging combination of drivers on local agricultural production are various, with a specific terminology recently proposed in Zscheischler et al. (2020). These can be temporally compounding, as in the case of the 2016 wheat production in France where high temperatures during winter followed by heavy precipitation during spring lead to unprecedented yield losses (Ben-Ari et al., 2018). These can be preconditioned where for instance, pre-sowing soil moisture water storage content interacts with within-season precipitation to affect rainfed maize yield in the US (Carter et al., 2018a) or multivariate/co-occurring such as

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in the case of hot-dry conditions in the growing season affecting crop yields (Feng and Hao, 2019; Matiu et al., 2017). One way to identify such drivers is through the use of statistical methods that empirically associate drivers to impacts (Vogel et al., 2021). Easily interpretable linear regressions in that context can be useful tools, in particular when fitted with alternative methods that allow for the consideration of a large number of potential predictors (i.e. subset selection, shrinkage or dimension reduction approaches) (Ben-Ari et al., 2018; Carter et al., 2018a; Laudien et al., 2020; Vogel et al., 2021).

Here we analyze soybean yields and climate time series for the U.S. at the county scale from 1982 to 2016 using regression models that are fitted with a reduced set of variables selected via a subset selection approach. The aim is to identify (1) the combination of climatic conditions affecting soybean yields at different stages of the growing season, and (2) potential interaction effects between drivers modulating the final impact on yield. Although other studies have looked at potential interactions between climate drivers (Leng et al., 2016), identifying key month and variables throughout the growing season (Mourtzinis et al., 2015; Troy et al., 2015), these studies did not look at such features jointly as done here. Finally, we investigate trends in the identified dominant climate drivers from 1946 to 2016 to assess how historic trends have affected current soybean production risk.

2 Data and Methods

2.1 Soybean yields and climate data for the U.S.

Soybean yields are analysed at the county scale for the period 1982-2016, based on census data obtained from the US Department of Agriculture (USDA) National Agriculture Statistics Survey (NASS) Quick Stats database (www.nass.usda.gov/Quick_Stats). Counties are selected on (i) having no missing data for the full 35 years analysed, (ii) have common planting dates (i.e. April-May) and (iii) a production area share of at least 90% rainfed agriculture. Consequently, a total of 389 counties are retained for the regression analysis (Fig. 1). These together account for at least 50% of US total rainfed soy production, where production per county is calculated as the average production over 1982-2016. Information on the soybean growing season and rainfed vs irrigated agricultural land cover is obtained from the monthly irrigated and rainfed crop areas database around the year 2000 (MIRCA2000), a global gridded dataset at 0.5° resolution (Portmann et al., 2010). The percent rainfed area is calculated by dividing the rainfed area in each grid cell by the total harvested area for each cell (Schauberger et al., 2017a). A linear trend is removed from yield values at the county scale to eliminate long-term effects largely due to technological improvements over the study period (Li et al., 2019; Zipper et al., 2016).

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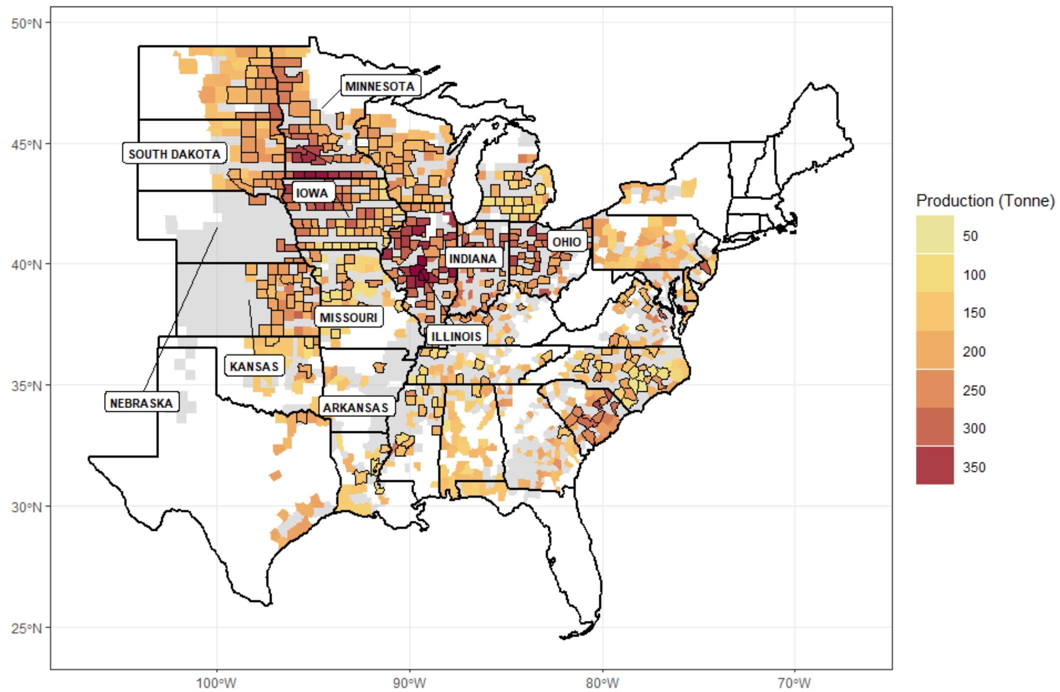

Figure 1. Average total production in tonnes over the period of study (1982-2016). Counties with 35 years of data are highlighted with a thin black perimeter. Grey regions represent filtered out counties where local agriculture is less than 90% rainfed.

Climate data are obtained from the bias-adjusted WFDE5 global reanalysis covering the same period (1982-2016) on a daily time step at a 0.5° grid resolution (Cucchi et al., 2020). Monthly values in each grid cell are calculated for the following variables: the monthly-mean daily maximum (Tmax) and minimum temperatures (Tmin) (°C), monthly-mean precipitation (mm), cumulative incident solar radiation (Wm^{-2}) in addition to extreme indicators such as number of days with temperature above 30 °C (i.e. soybean critical temperature threshold) (Schlenker and Roberts, 2009), and number of days with precipitation above 1, 20, and 30 mm to account for potential negative effects of excessive precipitation on yield (Li et al., 2019). Additional variables are created by aggregating over the spring (April-May), summer (June-July-August) and autumn (September-October) periods. Actual evapotranspiration (mm) and root zone soil moisture (m^3/m^3) from the satellite-based GLEAM dataset (Martens et al., 2017) are included in the analysis at the same spatio-temporal scale. All input data is then averaged over the area of each county. A summary of the considered variables is presented in Table 1. Dividing the growing season by calendar months allowed the identification of key phases throughout the season where soybean crops are most sensitive to climate variability. These can reflect both vulnerable physiological crop growth stages and important climatic thresholds. We could have used a more complex characterization of crop developmental stages based on phenological heat units (Schauberger et al., 2017b) or the consideration of sub-monthly aggregation periods for climatic time series, but these did not necessarily improve

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model performance in other assessments and therefore we opted here to simply rely on monthly and seasonal estimates (Ben-Ari et al., 2016; Sharif et al., 2017).

Table 1. Climate variables calculated at seasonal and monthly time scales throughout the growing season

	Variable abbreviation	Variable explanation	Unit
Heat-related	**rsds**	Shortwave radiation	W/m^2
	Tmin	Average minimum Temperature	°C
	Tmax	Average maximum Temperature	°C
	Num_tx30	Number of days with temperature above 30 °C	days
Moisture-related	**Precip_avg**	Average amount of precipitation	mm
	Num_wet	Number of days with precipitation above 1 mm	days
	Num_pr20	Number of days with precipitation above 20 mm	days
	Num_pr30	Number of days with precipitation above 30 mm	days
	SMroot	Root zone soil moisture	m^3/m^3
	ETact	Actual evapotranspiration	mm

2.2 Simulating yield variability

We used regression models to estimate yield variability at the county scale. Typically, three types of statistical models are used in such assessments (i.e. time-series, panel, and cross-sectional models) (Lobell and Burke, 2010). Here we opted for time-series model as these are (i) easy to interpret, (ii) often perform well compared to the other approaches, and (iii) allow for spatially heterogeneous parameter estimation that may highlight local and regional features (Gornott and Wechsung, 2016). To focus on robust precursors and to enhance model interpretability, we first selected one set of predictors for the full region by pooling US county yields together (see Fig. 2, box 'selection of predictors') (Troy et al., 2015). Out of all possible models constructed with a single input variable, we selected the most influential moisture- and heat-related variables based on the Bayesian Information Criterion (BIC) (Ben-Ari et al., 2018). We do this for early- (spring), mid- (summer) and late-growing season (autumn) periods separately considering both monthly and seasonal aggregates for each, and thus, ending up with a subset of six best predictors (see Table A1). To avoid multicollinearity, we pruned this list of selected predictors by setting a maximum allowable Pearson correlation coefficient between any two predictors to 0.5. Thus, whenever a pair of predictors was strongly collinear (Pearson's $r > 0.5$), we selected the predictor that preceded the other in timing within the growing season (i.e. we excluded soil moisture in September as August soil moisture was already selected). Finally, we applied a stepwise selection procedure to identify the best combination of these input variables, with and without interactions, picking the model with the lowest BIC value (Ben-Ari et al., 2018). The stepwise approach considers all selected variables and all possible interactions (i.e. products of all possible pairs of selected predictors). The procedure is then to start from a model with no predictors, sequentially adding and removing predictors until only a subset is left resulting in the most parsimonious model with the lowest prediction error on training data (See step.lm function of R, version 3.6.1). Only interactions that improved the model out of sample performance were kept in the final model as this was shown to reduce overfitting. The final list of selected predictors consisted of April-May evapotranspiration, August root-zone soil moisture, August maximum temperature, September-October minimum temperature, and the interaction between temperature and soil moisture in August (see Fig. 2, box 'unique set of predictors'). The resulting model is fitted at the county scale and its performance is evaluated using the coefficient of determination (R^2). A summary of the modelling framework is presented in Fig.2.

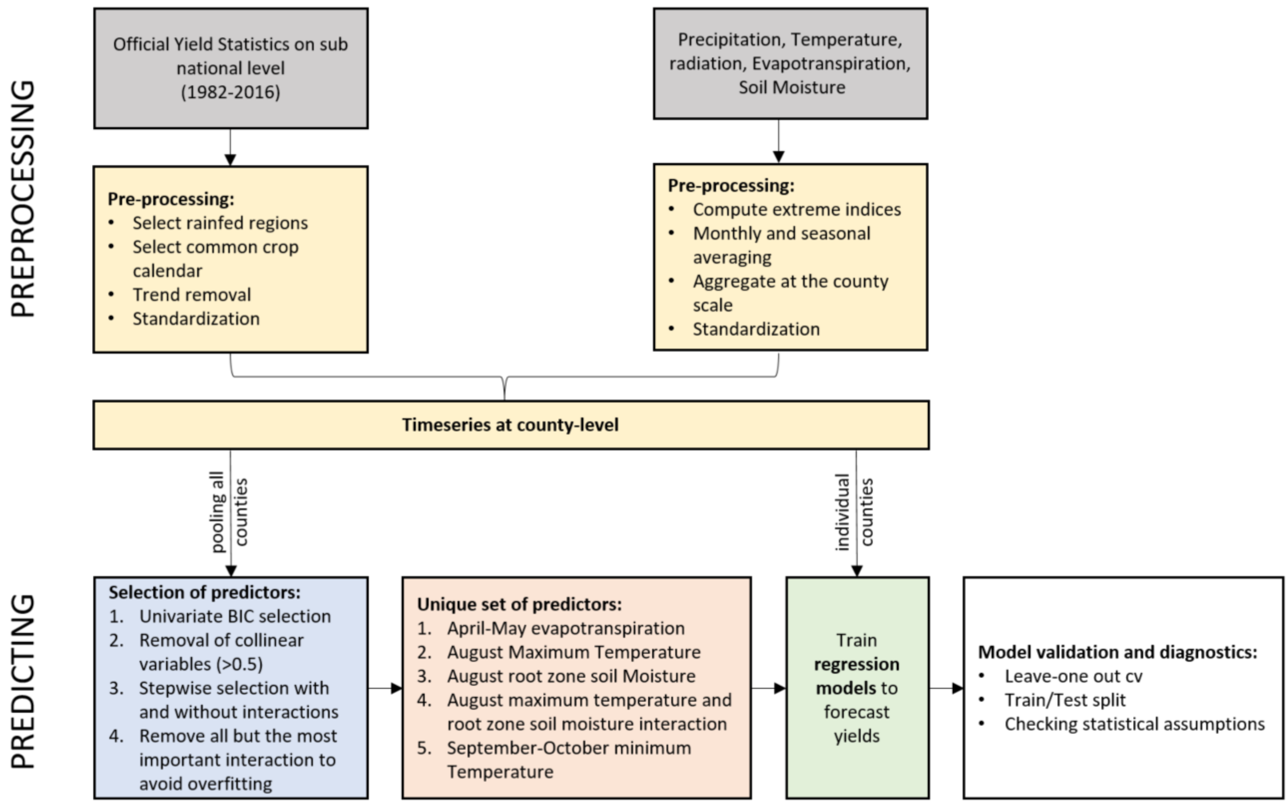

Figure 2. Overall modelling workflow applied for this study linking US yields to weather and climate variables.

2.3 Validating performance and testing modelling assumptions

To test robustness, we applied a leave-one-out cross-validation. We trained county-scale models on reduced datasets where we iteratively removed the to-be-forecasted year. In addition, we applied an alternative cross-validation method using a train-test split approach where we trained the model over the first 18 years and tested its performance over the remaining 17 years of data. The adequacy of applying linear models at the county scale for assessing the relationship between yield anomalies and selected predictors was successfully assessed using five statistical tests (Gornott and Wechsung, 2016; Schauberger et al.,

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2017b). The regression equation specification error test (RESET) assessed whether taking powers of the predictor variables would improve the model fit. The Breusch-Pagan test examined heteroscedasticity issues with the data. The Breusch–Godfrey test was used to assess autocorrelation and the Shapiro–Wilk test to examine normality of residuals. Multicollinearity was checked using the variance inflation factor calculated for each independent variable while setting acceptable levels to strictly below 3.

2.4 Changes in key climatic conditions from 1946 to 2016

Historic trends of the dominant climatic drivers were assessed for the period 1946 to 2016 using linear regressions (0.05 significance level). Furthermore, we assessed changes in concurrent hot-dry August conditions as these were shown to be particularly relevant for soybean production. The selected input datasets used in the crop-modelling analysis do not cover years preceding 1981. To overcome this limitation, we used precipitation and temperature minimum and maximum variables from the CRU V4 global dataset (Harris et al., 2020) covering the period 1901-2019 at a spatial resolution of 0.5°. Minimum temperature in the early season was used as a proxy for early season actual evapotranspiration as the latter tends to be mainly energy limited during spring, especially in climatologically wet regions. Moreover, minimum temperature was initially picked as most relevant temperature related variable for spring conditions, but later dropped in the stepwise selection. Mean summer precipitation over June-July-August was used as a proxy for August root zone soil moisture. To check the feasibility of these assumptions, we calculated correlation maps between GLEAM August root zone soil moisture and CRU averaged summer precipitation and between GLEAM spring actual evapotranspiration and CRU spring minimum temperature for the period 1982 to 2016. The mean Pearson's correlation coefficient over the whole spatial domain was 0.73 for summer precipitation and root zone soil moisture and 0.5 for spring actual evapotranspiration and minimum temperature (Fig. A1ab). The 10th and 90th percentiles of summer precipitation and maximum temperature are used to jointly define the compound hot-dry events at the local scale. Accordingly, we calculated the percent-change per grid cell based on the difference between the number of compound events over two distinct periods (1946-1980 relative to 1982-2016) normalized by the total amount of events over the entire analysis period. Moreover, we calculated a percent (%) area time series of the total rainfed producing region under compound August hot-dry conditions by summing the number of grid cells under such conditions for a given year and dividing by the total number of grid cells considered, similar to the approach applied in Mazdiyasni and AghaKouchak (2015). The trend in the aforementioned time series was assessed with the non-parametric Mann−Kendall trend test (0.05 significance level).

3 Results

3.1 Overall model performance

Based on the selection procedure shown in Fig. 2, we identify a set of predictors for the full region consisting of (1) April-May evapotranspiration, (2) September-October minimum temperature, (3) August root zone soil moisture, (4) August maximum

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temperature, and (5) the interaction between those two August variables. These unique predictors represent non-redundant moisture and heat conditions at different stages of the growing season. The regression models are trained on the country level with those identified predictors and are able to explain about half of the year-to-year yield variability (60% on all years and 40% on out-of-sample predictions). The train-test split approach gives quantitatively similar performance results so we limit ourselves here to presenting the leave-one-out cross-validated results (See Fig. A2). In general, for almost all years, the model provides a correct year-to-year direction of change as well as sign of the yield anomalies (i.e. positive or negative, see Fig 3a). Overall, the most important crop yield drivers are August root zone soil moisture and August maximum temperature, together responsible for 65% of the model out-of-sample explained variability. Including the interaction term between those variables contributed to 12.5% out of the total 65% attributed to August heat and moisture variables. The co-occurrence of low soil-moisture and hot conditions triggers the largest crop failures. Extreme hot-dry conditions (i.e. simultaneously exceeding the 95th and 5th percentiles of temperature and soil moisture, respectively) leads to 6 times more crop impacts compared to extreme hot conditions alone (i.e. 95th and 50th percentiles of temperature and soil moisture, respectively) and 3 times more impacts compared to extreme dry conditions alone (i.e. 50th and 5th percentiles of temperature and soil moisture, respectively). (Fig. 3a).

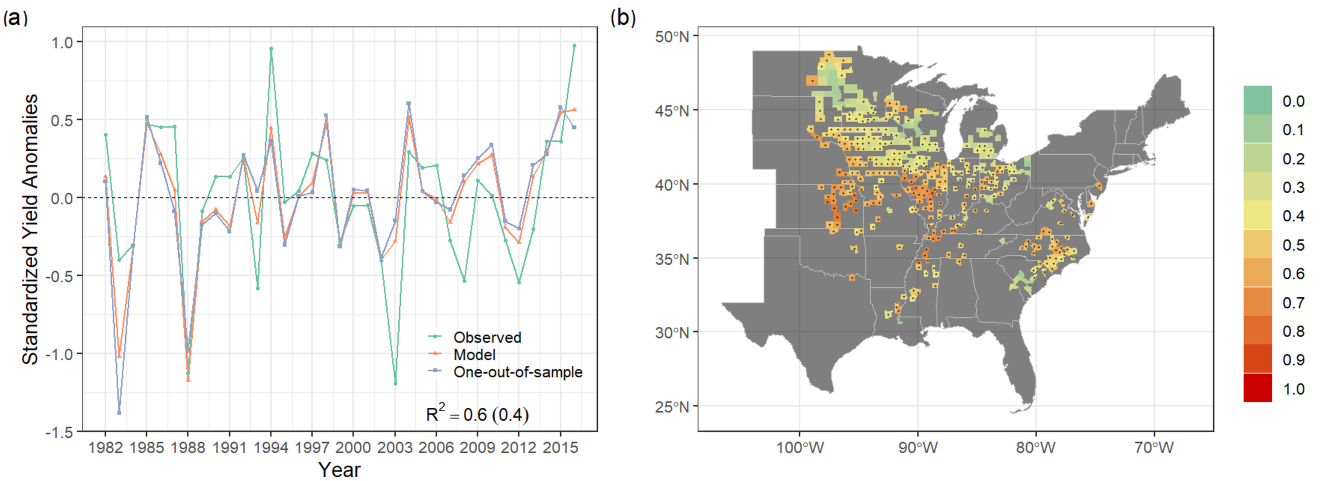

Figure 3. Explained variance (R-squared) of yield anomalies due to climate variability (a) spatially averaged and (b) at the county scale. Stippling in (b) shows F-tests with ($p < 0.05$) indicating that the model chosen is significantly better than a null model (accounting for false discovery rate due to multiple hypotheses testing).

In particular, extremely low yields occurring during heat and drought events, such as the 1988 and 2012 years, are well captured by the model. Spatially, the model is statistically significant (p-value < 0.05) for over 81% of considered counties and 77% when we adjusted for multiple hypotheses testing using the False Discovery Rate (FDR) method (Ventura et al., 2004). Yield variability is captured particularly well in southern counties (Fig. 3b), with high performance represented by red shading (R^2 ~ 0.8). On the other hand, the model performs generally poorer in northern counties, consistent with the results of Schauberger et al. (2017b) where regional colder and wetter climatology seems to reduce soybean yield sensitivity to climatic fluctuations.

Individual diagnostic tests for models built at the county scale shows that autocorrelation and heteroscedasticity did not occur for the majority of individual models whereas model residuals are mostly normally distributed. The RESET test shows that most models are properly specified meaning that considering quadratic variables would not have improved the model fit. Finally, the VIF value is strictly smaller than 3 for almost all considered models and variables showing minimal multicollinearity concerns (Fig. A3).

3.2 Spatial variability of model coefficients

The coefficient distribution for all variables, summarized across the spatial domain, is shown in Fig. 4a. Wide boxplot ranges reflect large spatial heterogeneity in coefficient estimation. This spatial variability is depicted in Fig. 4b-f showing county-based model coefficients and associated patterns across the spatial domain.

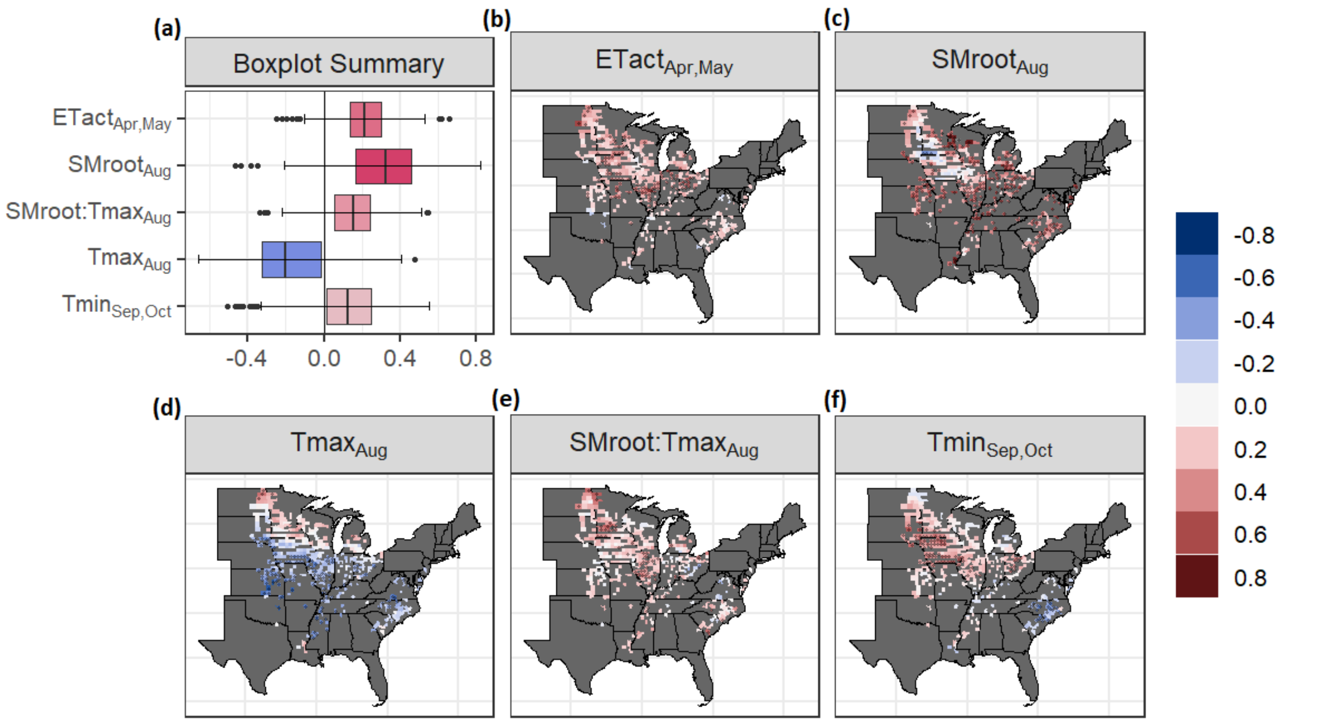

Figure 4. (a) Summary coefficient distributions across counties. The band inside the box represents the median, whereas the box depicts the 25th and 75th percentile values. The whiskers represent the maximum and minimum values as long as these are within the 1.5 interquartile-range from the median. Outliers outside this range are depicted as points. (b-f) Region- and season-specific estimated sensitivity coefficients for soybean yield and selected predictors. Stippling indicates statistical significance from a t-test at 95% confidence level. Values of coefficients are interpreted as the change in soybean yield standard deviation from a one-standard deviation change in the considered independent variable. In the case of interacting variables, this interpretation only applies when the other interacting variable is equal to zero.

Crop-sensitivity to maximum August temperatures shows a north-south gradient with strongly negative regression coefficients over the southern states and sensitivities close to zero in northern states (Fig. 4d). The climatological August maximum

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temperature in southern states is around 30°C highlighting negative temperature influences on yield when this value is exceeded (Fig. A4). The signal is less significant and leaning towards positive values in colder regions north of Iowa and Illinois. August root zone soil moisture is strongly positively associated to yield, with the exception of a small region near Iowa and Minnesota (Fig. 4c). Summer climatology is particularly humid over this region (Fig. A4) whereas the soil is generally poorly drained (i.e. high clay fraction, low saturated hydraulic conductivity) (Li et al., 2019). Such combination can make crops sensitive to the detrimental effects of excessive water on yields which could explain the negative soil moisture sensitivities here. The interaction between August heat and soil moisture variables is positive across the majority of counties (Fig. 4e). This implies that the impact of heat in August depends on the soil moisture value. The negative effects of high temperatures are amplified during dry conditions and alleviated during wet conditions. High evapotranspiration in the early season is positively associated to yield across the spatial domain with particular strong association in central and northern states (Fig. 4b), in line with Schauberger et al. (2017b). End of season minimum temperature reveals a north-south gradient in parameter estimation with significant positive effects over the colder northern regions and weaker association over the south (Fig. 4f). The only exception is noted for south eastern states where strong negative association between yield and end of season minimum temperature is shown. Interestingly, the link between August maximum temperature and yield for those same counties is weak/not significant, suggesting that crops in this area might be reaching the temperature vulnerable stage later during the season.

3.4 Compound hot-dry and associated impacts

Our results show that Illinois is particularly sensitive to hot and dry conditions in August (Fig. 4e), and that therefore models perform best over this area (average R^2 of 0.6-0.7). Moreover, Illinois is the largest soybean producing region in the US and hence we focus here in detail on the compounding hot-dry effects in August. Figure 5a shows pooled yield observations for Illinois (points) together with model predictions (contour lines) for various values of August root zone soil moisture (vertical-axis) and August maximum temperature (horizontal-axis). The coefficients for the sensitivity of soybean yields to August hot-dry conditions in Fig. 5a are obtained from averaging all regression coefficients from all county-specific models within Illinois (i.e. 51 individual models/counties).

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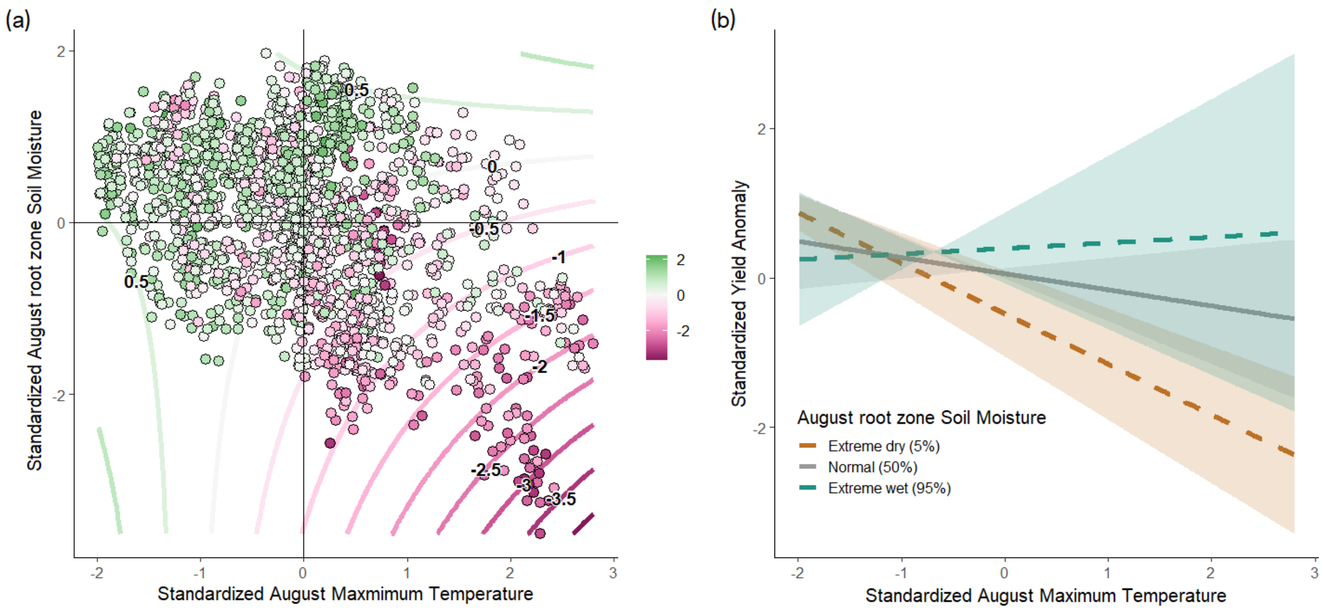

Figure 5. (a) contour lines for modelled yield anomalies under varying levels of standardized August maximum temperature and root zone soil moisture in Illinois state. Points represent observed yield values. The colour scale to the right is in the units of standardized yield. (b) Sensitivity of Illinois US yield anomaly to temperature change for three different root zone soil moisture percentiles (5th, 50th, 95th).

Yield is shown to decrease for increasing hot-dry conditions both in observations and model predictions. In particular, the bottom-right corner (representing August temperature and soil moisture values respectively above and below the 50th percentile) contain 75% of all observed low yields (defined as below one standard deviation). By including the interaction term, we estimate that the compounding impact of hot-dry conditions (i.e. 95th and 5th percentiles of temperature and soil moisture, respectively) in August leads to an additional crop-loss of 0.5 standard deviations as compared to excluding such interaction. On the other hand, the effects of extreme hot-wet conditions (95th percentile for both temperature and soil moisture values) leads to a 0.5 standard deviation positive increase in crop yield estimates when including the interaction term. This non-linearity is visualized in Fig. 5b showing model-derived yield sensitivities to temperature for different levels of root zone soil moisture. The association between yield and August maximum temperature is strongly negative for extremely dry conditions (brown dashed line) and slightly positive for extremely wet conditions (blue dashed line). This highlights the importance of accounting for interaction effects when estimating compound impacts on crops. Yield response to hot-wet conditions is nevertheless subject to high uncertainty (see shaded uncertainty range in Fig. 5b) as these conditions do not occur often and are represented by few observations (Fig. 5a). Still, The temperature sensitivities during wet conditions are significantly different from those during dry conditions (Fig. 5b).

3.5 Changes in compound hot-dry from 1946 to 2016

Linear trends for summer precipitation over the period 1946 to 2016 show significant increases particularly over the Midwest region (Fig. 6b). Only south-eastern states show significant drying trends. Maximum August temperature trends show significant cooling over the Midwest region but warming for north-eastern, north-western and southern states (Fig. 6a). Moreover, early and late season minimum temperature trends indicate warmer conditions across the spatial domain (see Fig.A5). Though summers generally got wetter and cooler in the eastern part of the Midwest and north eastern US regions, the percent-change in the number of concurrent hot and dry August months (i.e. 90th and 10th percentiles of August maximum temperature and summer precipitation, respectively) between 1946-1980 and 1982-2016 shows an increase in frequency here (Fig. 6c). This might have implications as compound hot-dry events appear to have increased in frequency in high producing regions, despite the apparent cooling and wetting patterns identified by univariate trends.

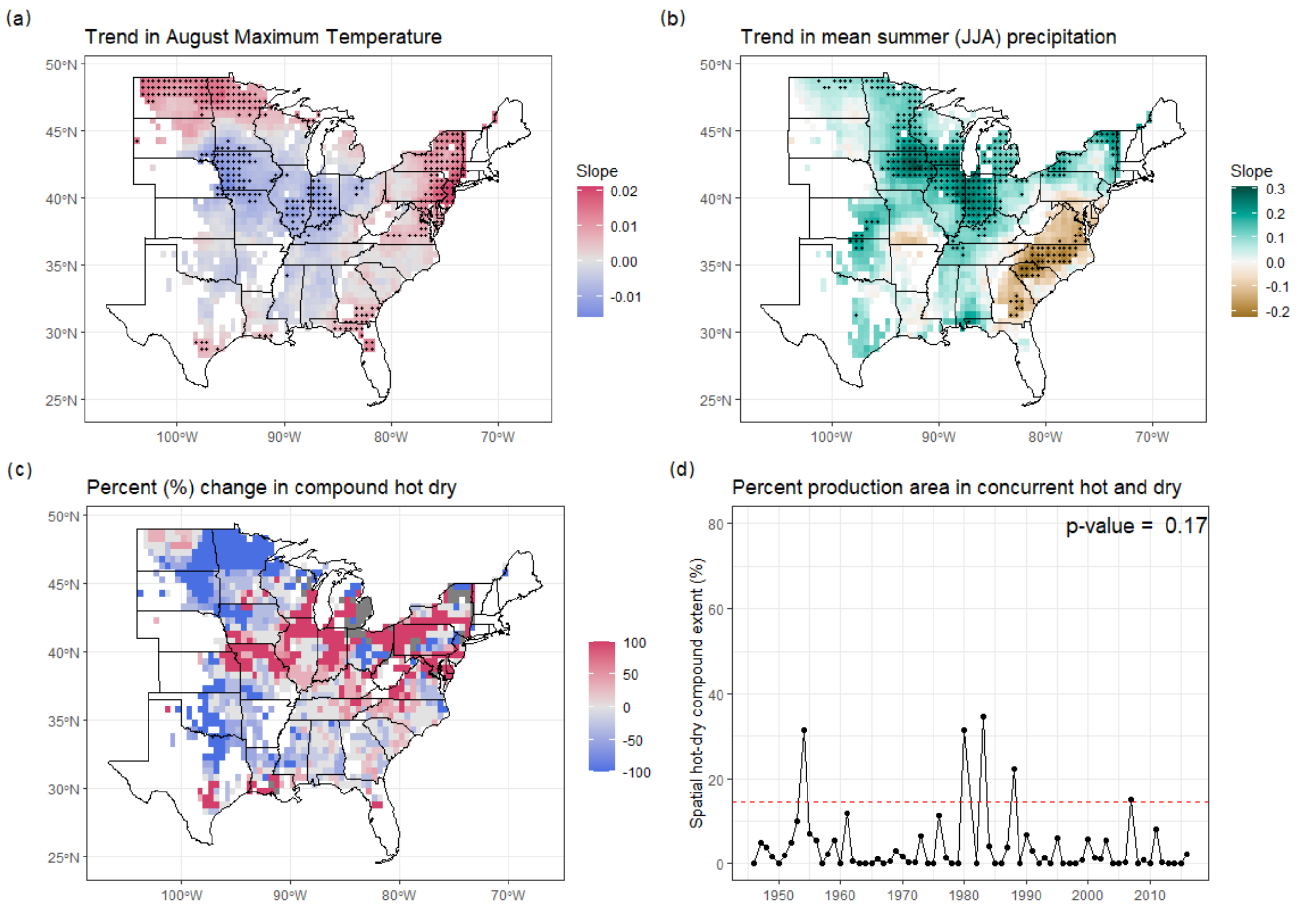

Figure 6. (a) Linear regression slope of August maximum temperature. (b) Linear regression slope for summer (JJA) precipitation. (c) Percent (%) change in concurrent dry (Summer JJA precipitation < 10th percentile) and hot (August Maximum Temperature > 90th percentile) during 1982–2016 relative to 1946–1980. (d) Time-series of percent producing regions in hot and dry conditions.

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Trends in (a, b and d) are calculated for the period 1946 to 2016. Stippling in (a) and (b) indicates statistical significance at the 95% confidence level P-value in d) corresponds to the Mann–Kendall monotonic trend test. Red dashed line in (d) represents a 15% threshold marking years with a large (>15%) spatial hot-dry extent.

Time series of percent production area in concurrent hot and dry conditions reflects the spatial extent of such conditions over the years (Fig. 6d). The red dashed line represents a threshold set at 15% exceeded by a number of years (i.e. 1956, 1980,1983,1988 and 2007). All those years except 1980 coincided with a developing La Niña summer reported to have important consequences on US crop production (Anderson et al., 2019; Jong et al., 2020). A large fraction of the production area under such conditions imply a high risk for country level agricultural production as regions are no longer able to balance out losses at the local scale. Here again, despite the dominant cooling and wetting trends over the US (Fig. 6 a & d), no significant monotonic trend was found in the fraction of US under hot-dry conditions over time.

4 Discussion

Predictors here are determined statistically, nevertheless, we aimed for a unique set of variables for all US counties to facilitate the physical interpretation of climatic drivers affecting soybean yield variability. This is in line with other studies that constructed semi-empirical crop models at the grid-cell level relying on a statistical framework driven by well-known physiological variables (Gornott and Wechsung, 2016; Schauberger et al., 2017b). The frugal method we used to select predictors means leaving out potentially useful and physiologically-relevant variables such as radiation and excessive precipitation. This choice is made as the least-squares model fit is highly sensitive to the ratio of predictors to the number of observations (James et al., 2013). Ideally, crop-observations (35 here) should be much larger than the number of predictors to avoid overfitting. Furthermore, including highly-correlated predictor variables (e.g. radiation and temperature) affect model parameter estimation and complicate physical interpretation of drivers. A reduced set of predictor variables where shared information between variables is minimized provides an easily-interpretable and robust model for assessing sensitivity of soybean crops to climate and weather variability (Ben-Ari et al., 2018; Gornott and Wechsung, 2016; Lobell and Burke, 2010; Schauberger et al., 2017b). It is possible to use more complex machine learning models such as random forests although these often tend to obscure result interpretation and do not always yield better predictions (Vogel et al., 2019, 2021). Note that non-climatic seasonal influences on crop yields are ignored in this study. These include planting densities, sowing dates, fertilizer applications and other socio-economic factors. This simplification is done as spatially-explicit time series for such components are rare and difficult to obtain (Schauberger et al., 2017b). Some of these factors were shown not to necessarily improve model performance in a case study done on crop yields in Germany (Gornott and Wechsung, 2016). Nevertheless, future studies should include these in whenever this becomes possible for extended time periods as climate has been shown to influence seasonal management practices for farmers in the US (Carter et al., 2018b).

We found that soybean yields were predominantly driven by heat and drought conditions occurring during the vulnerable summer crop reproductive stage. In particular, August month was highlighted as key month for soybean production in line

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with results from previous studies (Mourtzinis et al., 2015; Zipper et al., 2016). Furthermore, we noted a significant interaction effect between August variables modulating the final impact on yield. Drought and heat induce different growth inhibition patterns that can act simultaneously to reduce crop photosynthetic rates and eventual yield levels (Suzuki et al., 2014). August mean maximum temperature was found to be negatively associated with soybean yields for values exceeding 30°C in line with other studies reporting non-linear association between soybean and temperature where the relationship is mildly positive up until the 30°C mark and then declines sharply due to heat stress (Schauberger et al., 2017a; Schlenker and Roberts, 2009). Nevertheless, here we found that this relationship was dependent on concurrent soil moisture conditions where wet soils dampen the negative effect of high temperatures on yield via evaporative cooling. This result is in line with previous studies reporting the decoupling effect of irrigation on the relationship between heat stress and yield (Carter et al., 2016; Siebert et al., 2017; Troy et al., 2015). On the other hand, low moisture levels induce stomatal closure which leads to reduced latent heat flux and an increase in canopy temperature well above atmospheric temperatures increasing the crop sensitivity to hot conditions (Carter et al., 2016, 2018a; Siebert et al., 2017; Suzuki et al., 2014). Such interaction, although well documented in the literature on crop physiological response to primary abiotic stressors is rarely considered in large scale statistical analyses of climate impact on crop yields. This suggests a potential overestimation of temperature effects during wet conditions and an underestimation of compound hot-dry impacts in previous reports (Carter et al., 2018a; Leng et al., 2016). Our analysis further highlighted early season evapotranspiration conditions in addition to late season minimum temperature as important drivers of soybean yield variability. High evapotranspiration in the early season positively associated to yield reflects mainly non-limiting energy conditions as moisture levels are expected to not be restrictive in early spring. This can imply both a reduced frost risk in addition to a potentially longer growing season where soybean yield potential is maximized (Bastidas et al., 2008; Mourtzinis et al., 2019). End of season frost has also been reported as an important risk factor for soybean crops particularly in the northern states, and we interpret the predictor of minimum temperature during September and October as reflective of such conditions. These identified drivers of impact can serve as a basis for effective early warning systems that provide valuable information to decision makers (Merz et al., 2020). Acting in advance can be critical to avoid crop loss and associated socio-economic consequences. For instance, a short period of drought during the reproductive stage is reported to cause non-reversible damage to soybean yields (Daryanto et al., 2017). Hot and dry conditions in eastern US over summer has been shown to be forecastable at long lead times (~50 days ahead), associated with sea surface temperature anomalies over the northern Pacific Ocean (McKinnon et al., 2016; Vijverberg et al., 2020). Future work can further explore the link between drivers of compound hazards impacting yields to facilitate the development of actionable tools for stakeholders.

We showed that historic changes in climate have not increased the overall climate risk for rainfed soybean production in the US. This is in line with other studies that looked at the contribution of historic climate trends on soybean and maize yields in the US (Butler et al., 2018; Ray et al., 2019). This is particularly the case in the most northern states where the occurrence of compound hot-dry events has mostly decreased (Fig. 6d). Interestingly, soybean cropping regions have also shifted north-westerly in the US taking advantage of such changes in climate (Sloat et al., 2020). The summertime cooling is a well-

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documented phenomenon over US agricultural regions (Nikiel and Eltahir, 2019) and is likely attributable to agricultural intensification in the region (Alter et al., 2018; Mueller et al., 2016; Nikiel and Eltahir, 2019). A higher density of crops supported by increasing fertilizer rates leads to higher evapotranspiration rates which in turn induce large scale evaporative cooling and contribute to increasing precipitation (Basso et al., 2021; Mueller et al., 2016). Nevertheless, we highlighted that in key producing regions like Illinois, compound hot-dry events seem to have increased in frequency recently, despite the absence of a drying or warming trend. Potentially, during dry conditions, the actual evapotranspiration reduces, cancelling the land-change induced cooling effect and prompting a return to historic high temperature extremes (Mueller et al., 2016). Future risk assessment should account for such non-linear effects. Over the Midwest US, climate models project warmer summers which is likely to enhance the coupling between moisture and temperature via land-atmosphere feedbacks leading to a likely increase in the amplitude and frequency of compound hot-dry conditions (Cheng et al., 2019; Zscheischler and Seneviratne, 2017). Although annual precipitation levels are expected to remain constant or even increase, climate models generally project increased dry day length and decreased summer soil moisture levels (Dai, 2013; Dirmeyer et al., 2013; Wuebbles et al., 2014a, 2014b). Future research should quantify whether such trends could lead to an increase of hot-dry August months in the future. Nevertheless, high uncertainty remains with respect to atmospheric dynamical changes including quasi-stationary Rossby waves which are a key driver of hot-dry conditions in the eastern US as well as other mid-latitude regions (Di Capua et al., 2020; Coumou et al., 2014; Kornhuber et al., 2019; Shepherd, 2014; Winter et al., 2015). Until such contradictions are resolved, future impacts of climate change on US agricultural production remain uncertain. The Storyline approach has been proposed as an important tool to illustrate such epistemic uncertainty and can be explored in future studies with important consequences on current and future policy and decision making (Shepherd, 2019).

Here we focused on local types of compound events, however, global food supply is highly dependent on production in various countries. Spatially compounding events will be important to study in future assessments in order to understand large scale risk associated to breadbasket failures. Here we qualitatively identified that most of the large extent hot-dry conditions occurring over the US are associated to ENSO teleconnections. These are also highly influential over the South American continent where soybean production including the US account for more than 80% of total global supply (Anderson et al., 2017; Wellesley et al., 2017). Other examples of teleconnections are mid-latitude Rossby waves, particularly wave number 5, which has phase-locking behaviour in the northern hemisphere mid-latitudes driving simultaneous summer positive temperature anomalies over Midwest US, eastern Europe, and east Asia (Kornhuber et al., 2019). This is particularly of concern to soybean production when taking into consideration upcoming soybean hotspot production regions such as Russia and Ukraine (Deppermann et al., 2018).

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5 Conclusion

We presented a simple statistical framework that can identify climatic variables influencing soybean yield variability in the US at specific moments within the growing season. We found that compound August hot-dry conditions lead to the largest impacts on yield, i.e. beyond the estimated additive effects of each stressor separately. Furthermore, we identified early-season evapotranspiration and late-season minimum temperature to be important factors affecting soybean yield in the US. Understanding of these seasonally dependent crop-sensitivities paves the way for more effective early-warning tools that target timely drivers of yield variability throughout the growing season. The long-term cooling and wetting trend in summer, over large areas of our domain, has generally been beneficial for soybean. Nevertheless, we showed that the frequency of extreme hot-dry conditions remained largely unchanged over the full region, and increased in a key region like Illinois where crops are especially sensitive to such extremes. Given that climate models project summer warming and general declines in soil-moisture (albeit with substantial uncertainty) for the Midwest, crop sensitivities to compound hot-dry extremes are likely to present important future risks for US soybean production.

Appendix A: Additional tables and figures

Table A 1. List of all considered variables tested individually as potential predictors for the statistical model. The selected heat and moisture variables per period are highlighted in red.

Best heat and moisture related variables for each univariate model based on BIC								
Spring			Summer			Fall		
Name	BIC	Type	Name	BIC	Type	Name	BIC	Type
X4_5_ETact	38101.02	moisture	X8_SMroot	35671.27	moisture	X9_SMroot	35478.40	moisture
X4_5_Tmin	38114.13	heat	X6_7_8_ETact	36494.53	moisture	X9_ETact	35497.50	moisture
X4_ETact	38126.94	moisture	X8_Tmax	36502.21	heat	X9_10_ETact	35644.31	moisture
X4_Tmax	38135.90	heat	X8_rsds	36667.57	heat	X9_10_SMroot	35782.78	moisture
X4_5_Tmax	38158.38	heat	X6_7_8_precip_avg	36672.72	moisture	X10_SMroot	36388.79	moisture
X4_SMroot	38163.37	moisture	X8_precip_avg	36684.10	moisture	X10_ETact	37251.21	moisture
X5_ETact	38165.18	moisture	X6_7_8_num_wet	36719.33	moisture	X9_10_Tmin	37791.13	heat
X4_Tmin	38175.23	heat	X6_7_8_SMroot	36883.95	moisture	X10_Tmin	37940.51	heat
X5_Tmin	38176.42	heat	X8_ETact	36981.19	moisture	X9_Tmin	38003.55	heat
X4_5_SMroot	38181.28	moisture	X8_num_tx30	36986.02	heat	X9_10_rsds	38062.98	heat
X5_SMroot	38213.79	moisture	X8_num_wet	37065.40	moisture	X9_rsds	38095.34	heat
X5_num_pr20	38218.38	moisture	X6_7_8_rsds	37232.01	heat	X9_num_wet	38159.20	moisture
X4_5_num_pr20	38225.77	moisture	X7_SMroot	37321.64	moisture	X9_10_num_tx30	38179.84	heat
X5_num_pr30	38236.84	moisture	X6_7_8_Tmax	37387.85	heat	X9_10_num_wet	38180.22	moisture
X4_5_num_pr30	38239.45	moisture	X8_num_pr20	37397.33	moisture	X9_num_tx30	38193.27	heat

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X4_5_precip_avg	38243.69	moisture	X6_7_8_num_pr20	37413.15	moisture	X10_rsds	38211.16	heat
X5_precip_avg	38245.36	moisture	X7_ETact	37457.28	moisture	X10_Tmax	38219.46	heat
X5_Tmax	38253.65	heat	X7_precip_avg	37506.25	moisture	X9_10_precip_avg	38225.60	moisture
X4_num_tx30	38272.67	heat	X6_7_8_num_tx30	37556.24	heat	X10_num_tx30	38237.57	heat
X4_precip_avg	38273.35	moisture	X7_num_wet	37592.68	moisture	X9_precip_avg	38241.65	moisture
X4_num_wet	38274.49	moisture	X7_rsds	37717.13	heat	X9_Tmax	38247.62	heat
X4_rsds	38275.85	heat	X8_num_pr30	37747.78	moisture	X9_10_num_pr20	38248.19	moisture
X4_5_num_tx30	38276.22	heat	X7_Tmax	37757.88	heat	X9_num_pr20	38263.08	moisture
X4_num_pr20	38276.54	moisture	X6_7_8_num_pr30	37807.09	moisture	X9_10_num_pr30	38271.85	moisture
X5_num_tx30	38280.31	heat	X6_ETact	37846.45	moisture	X10_num_pr30	38274.50	moisture
X4_num_pr30	38281.21	moisture	X7_num_pr20	37913.19	moisture	X10_precip_avg	38280.89	moisture
X5_num_wet	38288.94	moisture	X6_SMroot	37925.90	moisture	X10_num_wet	38281.09	moisture
X4_5_num_wet	38289.06	moisture	X7_num_tx30	37996.85	heat	X10_num_pr20	38281.21	moisture
X4_5_rsds	38289.74	heat	X8_Tmin	38054.98	heat	X9_10_Tmax	38284.94	heat
X5_rsds	38290.43	heat	X7_num_pr30	38067.72	moisture	X9_num_pr30	38286.41	moisture
			X6_num_wet	38163.44	moisture			
			X6_Tmin	38186.92	heat			
			X6_rsds	38221.41	heat			
			X6_precip_avg	38239.57	moisture			
			X6_num_tx30	38240.49	heat			
			X6_7_8_Tmin	38260.96	heat			
			X6_num_pr20	38263.44	moisture			
			X6_Tmax	38281.99	heat			
			X7_Tmin	38282.28	heat			
			X6_num_pr30	38289.71	moisture			

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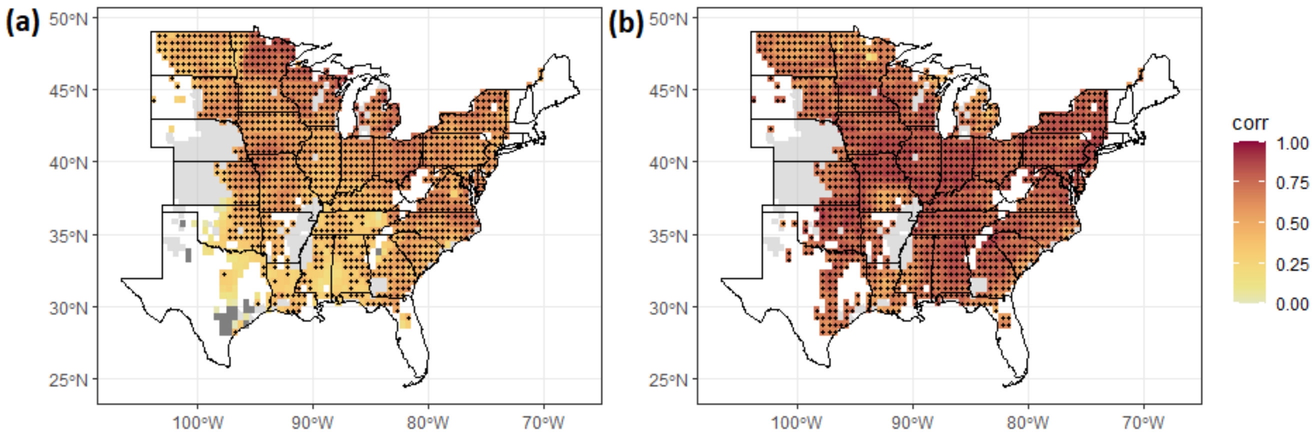
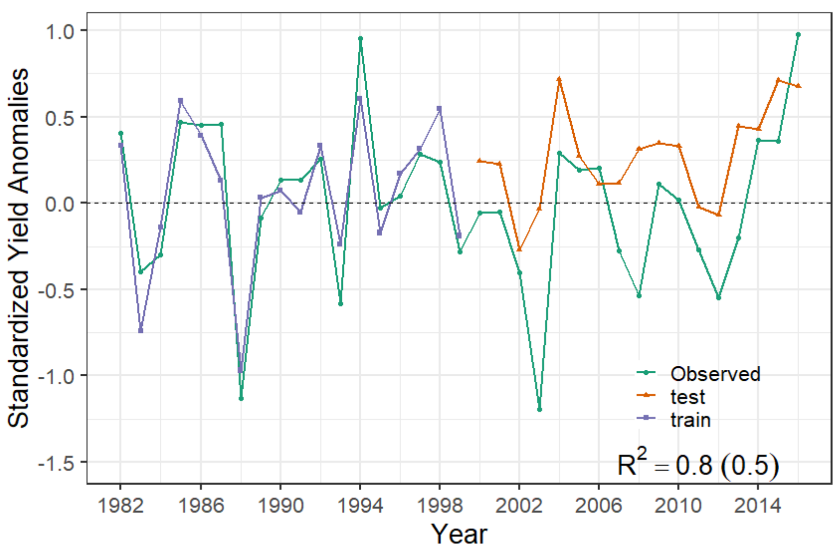


380

Figure A 1. (a) Correlation plot between CRU April-May minimum temperature and GLEAM April-May actual evapotranspiration over the period of study (1982-2016). (b) Correlation plot between CRU JJA precipitation average and GLEAM August root zone soil Moisture over the period of study (1982-2016). Stippling indicates statistical significance at the 95% confidence level.



385 **Figure A 2. Train test split validation approach where model is trained over 50% of the data (Blue line) and tested over the remaining 50% (Red).**

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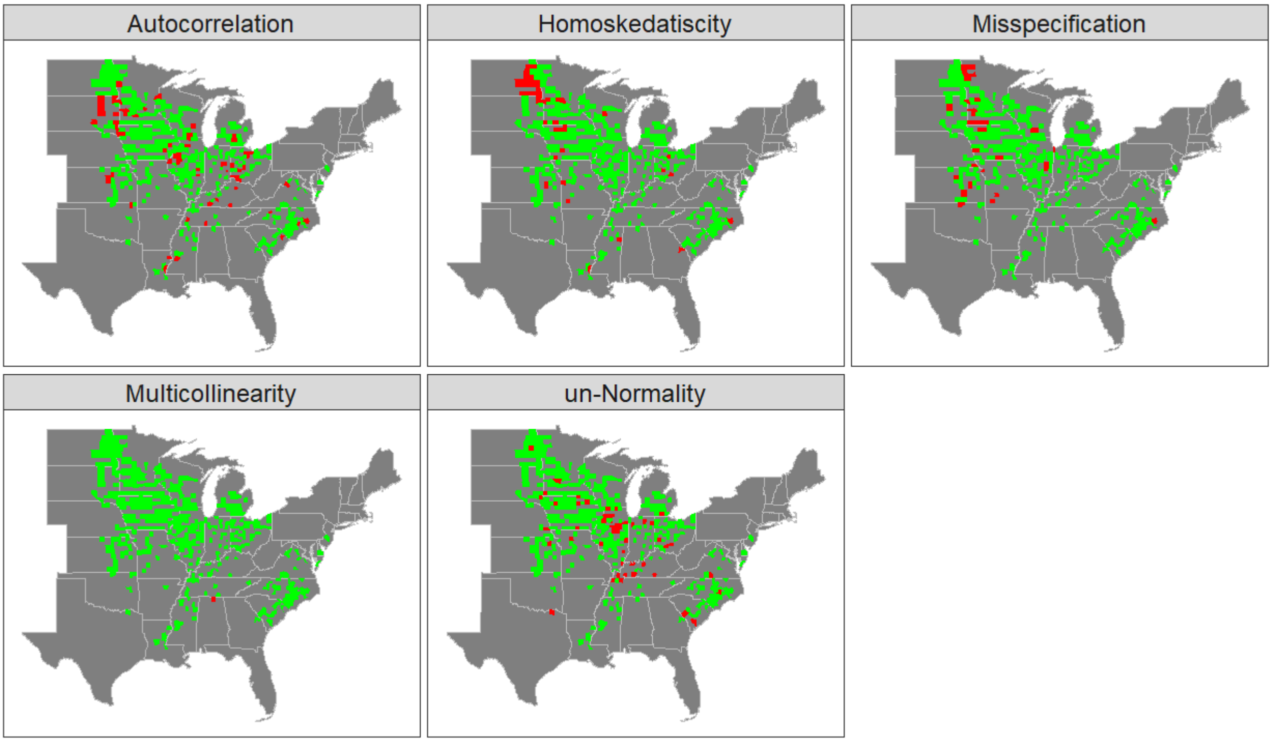

Figure A 3. Statistical test results for the US. Green indicates a "successful" test, i.e. no problem, while red indicates a rejection of the respective H0 of no autocorrelation/heteroscedasticity/ misspecification/multicollinearity/un-normality. Multicollinearity is checked with the variance inflation factor and marked in red if any of the variables report a value >3.

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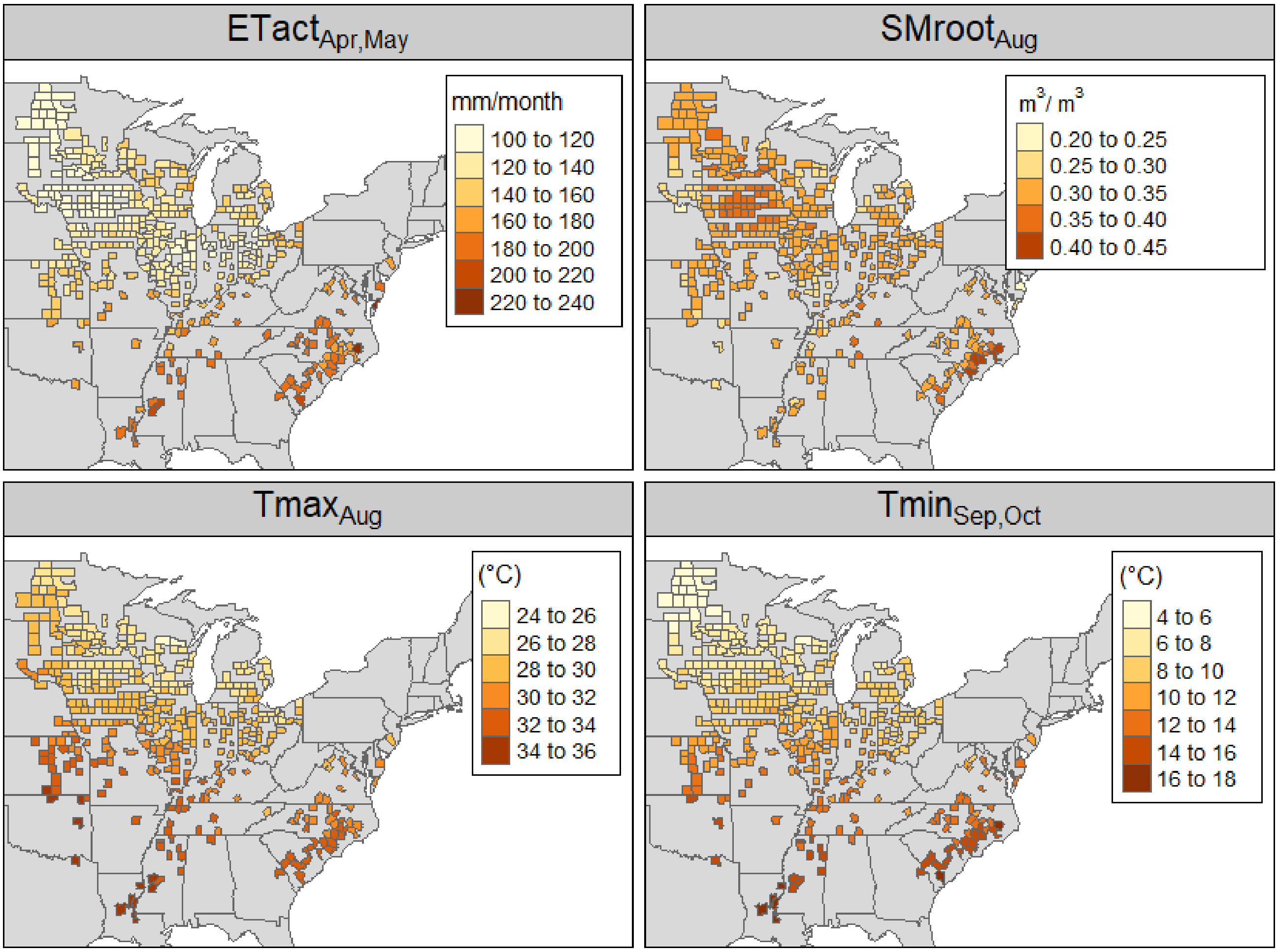

Figure A 4. Mean values for selected model predictors per county over the period of study 1982-2016.

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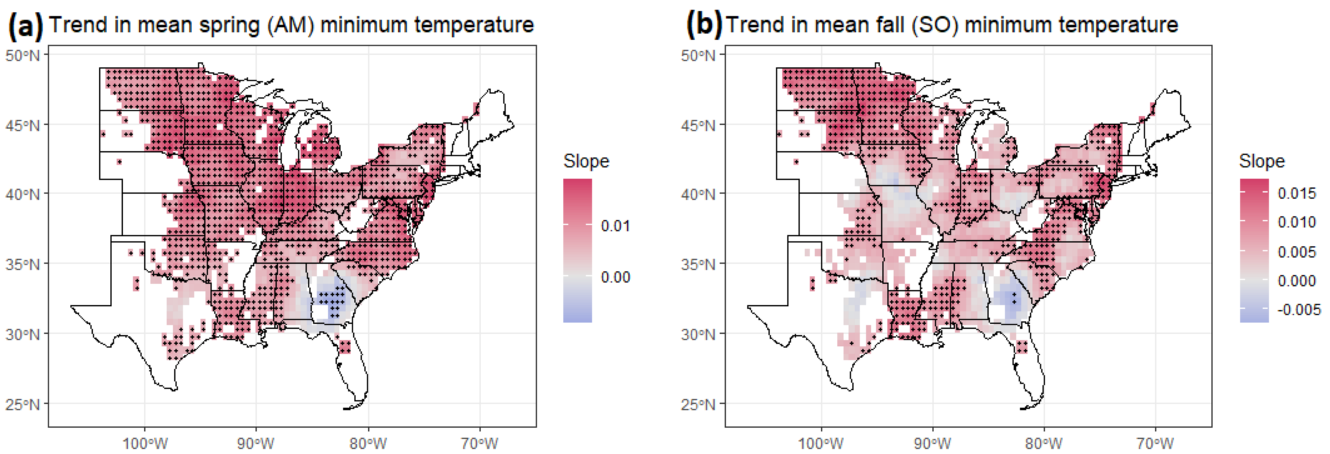

Figure A 5. (a) Linear regression slope for April-May (spring) minimum temperature. (b) Linear regression slope for September-October (fall) minimum temperature. Stippling indicates statistical significance at the 95% confidence level.

Code availability. The code is available upon request, by contacting the corresponding author.

Data availability. Data used in this study are freely available in the cited literature.

Author contributions. RH and DC designed the study. RH performed the analysis and wrote the initial draft of the manuscript. All authors discussed the analysis and results, and contributed to the writing of the paper. DC revised the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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