# Keeping global warming within 1.5°C reduces future risk of yield loss in the United States: a probabilistic modelling approach

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## Abstract

This study assess the possible outcomes of yield changes in the United States which is responsible for 40% of global maize supply under 1.5°C and 2°C global warming scenarios. Instead of providing deterministic estimates, this study introduces a probability-based approach that allow for examination of the associated probability of each outcome, which has great implications for decision-makings. Results show distinct spatial patterns in future yield loss risk associated with temperature rise at the county scale, with highest probability in central and southeastern US, and lowest risk in western US and high production regions such as Iowa. Comparing the estimates under 1.5°C global warming against that in 2.0°C warming indicates that keeping global warming within 1.5°C has great benefits for reducing future yield loss risk. Based on the ensemble mean of 97 climate model simulations, the risk of yield dropping below historical long-term mean is projected to decrease from 81% to 75% for the country as a whole. Such benefit is more evident when considering the risk of yield reduction by 10% and 20%, which is expected to decrease by 25% and 28%, respectively. This suggests that constraining global temperature rise to 1.5°C has more benefits for reducing extreme yield reductions. Spatially, keeping global warming within 1.5°C would benefit more in in Missouri, South Dakota, Eastern Kansas, Southern Texas and southeastern part of the country than other regions, highlighting the spatially variable benefits of climate mitigation efforts. The analysis framework introduced in this study can also be easily extended to other regions and crops. The results of this study highlight the areas where maize yield is most vulnerable to temperature rise, and the spatially variable benefits for reducing yield loss risk by keeping global warming within 1.5°C.



**Keywords:** global warming; agriculture; risk; 1.5°C; yield loss; US crops.

# 1. Introduction

Global food demand is expected to roughly double by 2050s (Godfray et al., 2010; Tilman et al., 2011). The challenge of feeding global population within the context of a changing climate calls for assessment on the potential impacts of climate change on global food production. Towards this, numerous studies have investigated climate change impacts on agricultural production in China (Piao et al., 2010; Tao et al., 2006; Yao et al., 2007), Africa (Jones and Thornton, 2003; Müller et al., 2011; Schlenker and Lobell, 2010), Europe (Bindi and Olesen, 2011; Olesen and Bindi, 2002; Reidsma et al., 2010), United States (Rosenzweig et al., 2014; Schlenker and Roberts, 2009; Urban et al., 2012), and the whole globe (Parry et al., 2004; Rosenzweig et al., 2014). Whilst these studies provided valuable insights, most of them are mainly based on a deterministic approach without considering the full range of possible outcomes of yields under given conditions.

Year-to-year variation of crop yields is often associated with variability of growing season mean temperature, without $CO_2$ fertilization or adaptations (Asseng et al., 2015; Deryng et al., 2011; Leng et al., 2016a; Liu et al., 2016; Lobell and Field, 2007; Peng et al., 2004; Ray et al., 2015; Schauberger et al., 2017; Schlenker and Roberts, 2009; Wang et al., 2017; Zhao et al., 2016). Besides temperatures, it is well recognized that yield is influenced by many other factors such as droughts, pests, $CO_2$, agricultural management, technology and etc. (Challinor, A. et al., 2014; Deryng et al., 2011; Hawkins et al., 2013; Iizumi et al., 2013; Ray et al., 2015; Schauberger et al., 2017). The incomplete information and ignorance of physical, biological, and socio-economic processes that are relevant to crop growth would therefore make it hard to derive certain estimates of temperature impacts on yield. The inherent uncertainty of assessing climate change impacts on crop yield has also been emphasized in the literature (Asseng et al., 2013; Challinor, A. J. et al., 2014; Lobell and Burke, 2008; Wang et al., 2017; Wheeler and von Braun, 2013). Therefore, to give a distribution of possible outcomes of crop yields under given temperatures would greatly contribute to our understandings, complement previous studies using a deterministic approach.

Recently, the Paris Agreement advocated pursuing efforts to keep global warming within 1.5°C while holding global temperature rise to well below 2°C (Rogelj et al., 2015; UNFCCC, 2015). Understanding regional patterns of crop loss probability under 1.5°C and 2°C can help guide adaptation and mitigation efforts. In this study, a probabilistic model is developed for assessing crop loss risk under 1.5° and 2° global warming and is applied for the United States which is responsible for around 40% and 70% of global maize supply and export. The author notes that several studies have used probabilistic approaches for estimating climate change impacts on crop yields (Tao et al., 2009; Tebaldi and Lobell, 2008; Wing et al., 2015), but their goal is to account for uncertainties from emission scenarios, climate models etc. Here, the probabilistic model developed in this study is featured with providing the full spectrum of possible outcomes and the associated probabilities, given a specific temperature rise. The analysis framework introduced in this study can also be easily extended to other regions and crops. Specifically, the following scientific questions are addressed in this study: 1) what are the possible outcomes of maize yield associated with temperature rise in the United States? How likely each possible outcome is to occur? Through a county-level analysis, we aim to identify where maize yield is most vulnerable to temperature rise across the growing areas of the country. 2) Whether, where and how much risk of yield loss can be reduced by constraining global temperature rise to 1.5°C? Understanding the spatial pattern of the benefits can help mitigation and adaptation strategies.

## 2. Materials and Methods

### 2.1. Crop yields and climate data

Census data on maize yield is obtained from the National Agriculture Statistics Survey's Quick Stats database maintained by the US Department of Agriculture (USDA) (http://www.nass.usda.gov/Quick_Stats). 97 climate model simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012) under four Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) (Moss et al., 2010) are used (Table S1). These climate model projections are statistically downscaled to 1/8 degree and bias-corrected against observations using bias-correction and spatial-downscaling approach (BCSD) (Leng et al., 2016b; Wood et al., 2004). The observed gridded climate is produced based on approximately 20,000 stations across the United States (Livneh et al., 2013; Maurer et al., 2002). (Jang and Kavvas, 2013) found that the BCSD method as a popular statistical downscaling method has limitations in projecting future precipitations. However, this study focus on yield changes associated with temperature rise without consideration of precipitation effects. In addition, the downscaled climate was bias corrected and widely validated against observations. The adjusted climate was found to have the same monthly climatology as the observed climate (Reclamation 2013), and has been used in previous climate change impact studies (Huang et al., 2017; Leng and Huang, 2017; Leng et al., 2016b).

**Table 1** The ensemble of climate model projections used in this study

| ID | Climate Model | Emission Scenarios | | | |
|---|---|---|---|---|---|
| 1 | access1-0 | | rcp45 | | rcp85 |
| 2 | bcc-csm1-1 | rcp26 | rcp45 | rcp60 | rcp85 |
| 3 | bcc-csm1-1-m | | rcp45 | | rcp85 |
| 4 | canesm2 | rcp26 | rcp45 | | rcp85 |
| 5 | ccsm4 | rcp26 | rcp45 | rcp60 | rcp85 |
| 6 | cesm1-bgc | | rcp45 | | rcp85 |
| 7 | cesm1-cam5 | rcp26 | rcp45 | rcp60 | rcp85 |
| 8 | cmcc-cm | | rcp45 | | rcp85 |
| 9 | cnrm-cm5 | | rcp45 | | rcp85 |
| 10 | csiro-mk3-6-0 | rcp26 | rcp45 | rcp60 | rcp85 |
| 11 | fgoals-g2 | rcp26 | rcp45 | | rcp85 |
| 12 | fio-esm | rcp26 | rcp45 | rcp60 | rcp85 |
| 13 | gfdl-cm3 | rcp26 | rcp45 | rcp60 | rcp85 |
| 14 | gfdl-esm2g | rcp26 | rcp45 | rcp60 | rcp85 |
| 15 | gfdl-esm2m | rcp26 | rcp45 | rcp60 | rcp85 |
| 16 | giss-e2-h-cc | | rcp45 | | |
| 17 | giss-e2-r | rcp26 | rcp45 | rcp60 | rcp85 |
| 18 | giss-e2-r-cc | | rcp45 | | |
| 19 | hadgem2-ao | rcp26 | rcp45 | rcp60 | rcp85 |
| 20 | hadgem2-cc | | rcp45 | | rcp85 |
| 21 | hadgem2-es | rcp26 | rcp45 | rcp60 | rcp85 |
| 22 | inmcm4 | | rcp45 | | rcp85 |
| 23 | ipsl-cm5a-mr | rcp26 | rcp45 | rcp60 | rcp85 |
| 24 | ipsl-cm5b-lr | | rcp45 | | rcp85 |

| | | | | | |
|---|---|---|---|---|---|
| 25 | miroc-esm | rcp26 | rcp45 | rcp60 | rcp85 |
| 26 | miroc-esm-chem | rcp26 | rcp45 | rcp60 | rcp85 |
| 27 | miroc5 | rcp26 | rcp45 | rcp60 | rcp85 |
| 28 | mpi-esm-lr | rcp26 | rcp45 | | rcp85 |
| 29 | mpi-esm-mr | rcp26 | rcp45 | | rcp85 |
| 30 | mri-cgcm3 | rcp26 | rcp45 | | rcp85 |
| 31 | noresm1-m | rcp26 | rcp45 | rcp60 | rcp85 |
| Number of Projections | 97 | 21 | 31 | 16 | 29 |

## 2.2. **Conditional probability estimation**

A probabilistic model describes the distribution of possible outcomes and associated probabilities under a given condition through Copulas (Nelsen, 2007). Specifically, a Copula is first fit to the time series of yield and temperature to derive their joint probability distribution function (PDF), based on which the probabilistic model is then constructed. A copula describes the multivariate distributions (C) of two or more uniformly distributed variables (Nelsen, 2007). In this study, five bivariate copulas which are frequently used in the literature are adopted for estimating the joint probability distribution between temperature (x) and yield (y).

$$F_{XY}(X,Y) = C[F_X(X), F_Y(Y)] \qquad (1)$$

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. Details on the five copula families and their mathematical descriptions can be found in Table 1. Besides the five commonly used copulas, there are several other copula families that have not fully been used in the literature (Sadegh et al., 2017), and are not considered in this study.

**Table 2** Copula families used in this study and the mathematical descriptions

| Name | Mathematical Description | Parameter Range | Reference |
|---|---|---|---|
| Gaussian | $\int_{-\infty}^{\emptyset^{-1}(u)} \int_{-\infty}^{\emptyset^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp(\frac{2\theta xy - x^2 - y^2}{2(1-\theta^2)}) \mathrm{dxdy}^{b}$ | $\theta \in [-1, 1]$ | (Renard and Lang, 2007) |
| t | $\int_{-\infty}^{t_{\theta_2}^{-1}(u)} \int_{-\infty}^{t_{\theta_2}^{-1}(v)} \frac{\Gamma\left(\frac{\theta_2+2}{2}\right)}{\Gamma\left(\frac{\theta_2}{2}\right)\pi\theta_2\sqrt{1-\theta_1^2}} \left(1 + \frac{x^2 - 2\theta_1 xy + y^2}{\theta^2}\right)^{\frac{\theta_2+2}{2}} \mathrm{dxdy}^{c}$ | $\theta \in [-1, 1]$; $\theta_2 \in [0, \infty]$ | (Demarta and McNeil, 2005) |
| Clayton | $\max(u^{-\theta} + v^{-\theta} - 1, 0)^{-1/\theta}$ | $\theta \in [-1, \infty]\backslash 0$ | (Clayton, 1978) |
| Frank | $-\frac{1}{\theta}\ln\left[1 + \frac{(\exp(-\theta u) - 1)(\exp(-\theta v) - 1)}{\exp(-\theta) - 1}\right]$ | $\theta \in \mathbb{R}\backslash 0$ | (Li et al., 2013) |
| Gumbel | $\exp\left\{-\left[(-ln(u))^{\theta} + (-ln(v))^{\theta}\right]^{\frac{1}{\theta}}\right\}$ | $\theta \in [-1, \infty]$ | (Zhang and Singh, 2006) |

Based on the fitted Copula, the conditional probability of yield dropping below a certain amount ($Y < y$) under a given temperature ($X = x$) is estimated; i.e., $F_{Y|X}(Y < y \mid X = x)$. Here, the conditional probability density function of $f_{y|x}(y|x)$ is calculated as follows:

$$f_{Y|X}(y \mid x) = c[F_X(X), F_Y(Y)] * f_Y(y) \qquad (2)$$

Where $c$ is the PDF of the Copula and $f_Y(y)$ is the PDF of marginal distribution of yield. Once the conditional PDF under a particular temperature is obtained from equation (2), the probability of yield dropping below a certain amount, i.e., $F_{Y|X}(Y < y \mid X = x)$, is estimated as the area under $f_{Y|X}(y|x)|$ for $Y < y$.

## 2.3. Analysis

The linear trend of maize yield is removed using the least squares method, to account for the effects of technological improvement. The growing season temperature is defined as the average of monthly temperatures during June-July-August following previous studies (Leng, 2017a; b; Lobell and Asner, 2003). All the five bi-variable copulas are fitted for each maize growing county based on de-trended maize yield and growing season temperature for the reference period 1986-2005, and the one that has the highest statistically significant (at 95% confidence level) maximum likelihood is selected as the best copula (Sadegh et al., 2017). The statistical significance is estimated according to the two-tailed Student's t-test. The selected copula for each maize growing county is shown in Supplementary Figure S1. Based on the fitted copula, the conditional probability (%) of yield dropping below a certain level is estimated for each maize growing county under 1.5°C and 2°C global warming scenarios. There are two approaches (i.e. transient and stabilized approaches) to evaluate climate change impacts under the 1.5 and 2.0 °C warming worlds. To date, most of previous studies evaluating climate change impacts at specific global temperature targets have relied on transient climate states extracted from the CMIP5 archive. Recently, simulations are made available by the Half a degree Additional warming, Projections, Prognosis and Impacts project (HAPPI), which is designed to provide stabilized scenarios for the 1.5 and 2.0 °C warming worlds (Mitchell et al., 2017). To inter-compare climate scenarios between transient and stabilized states is not within the scope of this study. A recent study by (Ruane et al., 2018) found that the stabilized scenarios from HAPPI are largely consistent with the transient scenarios extracted from CMIP5 simulations in agricultural regions.

In this study, to investigate future yield loss risk at under 1.5°C and 2°C global warming targets, analyses were performed using time-slice periods following the literature (Gosling et al., 2016;

Leng et al., 2015; Schewe et al., 2014; Zhang et al., 2018). Specifically, the 20-year periods with 1.5°C and 2°C global temperature target relative to pre-industrial era are extracted, based on which local temperature change is calculated relative to reference period (Lissner and Fischer, 2016). It should be noted that not all climate models projected 1.5°C and 2.0°C rise of global temperature under RCP2.6 (Supplementary Table S1). The projected change in local temperature is then used as input into the probabilistic model for estimating the probability of yield change in the future. It is noted that the reference period 1986-2005 is 0.6°C warmer than pre-industrial levels (IPCC, 2013). Thus, 1.5°C and 2°C warming target corresponds to a warming of 0.9°C and 1.4°C above the reference period, respectively (Lissner and Fischer, 2016).

The above processes are repeated for each climate model under each emission scenario. The multi-model ensemble mean is calculated for illustration, while inter-model spread is used for denoting the uncertainty from models. Through a county-scale analysis, the regions that are most vulnerable to temperature rise can be identified. Yield loss probability is compared between the 1.5°C and 2°C warming worlds to investigate whether, where and how much benefit would be achieved by constraining global warming to 1.5°C for reducing yield loss risk.

## 3. Results and Discussion

Figure 1a shows the temporal variations of de-trended maize yield and growing season temperature for the reference period. Maize yield for the country as a whole has exhibited substantial variations in recent decades, and yield reductions often correspond to above-normal temperatures. For example, maize yield shows a substantial decrease by up to 16% at above-normal temperatures compared to below-normal temperatures. Overall, more than one third of yield variation can be significantly (*P*<0.01) explained by growing season temperature anomalies. The negative temperature impacts on maize yields are consistent with previous studies at regional and global scales (Asseng et al., 2015; Deryng et al., 2011; Leng et al., 2016a; Liu et al., 2016; Lobell and Field, 2007; Ray et al., 2015; Schauberger et al., 2017; Schlenker and Roberts, 2009; Zhao et al., 2016), although the strength of yield-temperature relation differs to certain extent. Figure 1b shows the joint distributions between maize yield and temperature anomalies, as well as a full spectrum of likely outcomes of maize yields under various temperature conditions (see methods). Comparing the estimated maize yield distributions with observed maize yields (red dots) indicates that the majority of observed yields fall within the high-density region of PDFs, demonstrating that the fitted joint distribution function is reliable for describing maize yield at given temperatures.

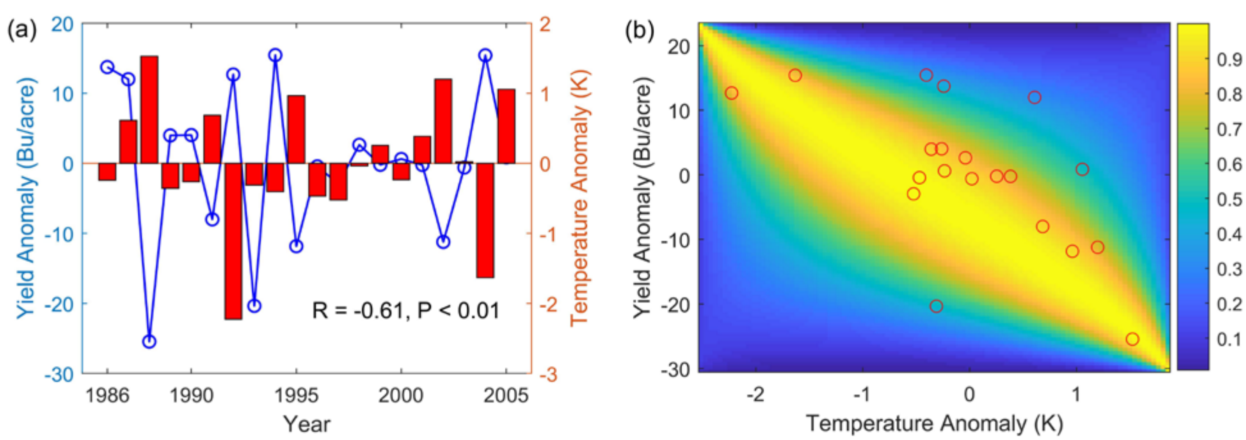


**Figure 1** Observed temperature-yield relations for the reference period 1986-2005. (a) temporal changes in de-trended yield anomaly and growing season temperature anomaly; (b) fitted joint distribution function between yield anomaly and temperature anomaly;

Based on the fitted joint distribution, the conditional probability of yield changes under given local temperature rise of 0.5°C, 1°C to 1.5°C and 2°C are estimated to explore the sensitivity of yield loss risk to temperature (see methods). Figure 2a shows that yield probability density curves gradually shift to the left side of the vertical dashed line (i.e. its long-term mean) with increase in temperature rise from 0.5°C to 2°C. This suggests a steady increase of yield loss risk (i.e. yield dropping below its long-term mean). There is 63.3% probability that 0.5°C rise of local temperature would result in yield reduction below its long-term mean for the country as a whole. With a 2°C increase in temperature, the probability would increase to 81.4% (Figure 2b). The sensitivity of yield loss probability to local temperature rise is found to become more pronounced when considering the risk of yield reduction by 10% and 20% below its long-term mean value. Given a 0.5°C rise of local temperature rise, the probability of yield reduction by 10% is only 15%. However, such risk would jump by a factor of 4 to 67% when experiencing a 2°C rise of local temperature. The risk of yield reduction by 20% which is negligible under 0.5°C (i.e. 0.9%) would even become 32.2% given 2°C temperature rise. These suggests that local temperature rise would have more pronounced effects in causing extreme yield reductions.

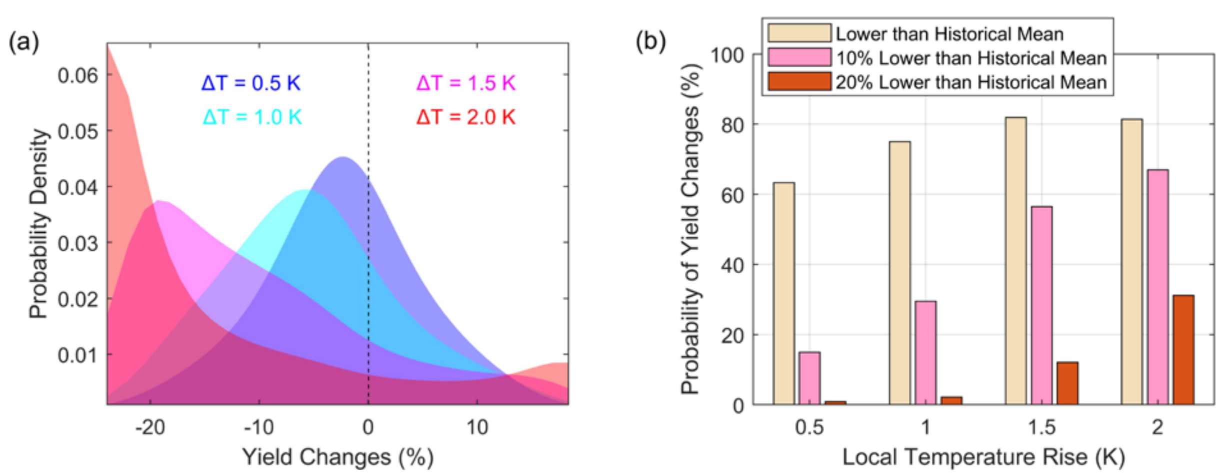


**Figure 2** (a) conditional probability of yields at given temperature rise of 0.5°C, 1°C, 1.5°C and

2°C. The shaded areas represents the probability of likely yield changes under different temperature rises.; (b) probability of yield dropping below and reducing by 10% and 20% of historical mean at given temperature rises.

How much risk there will be for future maize reduction under1.5°C and 2°C global warming targets? (Schlenker and Roberts, 2009) projected a decrease by 30–46% by the end of the century based on one climate model. (Urban et al., 2012) found that US maize yields are projected to decrease by an average of 18% by 2030–2050 relative to 1980–2000 based on 15 climate models. Instead of providing a deterministic projection in specific future periods, we examine future yield changes under 1.5°C and 2°C global warming targets in a probabilistic manner. Figure 3 shows the risk of yield dropping by 10% of the historical mean under 1.5°C and 2°C warming in four RCPs. Under the 2°C warming world, the multi-model ensemble mean shows that yield loss probability for the country as a whole is projected to be 65%, 61%, 60% and 44% under RCP8.5, RCP6.0, RCP4.5 and RCP2.6 emission scenario, respectively. Such risk is expected to decrease substantially in a 1.5°C warming world, independent of emission scenarios. However, larger uncertainty exist as indicated by the wide ranges among climate models under both 1.5°C than 2°C warmings. Compared to 2°C, larger uncertainty ranges are found under 1.5°C warming except for the RCP2.6 scenario. This could be attributed to the fact that global mean temperature rise simulated by some climate models may not reach 2°C under RCP26 scenario. Indeed, 15 and 7 climate models out of 21 that provided simulations under RCP26 scenario have simulated a global warming of 1.5°C and 2°C, respectively. The relatively smaller sample of climate model simulations under 2°C than 1.5°C leads to the larger range as indicated by the boxplot for the RCP2.6 scenario. Overall, the multi-model ensemble indicates that the probability of yield reduction by 10% would reduce by 20%, 19%, 19%, and 16% under RCP8.5, RCP6.0, RCP4.5 and RCP2.6 emission scenario, respectively, if global temperature rise is constrained to 1.5°C.

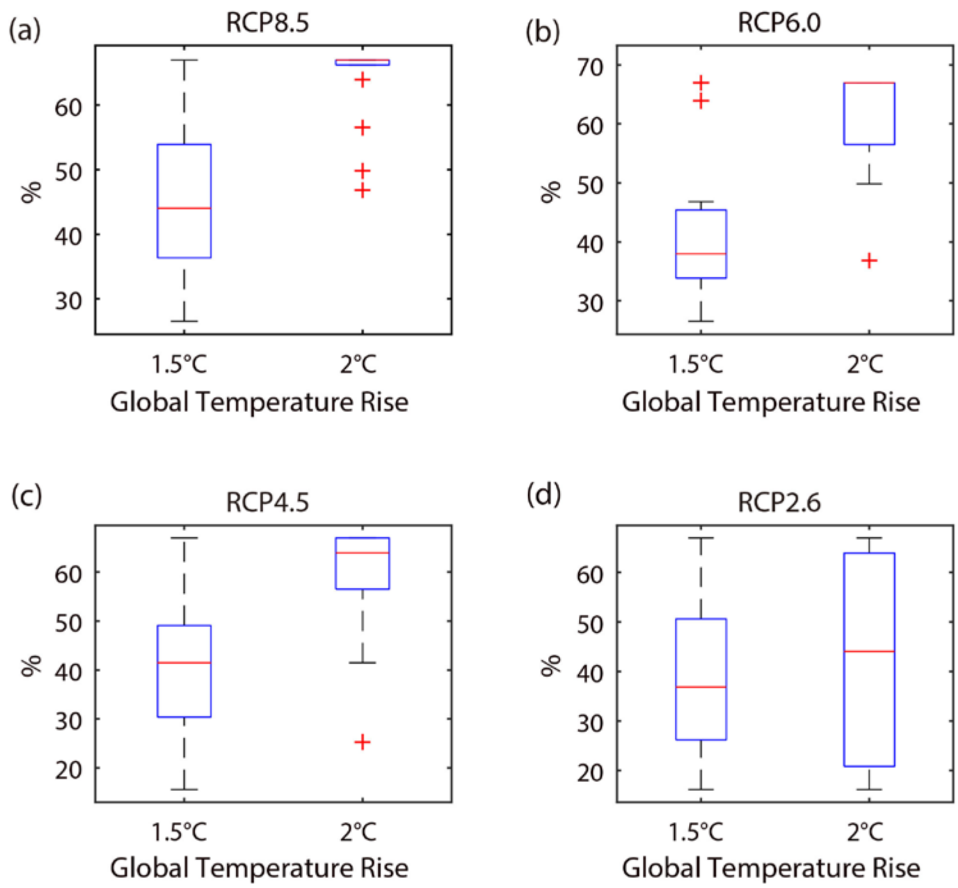


**Figure 3** Probability (%) of future yield reduction by 10% in 1.5°C and 2°C warming worlds. The probability is estimated for each climate model under each RCP scenario (See Table 1 for details). The central mark in the boxplot indicates the median, while the bottom and top edges indicate the 25th and 75th percentiles, respectively.

Spatially, the highest risk will be experienced in central and southeastern US, while the lowest risk is located in western US and high production regions such as Iowa (Figure 4). The physical mechanism behind the distinct spatial patterns is, however, an open question since many factors could influence yield sensitivity to temperature in farmers' fields. For example, the concurrent drought stress could to be a potential cause for yield reductions (Lesk et al., 2016; Lobell et al., 2014; Zipper et al., 2016), which may be partly alleviated by $CO_2$-induced increase in crop water use efficiency (McGRATH and Lobell, 2011). One obstacle for quantitative attributions has been lack of accurate field-level data on both environmental conditions and yield performance, which points to the importance of giving a distribution of possible outcomes rather than a deterministic estimate. Indeed, the negative temperature impact on crop yields could be reduced through management practices such as soil mulching (Qin et al., 2015), conservation tillage (Karlen et al., 2013) and multiple cropping (Seifert and Lobell, 2015). Recent observation-based studies showed that irrigation would dampen crop yield response to temperature (Leng, 2017b; Troy et al., 2015), which could partly explain the relatively low sensitivity of yield loss probability to temperature rise in western arid regions, western Kansas and Nebraska where irrigation is extensively applied (Leng et al., 2013).

Importantly, it is found that with increase in temperature, yield loss probability tends to grow progressively across the country, especially in Southeastern growing areas. Under 2°C global warming, the probability of yield reduction by 10% could exceed 50% in Missouri, South Dakota, Eastern Kansas, Southern Texas and southeastern part of the country. These hot-spot regions point to the need for adaptation and mitigation priorities for enhancing yield residence under global warming. Constraining global temperature rise to 1.5°C would lead to substantial decrease in yield loss risk. Such benefit is, however, spatially variable, with largest risk reduction in those hot spot areas, while negligible change is found in high production areas including

Illinois, Indiana and Ohio. Further analysis show that the spatial pattern of reduced yield loss risk is independent of emission scenario (Supplementary Figure S2-4), pointing to the robustness of the revealed maps on the uneven distribution of climate mitigation benefits. This has great implications for informing targeted adaptation and mitigation measures, through identifying the regions that are most vulnerable to global warming, and especially showing where and how much benefits would be achieved by constraining global temperature rise to 1.5°C.

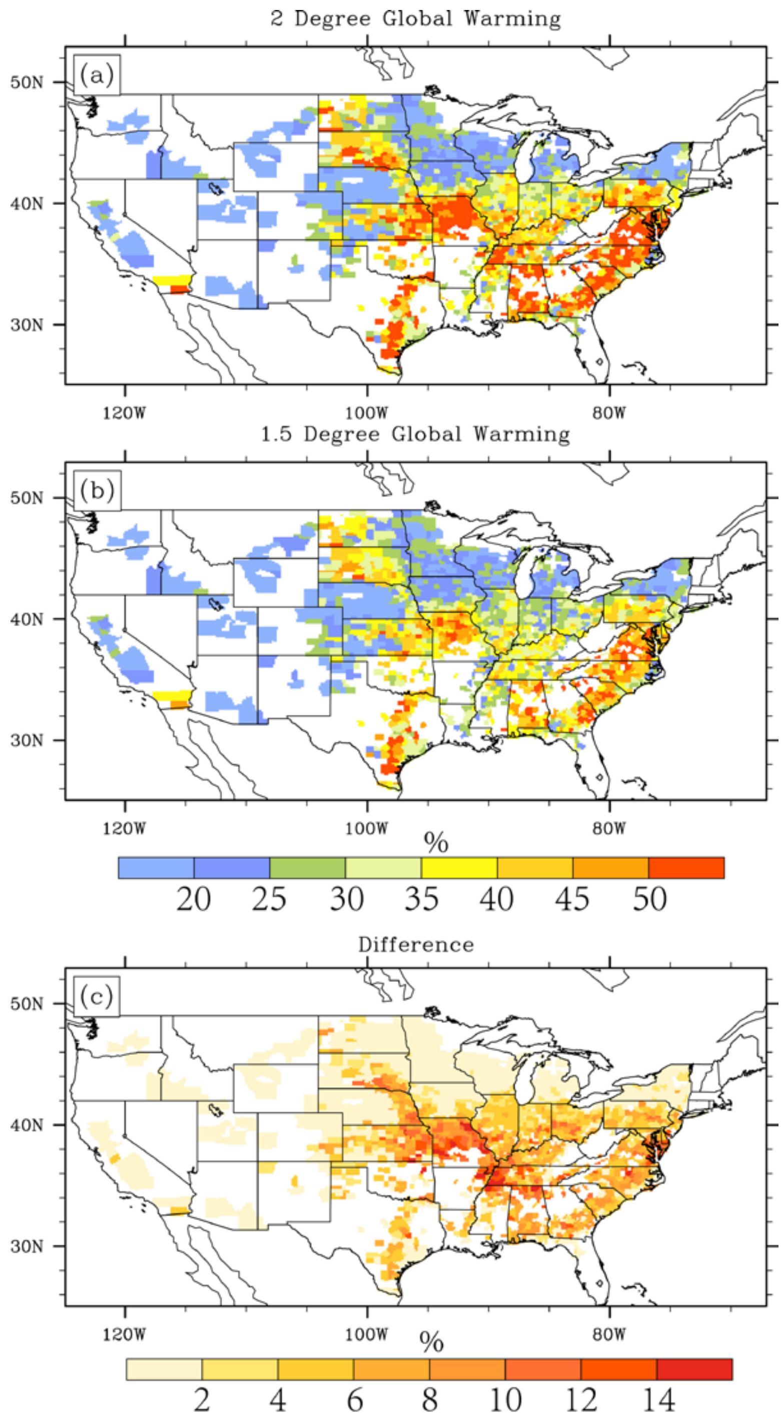


**Figure 4** Spatial distribution of the probability (%) of yield reduction by 10% under (a) 1.5°C and (b) 2°C global warming target in the RCP8.5 scenario. The probability is estimated for each climate model under each warming scenario and the multi-model ensemble mean is shown. The

benefit of constraining global temperature rise to 1.5°C is shown in (c), as calculated by the difference between (a) and (b).

## 4. Conclusion

Enhanced stability of maize production in the United States would greatly benefit global food security, as it provides 40% of global supply. Important in this regard is to understand the full range of possible outcomes of yields and the associated probabilities under future warming. Previous assessment on climate change impacts under global warming are mainly based on a deterministic approach, without providing the likelihood of different outcomes which is more relevant for decision-makers in selecting appropriate strategies. Here, this study provides a probabilistic assessment of maize yield changes associated with temperature rise in the United States at the county scale under 1.5°C and 2°C global warming worlds. Results show a significant association between temperature rise and maize yield reductions across the country during the past three decades. A probabilistic model is then developed to allow for examination of yield loss risk under given temperatures. It is found that yield loss risk (i.e. the probability of yield dropping below its long-term mean) tends to increase significantly with rise of temperature, and distinct spatial patterns exist at the county-scale. The highest risk is observed in central and southeastern US, while maize failure risk is relatively low in western US. Comparing the estimates under 1.5°C global warming against that in 2.0°C warming indicates that keeping global warming within 1.5°C has great benefits for reducing future yield loss risk. Based on a large ensemble of 97 climate model simulations, the risk of yield dropping below the long-term mean is projected to decrease by 6% from 81% for the country as a whole. Such benefit are more evident when considering the risk of yield reduction by 10% and 20%, which is excepted to decrease by 25% and 28% under 1.5°C warming, respectively. Spatially, constraining global temperature rise to 1.5°C would benefit more in Missouri, South Dakota, Eastern Kansas, Southern Texas and southeastern part of the country than other regions, and highlighting the spatially variable benefits of climate mitigation efforts.

There are a number of caveats that should be acknowledged when interpreting the results obtained in this study. First, it is assumed that the historical temperature-yield relation hold in the future, without considering adaptations and the possible changes in the temperature-yield relations. (Leng, 2017b) reported a weakening strength of temperature-corn yield relation in the United States during recent decades. Thus, the estimates obtained in this study would represent an upper-bound of possible yield changes associated temperature rise. Second, the magnitude of yield changes may differ if a different reference period is selected for constructing the probabilistic model. Indeed, several reference periods have been used in climate change impact assessment, e.g. 1980-2010 (Schewe et al., 2014), 1971-2000 (Haddeland et al., 2014) as well as 1986-2005 (Lissner and Fischer, 2016) which is adopted in this study. Third, only temperature is included for assessing future yield changes, without considering the concurrent changes in precipitation, wind field, humidity, extreme heat, droughts and vapor pressure deficit that are relevant to crop yield at different growth stages (Asseng et al., 2013; Challinor, A. et al., 2014; Deryng et al., 2011; Hawkins et al., 2013; Iizumi et al., 2013; Lobell et al., 2013; Schauberger et al., 2017). What’s more, estimates of future yield changes are based on the assumption of no adaptations. Thus, this study may not give the accurate estimate of yield changes in the future, rather it demonstrates the sensitivity of yield loss risk to temperature rise under global warmings in a probabilistic and spatially explicit manner.

Despite the limitations and uncertainties, this study has great implications for assessing climate change impacts on yields, through introducing a spatially explicit probabilistic modeling approach which can be easily extended to other regions and crops, considering other climatic variables such as precipitation, wind field and humidity conditions. The results are valuable for adaptation and mitigations by showing the probability distribution of possible yield changes in the United States under 1.5°C and 2°C global warming scenarios. This study highlights the regions where maize yield is most vulnerable to temperature rise, and importantly, the benefits for reducing yield loss risk by constraining global temperature rise to 1.5°C, which turns out to be spatially variable across the country.

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