ENVIRO.NAL RESEARCH LETTERS

Maize yield loss risk under droughts in observations and crop models in the United States

Guoyong Leng

Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, People’s Republic of China

E-mail: lenggy@igsnrr.ac.cn

Keywords: drought, risk, crop yield, crop model, climate change

Supplementary material for this article is available online

Abstract
The negative drought impacts on crop yield are well recognized in the literature, but are evaluated mainly in a deterministic manner. Considering the randomness feature of droughts and the compounding effects of other factors, we hypothesize that drought effects on yields are probabilistic especially for assessment in large geographical regions. Taking US maize yield as an example, we found that a moderate, severe, extreme and exceptional drought event (based on the standardized precipitation evapotranspiration index) would lead to a yield loss risk (i.e. the probability of yield reduction lower than expected value) of 64.3%, 69.9%, 73.6%, and 78.1%, respectively, with hotspots identified in Central and Southeastern US. Irrigation has reduced yield loss risk by 10%–27%, with the benefit magnitude depending on the drought intensity. Evaluations of eight process crop models indicate that they can well reproduce observed drought risks for the country as a whole, but show difficulty in capturing the spatial distribution patterns. The results highlight the diverse risk pattern in response to a drought event of specific intensity, and emphasize the need for better representation of drought effects in process models at local scales. The analysis framework developed in this study is novel in that it allows for an event-based assessment of drought effects in a risk manner in both observations and process crop models. Such information is valuable not only for robust decision-makings but also for the insurance sector, which typically require the risk information rather than a single value of outcome especially given the uncertainty of drought effects.

1. Introduction
Drought is an extreme climate phenomenon that has destructive impacts on agricultural production at regional to global scales (Lobell et al 2014, Lesk et al 2016, Zipper et al 2016). Globally, droughts during 1964–2007 have caused a cereal loss of 1820 million Mg equivalent to global maize and wheat production in 2013, and the loss during more recent droughts (1985–2007) was twice larger than that during earlier droughts (1964–1984) (Lesk et al 2016). Assessing drought impacts is critical for adaptation and mitigations, and has thus attracted huge attentions during the past decades (Hlavinka et al 2009, Lobell et al 2014, Shi and Tao 2014, Troy et al 2015, Araujo et al 2016, Potopová et al 2016, Zipper et al 2016, Madadgar et al 2017).

In general, there are two groups of models for evaluating climate impacts on crop yields: process and statistical crop models, and each has its own strengths and weaknesses (Lobell and Asseng 2017, Leng and Hall 2020). Process-based models represent the physiological and phenological dynamics of crop growth and yields, and allow for mechanistic separation of climate effects through numerical experiments that are impossible for large-scale field experiments. This unique capability has led to many useful impact assessment with process models, though most of them focus on the average and inter-annual variability of yields (Deryng et al 2011, Asseng et al 2013,
Hawkins et al (2013), Iizumi et al (2013), Challinor et al (2014), Ray et al (2015), Zhao et al (2017), Schaubberger et al (2017). Lack of observations combined with incomplete process understanding, however, often lead to substantial uncertainties in process model simulations (Bassu et al (2014); Leng et al (2016)). Calibration is proposed as an effective method to reduce such uncertainty of process model simulations. For example, Ceglar et al (2019) showed that calibration of phenology parameters leads to a substantial improvement of simulated crop yields by world food studies simulation model (WOFST) over Europe. Due to data limitations, process models often use the parameters calibrated in a few locations to a larger study region, or upscaled through the agro-climatic zonation schemes (Van Wart et al (2013), thus introducing uncertainties especially when applied outside locations/regions where they were developed (Elliott et al (2015), Müller et al (2017)). The underlying uncertainties of process crop models challenge their application for evaluating the effects of climate extremes such as droughts, though large-scale evaluation of process models in simulating drought effects is rare.

Through fitting a linear or non-linear relation between observed climate variables and census yield data, statistical models have been widely used for climate impact assessment given its simplicity and less computation cost (Schlenker and Roberts (2009), Leng (2017a, 2017b)). Troy et al (2015) investigated the empirical relations between crop yields and several climate extreme index, and revealed a non-linear sensitivity of US maize to droughts. Zipper et al (2016) showed a distinct pattern of US maize yield sensitivity to droughts, through examining the slope of a linear relationship between yield and a drought index. Similar correlation analysis has also been applied in other regions (Liu et al (2018), Zampieri et al (2017), Kim et al (2019)). Such deterministic approaches could provide valuable insights of the overall sensitivity of yield response to droughts, but have some issues in quantifying drought impacts on crops. First, drought by its definition is rare. Its randomness and slow evolution process make it hard to quantify its direct effects. Second, besides drought, crop yield is influenced by several other factors that occur concurrently such as high temperature (Leng (2019)), thus making it challenging to separate the role of drought in large geographic areas. Therefore, it is important to redefine drought effects in a risk-based manner. Indeed, providing a risk-based evaluation is valuable not only for robust decision-makings but also for the insurance sector, which typically rely on the many possible outcomes and the corresponding probabilities.

Recently, Leng and Hall (2019) investigated future drought impacts on global crop yields, but the performance of process models in the history remains under-examined. Before projecting what future crop yield may change under droughts using a large number of models, it is critical to determine how individual model performs compared to observations. Previous studies have well evaluated the skill of global gridded crop models (GGCMs) in yield simulations in terms of the mean and variability (Müller et al (2017), Leng and Hall (2020)), but little is known about its performance in simulating climate extreme impacts. Lecerf et al (2019) validated the process model WOFST over Europe, and showed a promising skill of WOFST in simulating the effects of water stress on crop yield. To the best of my knowledge, however, evaluation of an ensemble of process models have not been conducted in a probabilistic manner. Especially, the sensitivity of crop yields to droughts of various severities is not well reported.

To fill the gaps, we develop a framework to aid risk assessment of droughts on crop yields, with a focus on the validation of process-based crop models against observations. Here, risk is defined by the hazard (the probability of a drought event) and susceptibility/vulnerability (the probability of yield loss under the given drought intensity), following (UN/ISDR (2004), Yin et al (2014)). A case study is conducted for maize yield in the United States, which accounts for 31% and 33% of global maize supply and export in 2019, respectively (https://www.usda.gov/). Specifically, this study contributes to the literature by addressing the following scientific questions: (a) how much risk of yield loss would be expected when experiencing a drought event of specific intensity? (b) How such yield loss risk is distributed across the country? (c) Can process models reproduce the patterns of yield loss risk under droughts? Here, the eight process models are evaluated in a probabilistic manner, regarding their skills in simulating yield response to four drought intensity categories (i.e. moderate, severe, extreme and exceptional droughts). The analysis framework developed in this study can be extended to other regions, considering different crop types and drought indices as well. Section 2 describes the materials and methods, with the results and discussions presented in section 3. Section 4 summarizes the major conclusions obtained in this study.

2. Materials and methods

2.1. Crop yields and climate data

County-level annual maize yields and state-level growing seasons are obtained from the National Agriculture Statistics Survey (NASS) Quick Stats database maintained by the US Department of Agriculture (USDA) (www.nass.usda.gov/Quick_Stats). The NASS Cropland Data Layer is obtained used to mask out the maize growing areas. Maize yields simulated by eight process-based crop models
are obtained from the Agricultural Modelling Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al 2013). These process models show various differences and similarities in terms of input, processes, calibration, management, etc (supplementary tables S1 and S2 (available online at stacks.iop.org/ERL/16/024016/mmedia)). For example, the environmental policy integrated models-IIASA (EPIC-IIASA) uses four varieties, while the GIS-based EPIC model (GEPC) adopts a high-yielding and a low-yielding variety and the environmental policy integrated model - BOKU (EPIC-BOKU) used the high-yielding variety. In this study, the eight crop models are harmonized in terms of climate inputs, crop area, crop planting and harvesting calendar, and are run following the consistent simulation protocols (Elliott et al 2015). Gridded climate data is obtained from AgMERRA climate data set (Ruane et al 2015), as it is used for driving AgMIP crop models. Thus, adoption of AgMERRA climate data can allow for reasonable comparisons between statistical and process-based crop models. Similar patterns are obtained when using the observed climate from Parameter-elevation Relationships on Independent Slopes Model (Schneider et al 2017). The period 1980–2010 is selected because both census data and simulated yields are available during this period.

2.2. Probability modeling and uncertainty quantification

Copula are functions that can describe dependencies between variables, and are valuable for risk analysis (Nelsen 2007). Here, copula functions are used in this study to fit the joint probability distribution function (PDF) between a drought index (x) and crop yields (y).

\[ F_{XY}(X, Y) = C[F_X(X), F_Y(Y)] \]  

where C is the cumulative distribution function (CDF) of copula, while \( F_X(X) \) and \( F_Y(Y) \) are the marginal distributions of x and y, respectively. The PDF of crop yields conditioning on a given drought condition (i.e. \( f_{Y|x}(y|x) \)) is calculated as follows:

\[ f_{Y|x}(y|x) = c[F_X(x), F_Y(y)] \times f_Y(y) \]

where c is the PDF of copula, \( f_Y(y) \) is the PDF of crop yield. Based on the conditional probability distribution, yield loss probability is estimated as the area under \( f_{Y|x}(y|x) \) for yields lower than its long-term average value. The key features of copulas are its flexible structures in joining random variables with different types of marginal distributions, and its capability of measuring the non-linear dependence between variables (Nelsen 2007). In this study, five commonly used copulas are adopted (supplementary table S3), and the one that shows the highest statistically significant (at 95% confidence interval) maximum likelihood is selected as the best copula (Sadegh et al 2017).

To quantify the uncertainties associated with the probability analysis, the hybrid-evolution Markov chain Monte Carlo (MCMC) algorithm within a Bayesian framework is adopted to derive the posterior distribution of copula (i.e. \( p(\theta|\bar{E}) \)) as follows:

\[ p(\theta|\bar{E}) = \frac{p(\theta)p(\bar{E}|\theta)}{p(\bar{E})} \propto p(\theta)p(\bar{E}|\theta) \]

where \( p(\theta) \) is the prior distribution of copula parameter \( \theta \), \( p(\bar{E}|\theta) \) represents the likelihood function solved by following equation (4).

\[ p(\bar{E}|\theta) \propto L(\theta|\bar{E}) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\tilde{\sigma}^2}} \exp \left\{ -\frac{1}{2\tilde{\sigma}^2} \tilde{d}_i^2(\theta) \right\} \]

where \( \tilde{\sigma} \) denotes the standard deviation of measurement error. The 5th and 95th of the posterior distribution are used to represent the lower and upper bounds of our probability estimates, respectively.

2.3. Assessment of yield loss risk under drought

Despite the direct effects of soil moisture, this study assesses drought impacts from the climatic perspective, due to the lack of long-term continuous ground observations of soil moisture across a large geographical region. Using climate-based drought indicators allows for consistent comparison between statistical and process models, because both models can use the same climate dataset for drought calculations. It is well recognized that temperature is a critical factor that regulates drought effects on crop growth and yield (Lobell et al 2014, Zhao et al 2017, Leng 2017a). Recently, Mathieu and Aires (2018) compared 50 agro-climatic indices including soil moisture for US maize yield forecasting, and found that standardized precipitation evapotranspiration index (SPEI) is one of the best agro-climatic indices. Indeed, besides precipitation. Therefore, the SPEI (Vicente-Serrano et al 2010) which includes the effects of both precipitation and temperature is calculated for the growing season for our main analysis. SPEI is computed by fitting a PDF to precipitation minus potential evapotranspiration (which is a function of temperature), based on which the CDF is derived and transformed to a normal distribution (Vicente-Serrano et al 2010). The SPEI has also been widely used in previous investigation of drought impacts on crop yield (Potop et al 2012, Zampieri et al 2017, Peña-Gallardo et al 2019, Solaraju-Murali et al 2019, Sharma et al 2020). Sensitivity analysis is conducted
using the standardized precipitation index (McKee et al 1993), which includes precipitation effect only.

A drought event is identified with the drought index dropping below −0.8, following the definition by the US Drought Monitor (http://droughtmonitor.unl.edu/). Here, four categories of droughts (i.e. moderate, severe, extreme and exceptional droughts) are selected for analysis (supplementary table S4). To account for the effects of technological improvements, the linear trend of maize yield is removed using the least squares method (Hlavinka et al 2009, Lobell et al 2011), before it is used for fitting the risk model. Based on the fitted joint distribution function, the risk of yield loss (i.e. yield lower than its expected value) under the four categories of droughts is estimated. Similar analysis is conducted for both irrigated and non-irrigated yields to explore the potential benefits of irrigation in mitigating yield loss risk under droughts of various severity. Analysis is also repeated based on the simulated yields by eight process crop models and compared with observation-based results in order to evaluate the performance of current state-of-the-art crop models in simulating yield loss risk under droughts.

3. Results and discussions

During the past three decades, maize yield for the country as a whole has exhibited substantial inter-annual variations, which is significantly ($P < 0.05$) correlated with the drought conditions as measured by the SPEI (figure 1(a)). Such observed significant relation between yield anomaly and SPEI allows for modeling their full dependence structure (see section 2), which is shown in figure 1(b). Comparing the modeled yield distributions with observed yields (red dots) show that the majority of observed yields fall within the high-density region of PDFs, suggesting that our model is reliable for describing maize yield anomaly under droughts. Despite the tendency of high yields with increasing SPEI, low yields are observed under extreme wet conditions (with SPEI close to +2). Theoretically, this is possible because excessive rain water could induce waterlogging that could harm crop growth and yield. Li et al (2019) revealed the role of excessive rainfall in leading to yield loss over US. Our results confirmed this but have added value by quantifying the associated probabilities which tend to be relatively small. The unique value of our model lies in that it allows for examination of all possible yield responses to an individual drought event, complementing previous studies measuring the overall relation between the annual time series of crop yield and a specific drought index.

Figure 2 shows the estimated yield loss risk (i.e. the probability of yield reduction lower than expected value) under a moderate, extreme, severe and exceptional drought event in observations and process-based crop models. Based on census yield and observed climate data, the probability of yield loss for the country as a whole is expected to be 64.3% 69.9%, 73.6%, and 78.1% under moderate, extreme, severe and exceptional droughts, respectively. Comparing the estimates under the four drought events can also indicate the non-linear sensitivity of yield loss risk to the increase of drought intensity. For example, yield loss risk grows faster when experiencing a shift in drought severity from moderate to severe than that from extreme to the exceptional category, i.e. demonstrating the non-linear response of yield to the increase in drought severity. The substantial increase of yield loss risk when drought intensity shifts from moderate to extreme, severe and exceptional points to the needs for effective adaptive measures for ensuring resilience in agricultural production in a warming climate with greater likelihood of more frequent and severe droughts (Sheffield and Wood 2008, Dai 2013, Huang et al 2017).

Similarly, the process-based models simulated a consistent upward tendency of yield loss risk in response to the growth of drought intensity. However, large discrepancy is observed among the eight process models, and such spread becomes larger with increase in drought intensity. For example, the highest estimate of yield loss risk is 99.3% in the GIS-based EPIC model (GEPIc) under the exceptional drought category, while the lowest estimate is 57.9% in EPIC-Boku. Gridded crop models make a number of simplifications, and the large inter-model discrepancy could be due to the considerable differences in model structure, parameters, representation of management and drought effects, etc (Asseng et al 2011, Bassu et al 2014, Rosenzweig et al 2014, Elliott et al 2015, Folberth et al 2016). For example, all crop models calculate a water stress coefficient ranging from 0 to 1, which would affect processes such as canopy senescence, stomatal conductance, assimilation rate and grain yield. This can explain that crop models generally agree on the direction of yield change with increase in drought severity. However, how drought exerts impacts in process models are diverse and depend on soil water content (e.g. predicting ecosystem goods and services using scenarios (PEGASUS)), soil water supply to demand ratio (e.g. parallel agricultural production systems simulator (pAPSIM)), or actual to potential transpiration ratio (e.g. CGMS-WOFOST which also depends on soil moisture), which may contribute to the large spread in process model simulations. Like previous model evaluation works (Müller et al 2017), quantitatively examining the underlying reasons behind the diverse model performance is beyond the capabilities of this study, as it would require the coordination efforts of the modeling groups for attribution analysis.

How are yield loss risks spatially distributed across the country? Previous studies have well
examined the overall sensitivity of US maize yield to droughts (Zipper et al. 2016), but it is unclear how yields respond to a drought event of specific severity. Here, we implement the risk model for each maize growing county (supplementary figure S1), based on which yield loss risks under a moderate, extreme, severe and exceptional drought event are estimated (figure 3). Spatially, when experiencing an exceptional drought, the probability of yield loss could exceed 90% in most of the country. The highest risk is observed in central and southeastern US, while the lowest is in western US and high production regions such as the state of Illinois. Comparing the yield loss risk under the four categories of droughts indicates that maize yields in Southeastern US, Texas, High Plains are most vulnerable to the increase in drought severity than other areas. Notably, no counties show a 100% yield loss under an exceptional drought event, implying that other factors such as technology and management may have reduced yield sensitivity to drought (Elliott et al. 2018). This further demonstrates the value of assessing drought impacts in a risk manner, rather than providing a deterministic evaluation. The revealed spatial patterns are found to be robust when examining the lower and higher bounds of estimation derived with the MCMC technique, although uncertainties are considerable in some areas (supplementary figure S2). The spatial patterns of yield loss risk are also robust to the log yield effects (supplementary figure S3) and the choice of drought index (supplementary figure S4), which are valuable for informing targeted adaptation and mitigation measures.

However, process-based crop models failed to reproduce the distinct spatial distribution patterns of yield loss risk (figure 3), which simulated more uniform patterns of yield loss risk and its sensitivity to the increasing severity of droughts. This may be attributed to the lack of spatially variable representation.
Figure 2. Maize yield loss probability (%) in observations and process-based crop models under a moderate, severe, extreme and exceptional drought event. The boxplot shows the range of eight process-based crop model estimations with the red horizontal line indicating the median value. The increment of yield loss probability is statistically significant when drought intensity level shifts from moderate to severe, extreme and exceptional, from severe to exceptional, and from extreme to exceptional, while a non-significant increase is found between severe and extreme drought intensity.

Our evaluation of current state-of-art process models has great implications for understanding the model strength and weakness geographically across the country, especially regarding the representation of climate extreme effects in crop models. Indeed, previous crop model evaluation studies mainly focused on yield averages and variability, while only a few studies have been conducted assessing the performance of process models in representing the effects of climate extremes. An evaluation of process-based models in our study is valuable for enhancing our understanding of process model strength and weakness, through (a) validating an ensemble of process models (rather than a single model) in a probabilistic manner; (b) assessing yield responses to droughts of various severities (i.e. moderate, extreme, severe and exceptional droughts), rather than a generic drought event; (c) revealing the contrasting model performances among different scales. Overall, the validation results suggest that projection of yield loss risk using crop models would be reliable at the country scale, but has large uncertainty at fine-scales.

The physical mechanisms behind the distinct spatial patterns are an open question since many factors could influence drought sensitivity in farmers’ fields. In southeastern US, the relatively larger sensitivity of maize yield to droughts may be due to the poor water retention capacity by the sandy soils (Zipper et al 2015). In Iowa where tile drainage is extensively used, the relatively smaller sensitivity of maize yield to droughts may relate to excess water, high water table and wet soils over there (Schilling and Libra 2003). Maize yields also remain stable with increase in drought severity in irrigation in the western arid areas and Central High Plains, where irrigation is extensively applied. Indeed, results confirm that irrigation has well mitigated drought impacts on maize yields in areas where the...
Figure 3. Spatial distribution pattern of yield loss probability (%) under a moderate, severe, extreme and exceptional drought event. The left panel shows the optimal estimate based on observations, while the right columns represent the ensemble mean of crop models. The observation-based optimal estimations are generated by the Markov chain Monte Carlo algorithm (see methods section).

Figure 3. Spatial distribution pattern of yield loss probability (%) under a moderate, severe, extreme and exceptional drought event. The left panel shows the optimal estimate based on observations, while the right columns represent the ensemble mean of crop models. The observation-based optimal estimations are generated by the Markov chain Monte Carlo algorithm (see methods section).

Despite the great benefits by irrigation, yield loss risk still grows with increase in drought severity (figure 4(a)), which implies that water stress may not be the sole factor affecting crop yields or farmers are not able to access sufficient irrigation water. The former suggests the compound effects by other important factors such as temperature, radiation, vapor pressure deficit and CO₂ (Lobell et al 2014, Deryng et al 2016, Siebert et al 2017) and confirms the value for our probabilistic assessment of drought effects, while the latter highlights the need for considering the constraints of irrigation water availability on agricultural production (Elliott et al 2014). Process crop models have well captured the role of irrigation in reducing yield loss risk under droughts, although the simulated benefits tend to become smaller with increase in drought severity (figure 4(b)). The remaining risk under irrigation in process models may suggest that other important compounding factors/stresses have exerted influences on the yield-SPEI relations (e.g. extreme high temperatures), which in turn confirms the value for conducting a probabilistic assessment of drought impacts. These event-based findings have important implications not only for ensuring food security but also for water resource management. Indeed, substantial irrigation water withdrawals would lead to severe environmental problems (e.g. depleting environmental flows and groundwater resources, decreasing other human water uses), and is expected to exceed the water planetary boundary which defines...
the safe-operating space for humanity (Rockström et al. 2009, Steffen et al. 2015, Gerten et al. 2020).

Therefore, the revealed marginal benefits of irrigation under a specific drought event is important for guiding sustainable water use within the water Planetary Boundary.

4. Conclusions

Previous studies have well demonstrated drought impacts on crop yield at the regional and global scales. But the possible outcomes of crop yield in response to a specific drought event and their corresponding probabilities have been relatively under-examined, and especially an inter-comparison of observation-based statistical and process-based crop models is lacking. In this study, we develop a probabilistic framework to enable risk assessment of US maize yield response to a drought event in observations and crop models.

Results show that a single moderate drought event (with the drought indicator SPEI ranging from $-0.8$ to $-1.2$) would lead to a 64.3% chance of yield loss (i.e. yield lower than expected value) for the country as a whole. The risk, however, would jump to 69.9% when experiencing an extreme drought event (i.e. SPEI ranging from $-1.6$ to $-1.9$). Under an exceptional drought (i.e. SPEI ranging $<-2.0$), US maize yield would have a 78.1% probability of loss risk. The highest risk is observed in central and southeastern US, while maize loss risk is relatively low in western US, where irrigation has reduced yield loss risk by 10%, 17%, 22% and 27% under moderate, extreme, severe and exceptional droughts, respectively. Further analysis showed that current state-of-art process-based crop models can well capture the magnitudes and the sensitivity of yield loss risk to droughts for the country as a whole, but have difficulty in reproducing the distinct spatial patterns across the country. This suggests that continued efforts are required to improve the skill of process models especially at local scales, or conduct bias-correction before their applications.

Information on how crop yield will change in response to an individual drought of specific severity is critical for targeted adaptation and mitigations. Moreover, a risk-based analysis of yield response to droughts is valuable not only for robust

---

**Figure 4.** Comparison of yield loss probability (%) under irrigated and non-irrigated conditions, based on (a) observations and (b) ensemble mean of crop models. Note only limited counties report separate estimates of irrigated and non-irrigated yields, and the distribution of these counties can be found in the supplementary figure S5.
decision-makings but also for the insurance sector, which typically require the risk information rather than a single value of outcome especially given the randomness of droughts. The analysis framework developed in this study allows for estimation of possible yield changes under a drought event of specific severity, which has the potential to be combined with existing drought monitoring systems, thus facilitating integrated and event-based risk assessment of drought effects on crop yield.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

I would like to thank the editor and three anonymous reviewers for their helpful comments and suggestions that led to substantial improvement of this manuscript. This research was funded by the National Natural Science Foundation of China (No. 42077420).

ORCID iD

Guoyong Leng @ https://orcid.org/0000-0001-6345-143X

References

Araujo J A, Abiadoun B J and Crespo O 2016 Impacts of drought on grape yields in Western Cape, South Africa Theor. Appl. Climatol. 123 117–30
Asseng S et al 2013 Uncertainty in simulating wheat yields under climate change Nat. Clim. Change 3 827–32
Asseng S, Foster I and Turner N C 2011 The impact of temperature variability on wheat yields Glob. Change Biol. 17 997–1012
Bassu S et al 2014 How do various maize crop models vary in their responses to climate change factors? Glob. Change Biol. 20 2301–20
Ceglar A, Van der Wijngaart R, De Wit A, Lecerf R, Boogaard H, Seguin I and Baruth B 2019 Improving WOFOST model to simulate winter wheat phenology in Europe: evaluation and effects on yield Agric. Syst. 168 168–80
Challinor A, Watson J, Lobell D, Howden S, Smith D and Chhetti N 2014 A meta-analysis of crop yield under climate change and adaptation Nat. Clim. Change 4 287–91
Dai A 2013 Increasing drought under global warming in observations and models Nat. Clim. Change 3 52–58
Deryng D et al 2016 Regional disparities in the beneficial effects of rising CO2 concentrations on crop water productivity Nat. Clim. Change 6 786–90
Deryng D, Sacks W, Barford C and Ramankutty N 2011 Simulating the effects of climate and agricultural management practices on global crop yield Glob. Biogeochim. Cycles 25 GR06
Dobor L, Barcza Z, Hlásny T, Arendás T, Spítko T and Fodor N 2016 Crop planting date matters: estimation methods and effect on future yields Agric. For. Meteorol. 223 103–15
Elliott J et al 2014 Constraints and potentials of future irrigation water availability on agricultural production under climate change Proc. Natl Acad. Sci. 111 3239–44
Elliott J et al 2015 The global gridded crop model intercomparison: data and modeling protocols for phase 1 (v1.0) Geosci. Model Dev. 8 261–77
Elliott J, Glotter M, Ruane A C, Boote K J, Hatfield J L, Jones J W, Rosenzweig C, Smith L A and Foster I 2018 Characterizing agricultural impacts of recent large-scale US droughts and changing technology and management Agric. Syst. 159 275–81
Folberth C et al 2016 Uncertainties in global crop model frameworks: effects of cultivar distribution, crop management and soil handling on crop yield estimates Biogeosci. Discuss. (https://doi.org/10.5194/bg-2016-527)
Gerten D, Heck V, Jägermeyer J, Bodirsky B L, Felzer I, Jalava M, Kummu M, Lucht W, Rockström J and Schaphoff S 2020 Feeding ten billion people is possible within four terrestrial planetary boundaries Nat. Sustain. 3 280–8
Hawkins E, Fricker T E, Challinor A J, Ferro C A, Ho C K and Osborne T M 2013 Increasing influence of heat stress on French maize yields from the 1960s to the 2030s Glob. Change Biol. 19 937–47
Hlavinka P, Trnka M, Semeradova D, Dubrovsky M, Žáhal Z and Možny M 2009 Effect of drought on yield variability of key crops in Czech Republic Agric. For. Meteorol. 149 431–42
Huang S, Leng G, Huang Q, Xie Y, Liu S, Meng E and Li P 2017 The asymmetric impact of global warming on US drought types and distributions in a large ensemble of 97 hydro-climatic simulations Sci. Rep. 7 5891
Iizumi T, Sakuma H, Yokozawa M, Luo J-J, Challinor A J, Brown M E, Sakurai G and Yamagata T 2013 Prediction of seasonal climate-induced variations in global food production Nat. Clim. Change 3 904–8
Jägermeyer J and Frieler K 2018 Spatial variations in crop growing seasons pivotal to reproduce global fluctuations in maize and wheat yields Sci. Adv. 4 eaat4517
Kim W, Iizumi T and Nishimori M 2019 Global patterns of crop production losses associated with droughts from 1983 to 2009 J. Appl. Meteorol. Climatol. 58 1233–44
Lecerf R, Ceglar A, López-Lozano R, Van Der Velde M and Baruth B 2019 Assessing the information in crop model and meteorological indicators to forecast crop yield over Europe Agric. Syst. 168 191–202
Leng G 2017a Recent changes in county-level corn yield variability in the United States from observations and crop models Sci. Total Environ. 607 683–90
Leng G 2017b Evidence for a weakening strength of temperature-corn yield relation in the United States during 1980–2010 Sci. Total Environ. 605 551–8
Leng G 2019 Uncertainty in assessing temperature impact on US maize yield under global warming: the role of compounding precipitation effect J. Geophys. Res. 124 6238–46
Leng G and Hall J W 2020 Predicting spatial and temporal variability in crop yields: an inter-comparison of machine learning, regression and process-based models Environ. Res. Lett. 15 044027
Leng G and Hall J 2019 Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future Sci. Total Environ. 654 811–21
Leng G, Zhang X, Huang M, Yang Q, Rafique R, Asrar G R and Leung I. 2016 Simulating county-level crop yields in the conterminous United States using the community land model: the effects of optimizing irrigation and fertilization J. Adv. Model. Earth Syst. 8 1912–31
Lesk C, Rowhani P and Ramankutty N 2016 Influence of extreme weather disasters on global crop production Nature 529 84–87
Li Y, Guan K, Schmitzey G D, Delucia E and Peng B 2019 Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States Glob. Change Biol. 25 2325–37
Liu X, Pan Y, Zhu X, Yang T, Bai J and Sun Z 2018 Drought evolution and its impact on the crop yield in the North China Plain J. Hydrool. 564 984–96

9
Lobell D B and Asseng S 2017 Comparing estimates of climate change impacts from process-based and statistical crop models Environ. Res. Lett. 12 015001

Lobell D B, Roberts M J, Schlenker W, Braun N, Little B B, Rejesus R M and Hammer G L 2014 Greater sensitivity to drought accompanies maize yield increase in the US Midwest Science 344 516–9

Lobell D B, Schlenker W and Costa-Roberts J 2011 Climate trends and global crop production since 1980 Science 333 616–20

Madadgar S, Aghakouchak A, Farahmand A and Davis S J 2017 Probabilistic estimates of drought impacts on agricultural production Geophys. Res. Lett. 44 7799–807

Mathieu J A and Aires F 2018 Assessment of the agro-climatic indices to improve crop yield forecasting Agric. For. Meteorol. 253 15–30

Mckeever T B, Dwoisen N J and Kleist J 1993 The relationship of drought frequency and duration to time scales Proc. 8th Conf. on Applied Climatology (Boston, MA: American Meteorological Society)

Müller C et al 2017 Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications Geosci. Model Dev. 10 1403

Nelson R B 2007 An Introduction to Copulas (Berlin: Springer)

Peña-Gallardo M, Vicente-Serrano S M, Quiring S, Svoboda M, Hannaford J and Tomas-Burguera M 2019 Response of crop yield to different time-scales of drought in the United States: spatio-temporal patterns and climatic and environmental drivers Agric. For. Meteorol. 264 40–55

Potop V, Moźny M and Soukup J 2012 Drought evolution at various time scales in the lowland regions and their impact on vegetable crops in the Czech Republic Agric. For. Meteorol. 156 121–33

Potopová V, Boroneanţ C, Boincean B and Soukup J 2016 Impact of agricultural drought on main crop yields in the Republic of Moldova Int. J. Climatol. 36 2063–82

Ray D K, Gerber J S, MacDonald G K and West P C 2013 Climate variation explains a third of global crop yield variability Nat. Commun. 6 5989

Rockström J, Steffen W, Noone K, Persson Å, Chapin F S, Lambin E F, Lenton T M, Scheffer M, Folke C and Schellnhuber H J 2009 A safe operating space for humanity Nature 461 472–5

Rosenzweig C et al 2013 The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies Agric. For. Meteorol. 170 166–82

Rosenzweig C et al 2014 Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparisonProc. Natl Acad. Sci. 111 3268–73

Ruane A C, Goldberg R and Chrysanthacopoulos J 2015 Climate forcing datasets for agricultural modeling: merged products for gap-filling and historical climate series estimation Agric. For. Meteorol. 200 233–48

Sadegh M, Ragno E and Aghakouchak A 2017 Multivariate copula analysis toolbox (MvCAT): describing dependence and underlying uncertainty using a Bayesian framework Water Resour. Res. 53 5166–83

Schauberger B et al 2017 Consistent negative response of US crops to high temperatures in observations and crop models Nat. Commun. 8 13931

Schilling K E and Libra R D 2003 Increased baseflow in Iowa over the second half of the 20th century J. Am. Water Resour. Assoc. 39 851–60

Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to US crop yields under climate change Proc. Natl Acad. Sci. 106 15594–8

Sharma T, Vittal H, Karmakar S and Ghosh S 2020 Increasing agricultural risk to hydro-climatic extremes in India Environ. Res. Lett. 15 034010

Sheffield J and Wood E F 2008 Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations Clim. Dyn. 31 79–105

Shi W and Tao F 2014 Vulnerability of African maize yield to climate change and variability during 1961–2010 Food Security 6 471–81

Siebert S, Weiher H, Zhao G and Ewert F 2017 Heat stress is overestimated in climate impact studies for irrigated agriculture Environ. Res. Lett. 12 054023

Solaraju-Murali B, Caron I P, Gonzalez-Reviriego N and Doblas-Reyes F J 2019 Multi-year prediction of European summer drought conditions for the agricultural sector Environ. Res. Lett. 14 124014

Steffen W, Richardson K, Rockström J, Cornell S E, Fetzer I, Bennett E M, Biggs R, Carpenter S R, de Vries W and De Wit C A 2015 Planetary boundaries: guiding human development on a changing planet Science 347 1259855

Troy T, Kippen C and Pal I 2015 The impact of climate extremes and irrigation on US crop yields Environ. Res. Lett. 10 054013

UN/ISDR 2004 Living with Risk: A Global Review of Disaster Reduction Initiatives (New York: UN Publications)

van Bussel L, Stehfest E, Siebert S, Müller C and Ewert F 2015 Simulation of the phenological development of wheat and maize at the global scale Glob. Ecol. Biogeograph. 24 1018–29

Van Wart J, van Bussel L G, Wolf J, Licker R, Grassini P, Nelson A and van Ittersum M K 2013 Use of agro-climatic zones to upscale simulated crop yield potential Field Crops Res. 143 44–55

Vicente-Serrano S M, Beguería S and López-Moreno J I 2010 A multicriteria drought index sensitive to global warming: the standardized precipitation evapotranspiration index J. Clim. 23 1696–718

Yin Y, Zhang X, Lin D, Yu H, Wang J A and Shi P 2014 GEPI-C-V-R model: a GIS-based tool for regional crop drought risk assessment Agric. Water Manage. 144 107–19

Zampieri M, Ceccato P, Dentener F and Toteti A 2017 Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales Environ. Res. Lett. 12 064008

Zhao C et al 2017 Temperature increase reduces global yields of major crops in four independent estimates Proc. Natl Acad. Sci. 114 9326–31

Zipper S C, Huijberts A J M, Kucharik C J and Stრeeks J M 2016 Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes Environ. Res. Lett. 11 094021

Zipper S C, Soylu M E, Booth E G and Leidehe S P 2015 Untangling the effects of shallow groundwater and soil texture as drivers of subfield-scale yield variability Water Resour. Res. 51 6338–58