Weather and Climate Extremes 33 (2021) 100369

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

A generic risk assessment framework to evaluate historical and future climate-induced risk for rainfed corn and soybean yield in the U.S. Midwest

Wang Zhou [a,b,*], Kaiyu Guan [a,b,c,*], Bin Peng [a,b,c,*], Zhuo Wang [d], Rong Fu [e], Bo Li [f], Elizabeth A. Ainsworth [b,g,h], Evan DeLucia [g], Lei Zhao [i], Zhangliang Chen [a,b]

[a] Agroecosystem Sustainability Center, Institute for Sustainability, Energy, and Environment, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA
[b] Department of Natural Resources and Environmental Sciences, College of Agricultural, Consumer and Environmental Sciences, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA
[c] National Center for Supercomputing Applications, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA
[d] Department of Atmospheric Sciences, University of Illinois at Urbana–Champaign, Urbana, IL, 61801, USA
[e] Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, CA, 90095, USA
[f] Department of Statistics, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA
[g] Department of Plant Biology, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA
[h] USDA ARS Global Change and Photosynthesis Research Unit, Urbana, IL, 61801, USA
[i] Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, IL, 61801, USA

ARTICLE INFO

Keywords:
Risk assessment
Synthetic climate generation
Crop yield prediction
U.S. Midwest
Rainfed corn
Rainfed soybean
Climate change

ABSTRACT

Fluctuations in temperature and precipitation are expected to increase with global climate change, with more frequent, more intense and longer-lasting extreme events, posing greater challenges for the security of global food production. Here we proposed a generic framework to assess the impact of climate-induced crop yield risk under both current and future scenarios by combining a stochastic model for synthetic climate generation with a well-validated statistical crop yield model. The synthetic climate patterns were generated using the extended Empirical Orthogonal Function method based on historically observed and projected climate conditions. We applied our framework to assess the corn and soybean yield risk in the U.S. Midwest for historical and future climate conditions. We found that: (1) in the U.S. Midwest, about 45% and 40% of the interannual variability in corn and soybean yield, respectively, can be explained by the climate; (2) the risk level is higher in the southwest and northwest regions of the U.S. Midwest corresponding to 25% yield reduction for both corn and soybean compared to other regions; (3) the severity for the 1988 and 2012 major droughts quantified by our method represent 21-year and 30-year events for corn, and 7-year and 12-year events for soybean, respectively; (4) the crop yield risk will increase under a future climate scenario (i.e., Representative Concentration Pathway 8.5 or RCP 8.5 at 2050) compared with the current climate condition, with averaged yield decreases and yield variability increases for both corn and soybean. The framework and the results of this study enable applications for risk management policies and practices for the agriculture sectors.

* Corresponding authors. Agroecosystem Sustainability Center, Institute for Sustainability, Energy, and Environment, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA.
E-mail addresses: wangzhou@illinois.edu (W. Zhou), kaiyug@illinois.edu (K. Guan), binpeng@illinois.edu (B. Peng).

https://doi.org/10.1016/j.wace.2021.100369
Received 16 April 2021; Received in revised form 25 July 2021; Accepted 5 August 2021
Available online 6 August 2021

1. Introduction

Climate fluctuations are expected to increase under future warming climates, with more frequent, more intense and longer-lasting extreme climate events (e.g., heatwaves, droughts and floods) (Meehl and Tebaldi, 2004; Deryng et al., 2014), which pose great challenges for the security of global food production (Kang et al., 2009; Challinor et al., 2014; Rosenzweig et al., 2014). The risk of crop yield loss will increase with greater frequencies of such extreme climate events, especially in rainfed croplands. Previous studies showed that about one third of yield variability was explained by the interannual climate variability at the global scale (Lobell and Field, 2007; Ray et al., 2015); for the U.S., about 39% of corn yield variability and 35% of the soybean yield variability was explained by variation in climate (Ray et al., 2015). As one of the world's largest crop production areas, the U.S. Midwest produces about 85% of U.S. corn and soybean (USDA, 2020), the majority of which is from rainfed farmland. Thus, an assessment of the impact of climate-induced crop yield risk under both current and future climate in the U.S. Midwest is urgently needed to ensure the security of global food production, especially in the rainfed agricultural landscape. In addition, the climate-based crop yield risk assessment is a useful tool to support decision making for farmers, the agricultural industry, and government agencies for climate changes. The risk level of crop production and how it will change in the future is essential for both policy makers and crop (re)insurance companies to understand and manage crop insurance risks, and could be used to optimize the agriculture supply chain (Benami et al., 2021).

The data-driven crop yield risk analysis method is the most direct way to obtain the yield risk based on empirical or fitted distributions of crop yield from the historical records (Pease, 1992; Goodwin and Ker, 1998; Sherrick et al., 2004). This method is straightforward to apply but its accuracy largely depends on the length and quality of the records (Stojanovski et al., 2015). However, long-term records of crop yield are rare around the world, limiting the application of this method for crop yield risk assessment. Although about 80 years of county scale crop yield data has been provided by the United States Department of Agriculture (USDA), it is still insufficient to capture the most extreme events. Furthermore, crop varieties have changed significantly during the past 80 years, and older varieties may not have the same responses to climate variability as modern varieties, due to the improvements in various crop traits, such as canopy and root architectures, maturity group, and crop management practices (Hammer et al., 2009; Lobell et al., 2014). In general, only the most recent 30-year record represents modern varieties, making the dataset even smaller. Clearly, the 30-year record is not long enough to fully capture the different climate conditions and their impacts on crop yield loss, especially in the extreme years. In addition, this method is based on the yield data under historical climate conditions, which is not applicable in the future climate scenarios due to the shift of climate conditions. Thus, the data driven crop yield risk analysis method has been rarely used to assess the climate-induced crop yield risk at high spatial resolution with reasonable accuracy in the U.S. Midwest.

Another approach to assess the yield risk is to use models, either process-based or empirical statistical models (Li et al., 2009; Rosenzweig et al., 2014; Jin et al., 2017). Although the process-based models have more comprehensive mechanism processes, various types of uncertainties (e.g., model structure, model parameters, and model input) may compromise its ability in assessing climate risks on crop yield (Maiorano et al., 2017; Tao et al., 2018). To properly run the process-based models usually requires observational constraints and mathematical methods to integrate data and model, both of which are hard to achieve at the county scale, especially for risk assessments with multitudinous climate scenarios (Peng et al., 2020; Zhou et al., 2021). The empirical statistical crop yield models, based on the historical climate observations and yield measurements, provide an alternative way to connect the crop yield and climate variables (Lobell and Burke, 2010), which can also be applied to analyze the near term future (i.e., 2050) climate scenarios (Lobell et al., 2006). However, it is hard to get a sufficiently long record of historical climate and yield observations for crop yield risk assessment, especially under extreme conditions, even for data-rich countries such as U.S. Thus, the crop yield model and climate observations-based approach still can not fully capture crop yield variability under both current and future climate scenarios.

To overcome the above limitations, we developed a generic risk assessment framework by integrating a stochastic model for synthetic climate generation and a statistical crop yield model for corn and soybean in the U.S. Midwest under both current and future climate scenarios. The synthetic county-scale rainfed yield databases for corn and soybean were built based on the crop yield model and generated climate patterns under both current and future climate scenarios. Two widely used risk metrics, i.e., (i) return period of crop yield loss, and (ii) coefficient of variation of crop yield, had been calculated based on the synthetic crop yield databases to quantify the risk level of rainfed corn and soybean yield reduction in the U.S. Midwest. Return period focuses on the left-tail behavior of crop yield, which has a direct implication for premium rating in the crop insurance system (Wouter Botzen, 2013). Coefficient of variation, on the other hand, captures the overall variation of the crop yield, which can provide storage and logistics guidance to the agriculture supply chain (Crane-Droesch et al., 2019). Through the analysis, we focus on the following key questions: (1) How much interannual variability of corn and soybean yield is explained by the climate variability, and how does this vary spatially? (2) What is the risk level of 1988 and 2012 droughts in terms of the corn and soybean yield loss? (3) What are the impacts of climate change on the crop yield risk in the U.S. Midwestern rainfed cropland?

2. Materials and methods

2.1. Study area

This study assessed the climate-induced rainfed corn and soybean yield risk in the U.S. Midwest (Fig. 1), where corn and soybean dominate the landscape, producing about one third of global corn and soybean. The climate within this area shows some heterogeneity, covering four different Köppen-Geiger climate zones with precipitation ranging from 200 to 450mm from northwest to southeast (Fig. 1a) and temperature from 15 to 25°C from north to south (Fig. 1b) during the growing season. The heterogeneous climate and soil conditions in this area result in varying crop production potential and crop yield interannual variability, with higher production in Illinois, Iowa, and Indiana, and lower production over other areas. Most counties within the U.S. Midwest have long corn and soybean production records, and we selected the counties with corn or soybean planting records for at least 35 years for the following analysis.

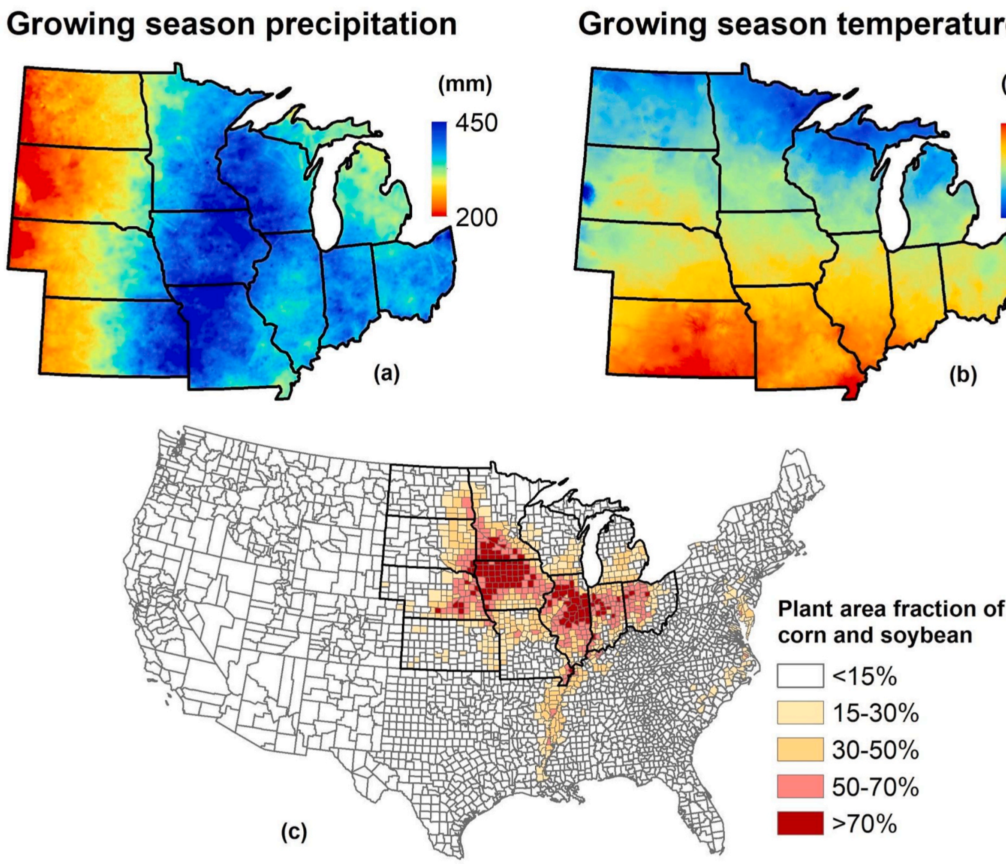

Fig. 1. The location of the study area and its climate conditions. (a) Spatial pattern of growing season (June to September) accumulated precipitation in the U.S. Midwest during 1981–2018, (b) spatial pattern of growing season averaged temperature in the U.S. Midwest during 1981–2018, and (c) corn and soybean planting area fraction in the Contiguous U.S. (CONUS), and the location of the U.S. Midwest (12 states highlighted in black lines).

2.2. Data

2.2.1. Precipitation Regression on Independent Slopes Model (PRISM) dataset

Monthly temperature and precipitation data from the Precipitation Regression on Independent Slopes Model (PRISM) (Daly et al., 2008, 2015) was used as the major historical climate dataset. This dataset was used together with historical crop yield records to build the climate-based statistical crop yield model and to generate synthetic climate patterns. PRISM is based on quality-controlled observations from the weather stations network throughout the Contiguous U.S. (CONUS), and a climate–elevation regression was used to generate a suite of gridded (i.e., 4 km) high-accuracy climate variable datasets by considering location and topographic information (Daly et al., 2008, 2015). For generating the synthetic climate patterns, we used all the data throughout the CONUS with a time period covering 1895 to 2018 to capture the impacts of both large-scale climate dynamics (such as El Niño) and the local-scale climate events as much as possible. Although the temperature increased globally in the past 100 years, the change of temperature in the U.S. Midwest was smaller due to the cooling effects of agricultural intensification (Alter et al., 2018; Li et al., 2020), which ensures the useability of such long-term climate data for climate pattern generation. Considering the computational resources and memory issue as well as the spatial variance of climate variables at county scale, the PRISM dataset was regrided to 0.5° (approximately to a county in Midwest) by averaging the PRISM grids within the target grid for synthetic climate patterns generation. To build the crop yield model, we averaged the 4 km PRISM monthly temperature and precipitation dataset from 1981 to 2018 across the county-scales to be consistent with crop yield records.

2.2.2. Coupled model intercomparison project phase 5 (CMIP5) data

We used an ensemble dataset of 15 CMIP5 Atmosphere-Ocean General Circulation Models (AOGCMs) (Wang et al., 2016) for the climate scenarios in the future for the following analysis. The multi-model averaged and downscaled monthly temperature and precipitation data for the decade of 2050 in Representative Concentration Pathway (RCP) 8.5 were used to analyze the risk of crop yield reduction under future climate scenarios. This dataset is based on the CMIP5 database for the future climate scenarios, and PRISM and WorldClim for current climate using the locally downscaled method with the inputs of location and elevation (Wang et al., 2016). Both the RCP 8.5 of the future period 2050 and current climate (1981–2010) were resampled to 0.5°, and the change of temperature and precipitation (absolute difference for temperature and relative difference for precipitation) between future and current climate (Hijmans and Graham, 2006) were calculated and applied to the historical monthly PRISM dataset for the synthetic climate generation under future scenarios.

2.2.3. Crop yield data

County level corn and soybean yields in the U.S. Midwest from 1981 to 2018 were collected from USDA National Agricultural Statistics Service (NASS). This dataset was used for building the county scale statistical-based crop yield model, and also used as the benchmark for historical crop yield interannual variability. Since irrigation may influence the impacts of climate (i.e., drought) on crop yield loss, we only focused on the rainfed yield in this study. If the NASS crop yield record was not designated as either irrigated or non-irrigated conditions, we treated it as rainfed yield data.

2.3. Methods

2.3.1. Overview of proposed framework

Three major steps were taken to conduct the crop yield risk assessment in this study (Fig. 2). In the first step, we used the extended Empirical Orthogonal Function (EOF) to generate synthetic climate patterns based on the PRISM dataset for current climate conditions or RCPs-adjusted PRISM dataset for future scenarios. In the second step, we used a well-validated statistical crop yield model (Peng et al., 2018; Li et al., 2019a) to predict county-scale crop yield in the U.S. Midwest with growing season monthly temperature and precipitation as inputs. In the third step, we obtained estimates of possible crop yield under both current and future climate scenarios by combining the generated climate patterns and the crop yield model, and used it for crop yield risk assessment.

2.3.2. A stochastic model for synthetic climate generation

For generating climate patterns, we (1) used the extended EOF to decompose the history or RCPs-adjusted climate observations (see section 2.2.2), and generated synthetic climate patterns based on the decomposed components; (2) built a residual model to reproduce climate variability that was not captured in (1), and added it into the generated climate patterns; (3) applied two different distribution test methods to verify the similarity of the distributions of climate variables between the original and generated datasets.

(1) Using extended EOF for climate pattern generation

The EOF method is a statistical method to transform variables from the original dimensions to uncorrelated dimensions, and identify temporal and spatial patterns of variability as well as their importance (Björnsson and Venegas, 1997; Kim et al., 2011). The extended EOF is an extension of the simple EOF, putting multivariate data together for the transformation. Compared to the simple EOF, the extended EOF can take

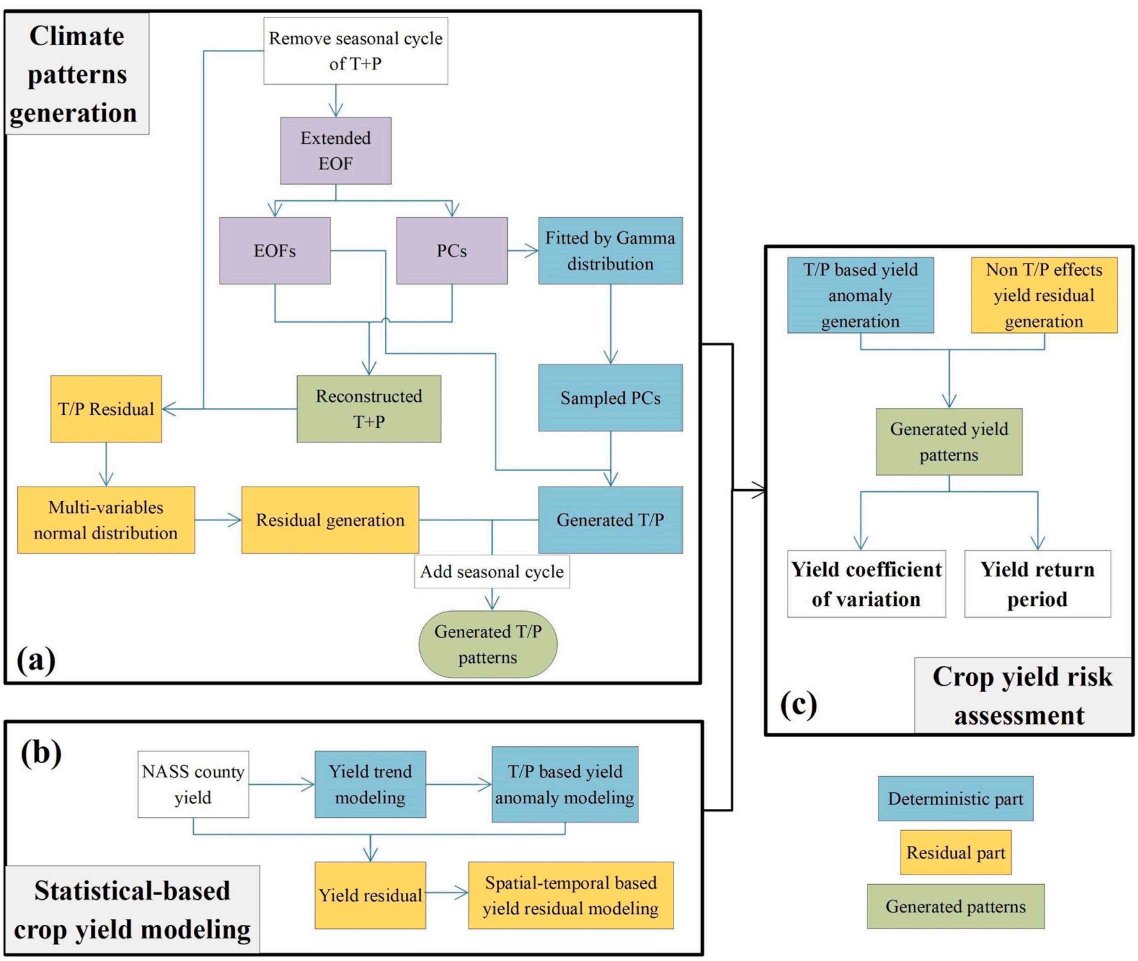

Fig. 2. The risk assessment framework to assess climate-induced risks of crop yield, by integrating stochastic generation of climate patterns and statistical crop yield modeling. T, P, EOF, and PC in this figure mean the monthly temperature, monthly precipitation, eigenvectors of EOF decomposition, principal components of EOF decomposition, respectively.

both the spatial and temporal correlation of the variables as well as their intercorrelation into account (Weare and Nasstrom, 1982). In this study, the multi-year averaged monthly climate data was subtracted from the resampled climate datasets to remove the seasonal cycle of temperature and precipitation. The anomalies of temperature and precipitation were normalized at each grid for each month using the Z-Score Normalization method, respectively. The normalized anomalies of temperature and precipitation from June to September at different grids were put into a single data matrix F as Eq. (1), and decomposed using EOF decomposition methods to obtain EOFs and the corresponding principal components (PCs). We fitted the distribution of each PCs using the Gamma distribution (Fig. S1, fitted with shift and scale using Python SciPy package, https://www.scipy.org/), and got 10,000 PCs sampled from the fitted PCs' distributions. The first k EOFs (the k was determined when about 70% of the variance explained by the first k EOFs) (Kim et al., 2011; Stojanovski et al., 2015; Zhou et al., 2019) and the corresponding sampled PCs were used to generate the possible temperature and precipitation patterns using Eq. (2).

$$F = \begin{bmatrix} T_{1,Jun} & \cdots & T_{1,Sep} & P_{1,Jun} & \cdots & P_{1,Sep} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ T_{n,Jun} & \cdots & T_{n,Sep} & P_{n,Jun} & \cdots & P_{n,Sep} \end{bmatrix} \tag{1}$$

where $T_{i,j}$ is the normalized anomaly of monthly temperature at grid i and month j, $P_{i,j}$ is the normalized anomaly of monthly precipitation at grid i and month j, n is the total number of grids used for the calculation.

$$\left[T_{Jun}\dots T_{Sep}, P_{Jun}\dots P_{Sep}\right] = \sum_{i=1}^{k} \overrightarrow{PC}_i \times EOF_i^T + \varepsilon \tag{2}$$

where EOF_i is the i^{th} EOF, $\overrightarrow{PC}_i$ is the i^{th} principal component of EOFs, and ε is the residual that was not captured by the first k EOFs.

(2) Building the residual model to generate uncaptured climate variability of EOF

Eq. (3) was used to build the multivariate normal distribution model (Papoulis and Unnikrishna Pillai, 2002) to fit the distribution of residual ε in Eq. (2) at each month for temperature and precipitation respectively, taking the intercorrelation of ε in different grids into account. The fitted residual distribution models were used to generate temperature and precipitation residuals for each grid at each month, which were added back to Eq. (2) to get the final climate patterns.

$$f\left(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n\right) = \frac{exp\left(-\frac{1}{2}(\varepsilon-\mu)^T \Sigma^{-1}\left(\varepsilon-\mu\right)\right)}{\sqrt{(2\pi)^k|\Sigma|}} \tag{3}$$

where μ is the mean value of ε, Σ is the covariance matrix of ε, and ε_i is the residual vector at grid i.

(3) Assessing the generated climate pattern

We used two different distribution test methods (i.e., Kolmogorov–Smirnov test and Anderson–Darling test) to assess the similarity of the distributions between original and generated climate variables at each grid. These two methods are widely used to test whether a sample of data comes from a certain population. They show different sensitivity to different parts of the distribution. The Kolmogorov–Smirnov test (Massey, 1951; Hodges, 1958) is most sensitive when the empirical cumulative distribution function differs in a global fashion near the center of the distribution; while the Anderson–Darling test (Scholz and Stephens, 1987) places more weight to the tails of the distribution.

2.3.3. Statistical crop yield model

We used the statistical crop yield model developed by Li et al. (2019a) and Peng et al. (2018) for crop yield prediction. Growing season monthly temperature and precipitation from 1981 to 2018 and county level rainfed corn and soybean yield during the same period in the U.S. Midwest were used to build a statistical crop yield model. The crop yield increase trend was obtained by fitting the relationship between crop yield and years using the linear regression (Eq. (4)). The yield anomaly (Eq. (5)) was obtained by removing the overall trend yield, and modelled using universal temperature and precipitation response curves (fitted using piecewise linear spline method with growing season monthly temperature and precipitation) and county-wise fixed effects (Eq. (6)) (Peng et al., 2018; Li et al., 2019a). The distribution of residuals of the model in Eq. (6) was fitted using the multivariate normal distribution, similar to Eq. (3). Crop yield predicted by the statistical-based crop yield model and the residual generated from the normal distribution model were added together as the final predicted crop yield for the crop yield risk assessment.

$$Y_{trend} = A \times Year + B \tag{4}$$

where Y_{trend} is the trend yield, A is the yield increase trend, and B is the constant intercept.

Let Y be the measured yield in each county and each year, the yield anomaly can be obtained as following,

$$Y_{anomaly} = Y - Y_{trend} \tag{5}$$

where $Y_{anomaly}$ is the detrend yield in each county.

$$Y_{anomaly} = \sum_{m=6}^{8} spline(T_m) + \sum_{m=6}^{9} spline(P_m) + C(FIPS) + \varepsilon \tag{6}$$

where T_m and P_m are the temperature and precipitation at month m, $C(FIPS)$ is the fixed effects at each county, which is the time-invariant and location-specific characteristics (i.e., soils, management practices, seed varieties) that are not reflected in climate data, ε is the residual of the crop yield model.

For crop yield predicted in future scenario, the impacts of CO_2 concentration ([CO_2]) on crop yield was calculated based on the meta-analysis of elevated [CO_2] on crop yield in Free-air concentration enrichment (FACE) (Long et al., 2006), with response ratio of crop yield under elevated [CO_2] (550 ppm) and ambient [CO_2] (380 ppm) as 0.99 (with 90% confidence intervals (CI) ranges 0.94–1.05) and 1.13 (with 90% CI ranges 1.11–1.15) for corn and soybean, respectively. To consider the CO_2 fertilizer effects on yield in the future scenario, we calculated the response ratio and its uncertainties (based on 90% CI) based on the [CO_2] difference in future and climate conditions, and applied that ratio to adjust crop yield from Eq. (6) for corn and soybean, respectively. This approach is commonly adopted in crop models that do not consider the [CO_2] effects explicitly (Tubiello et al., 2007; Lobell and Field, 2008). To derive the impacts of technical improvement on yield, we adjusted the historical yield to the [CO_2] level in 2000 based on the yearly [CO_2] data (http://www.pik-potsdam.de/~mmalte/rcps) and the response ratio of crop yield to [CO_2]. The historical technical improvement on yield was obtained from the historical [CO_2] adjusted yield using the linear regression, and we assumed the future technical improvement on yield will be the same or half as that in historical period to consider the uncertainty of technical improvement in the future (Burchfield et al., 2020; Ortiz-Bobea and Tack, 2018). Since the statistical models may not be extrapolated to the distant future which may be outside the range of historical climate conditions (Jones et al., 2017), we only studied the next 30 years until 2050.

2.3.4. Risk measures of crop yield under different climate conditions

Two yield risk measures, return period and coefficient of variation of crop yield, were applied to quantify the crop yield risk level under different climate conditions (Fig. 3). A recurrence interval of yield reduction higher than a certain value was defined as the return period

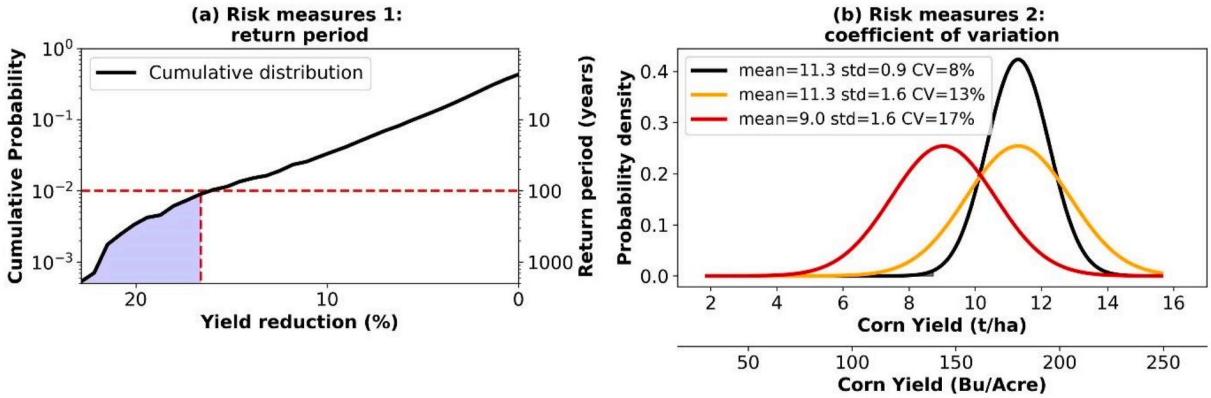

Fig. 3. The conceptual diagram of crop yield risk measures adopted in this study. (a) The conceptual diagram of return period, and its relationships with crop yield reduction and cumulative probability; (b) The conceptual diagram of the relationship between the coefficient of variation (CV) of crop yield and crop yield risk.

here, which corresponds to the cumulative distribution of the crop yield reduction (Fig. 3a). A small return period for a certain level of crop yield reduction means such yield reduction is more likely to happen, therefore indicating a higher yield risk level. We calculated the return period corresponding to 25% yield reduction, which is close to the overall U.S. corn yield reduction in the U.S. 2012 drought (Rippey, 2015), based on the predicted yield using the generated 10,000 years of climate patterns for each county in the U.S. Midwest, and used these return periods to study the spatial distribution of corn and soybean yield risk. To assess the overall crop yield loss risk in the Midwest, the county level crop yield from each simulation was aggregated to regional weighted average crop yields for the entire Midwest with the planting acreages of each county used as weights. The return period of the historical extreme drought year 1988 (Kogan, 1995) and 2012 (Mallya et al., 2013) in this region were also obtained based on the yield simulations. We also analyzed the changes of return periods of crop yield loss events under the future climate scenarios with both CO_2 fertilizer effect and technical improvement taking into account as well.

The coefficient of variation (CV), defined as the ratio of standard deviation to mean value of crop yield (Bindu et al., 2019), is another widely-used measure of crop yield risk level in the literature (Crane--Droesch et al., 2019). For a specific county, if the average yield becomes lower or the yield variance becomes larger, the coefficient of variation of crop yield will become larger, which indicates increased yield risk (Fig. 3b). To evaluate the impacts of climate change on crop yield risk, we compared the changes of average yield, yield variance, and coefficient of variation of yield under future and current climate scenarios for both corn and soybean.

3. Results

3.1. Climate pattern generation based on the extended EOF

The growing season monthly climate patterns were generated based on the EOFs and PCs obtained from 124 years of historical monthly climate data which was described in section 2.3.2. The percentage of climate spatial-temporal variance represented by the EOFs, the first EOF of temperature and precipitation, and corresponding PC were provided in Fig. S2. Most temperature and precipitation variance can be explained by the first few EOFs (Fig. S2a), covering the patterns of the frequently happening climate events indicating the impacts of large-scale atmospheric circulation over this region. Specifically, 9.2% variability of the temperature and precipitation over CONUS can be explained by the first EOF component, indicating the impacts of large-scale climate events on the spatial-temporal distribution of temperature and precipitation (Fig. S2d). To maintain the major variance of temperature and precipitation, 29 EOFs were selected for the climate patterns generation, which can explain 70% variance of the temperature and precipitation in the past 124 years (Fig. S2a).

10,000 years of temperature and precipitation patterns were generated by combining the PCs sampled from the fitted PCs distribution (Fig. S1) and the corresponding EOFs, adjusted by residuals generated from the residual model (Eq. (2)). At both 0.05 and 0.01 significance levels, the False Discovery Rate (FDR) adjusted p value of Anderson-Darling test and Kolmogorov-Smirnov test failed to reject the null hypothesis that the generated and observed temperature and precipitation data comes from the same distribution (Fig. S3). For temperature, no significant (i.e., p-value > 0.1) difference between the distribution of the generations and observations was found throughout CONUS using these two different test methods; for precipitation, the difference of the generated and observed distributions was not significant (i.e., p-value $>$ 0.1) in most regions of CONUS. The Western U.S. was the exception, but was not considered in the crop yield risk analysis in this study. The consistency of the distributions of generated and observed climate over the U.S. Midwest ensured the climate variables were realistic for the crop yield distribution prediction in the following analysis.

3.2. Assessing the performance of the statistical-based crop yield model in the U.S. Midwest

To evaluate the crop yield model performance, we used the county-scale crop yield data in odd years during 1981–2018 for model training and even years for model validation. The model performance was evaluated at both the county scale and Midwest scale for corn and soybean, respectively (Fig. 4). The validation results showed that the adopted crop yield model had a high performance in both corn and soybean yield prediction with monthly temperature and precipitation as inputs, with high R^2 and low RMSE at both the county scale and the U.S. Midwest scale. For the county scale, the RMSE and R^2 were 1.15 t/ha (18.32 Bu/Acre) and 0.79 for corn, and 0.36 t/ha (5.35 Bu/Acre) and 0.75 for soybean, respectively. For the whole Midwest, the RMSE and R^2 were 0.68 t/ha (10.83 Bu/Acre) and 0.85 for corn, and 0.20 t/ha (2.97

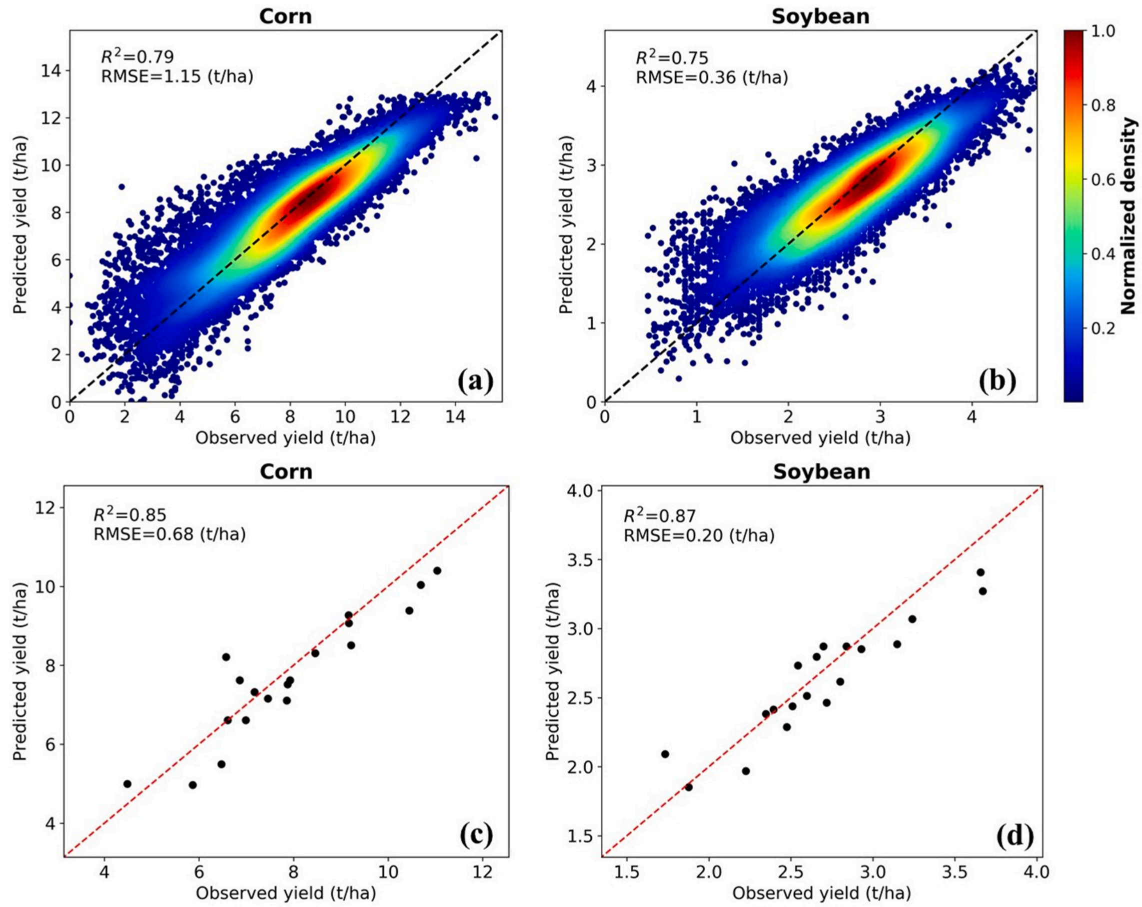

Fig. 4. Evaluating the performance of the statistical-based crop yield model at the county scale and the Midwest scale using the odd years data for model training and even years data for model validation. (a) and (b) are the model validation performance at the county scale for corn and soybean, respectively; (c) and (d) are the model validation performance at the regional scale (Midwest) for corn and soybean, respectively.

Bu/Acre) and 0.87 for soybean, respectively. The high R^2 and low RMSE of the crop yield model within the U.S. Midwest supported further use of this model for the crop yield risk assessment within this region.

3.3. Crop yield risk assessment over the U.S. Midwest

3.3.1. Comparing the observed and generated crop yield patterns

The spatial distribution of crop yield and its interannual variance can be recovered by the proposed framework (Fig. 5), by integrating the EOF-based climate pattern generation method, statistical crop yield model, and crop yield residual model. We reconstructed the historical yield using the proposed crop yield model (including the crop yield residual model) and historical climate data from 1981 to 2018, and generated 10,000 years of synthetic crop yield data based on the crop yield model (including the crop yield residual model) and the EOF-based synthetic climate patterns. The multi-year averaged crop yield from the NASS observation, historical crop yield reconstruction, and synthetic yield generation showed similar spatial patterns (Fig. 5a and b), indicating the proposed method can capture the general distribution of crop yield with small biases. In both observed, reconstructed, and generated crop yield, higher yields appeared in the northern and central parts of Iowa, Illinois, and Indiana for both corn and soybean. The standard deviation of crop yield from observation, reconstruction, and generation also showed similar spatial patterns (Fig. 5c and d), indicating that the proposed method captured the interannual variance of crop yield over the region. In all of these three data sources, the southern part of the study region showed larger crop yield variance for corn, and the western part showed larger crop yield variance for soybean. The similar standard deviation of crop yield was obtained from different approaches indicating the proposed method can capture the spatial heterogeneity of crop yield variances, justifying the reliability of the crop yield risk analysis in section 3.3.2.

We also partitioned the crop yield interannual variance into the variance explained by the crop yield model and variance explained by the residual model based on the generated crop yield dataset (Fig. 6). The yield interannual variance explained by the crop yield model indicates the yield variance induced by climate fluctuation, while variance explained by the residual model is attributed to pests, disease, nutrition, or other factors. The percentages of the crop yield variance explained by these two different models vary across the region. For example, most of the interannual yield variance was explained by the crop yield model in the southern part, while most of the yield variance was explained by the residual model in the northern part for both corn and soybean, which means that the climate fluctuation more directly influenced crop production in the southern part than that in the northern part of the U.S. Midwest.

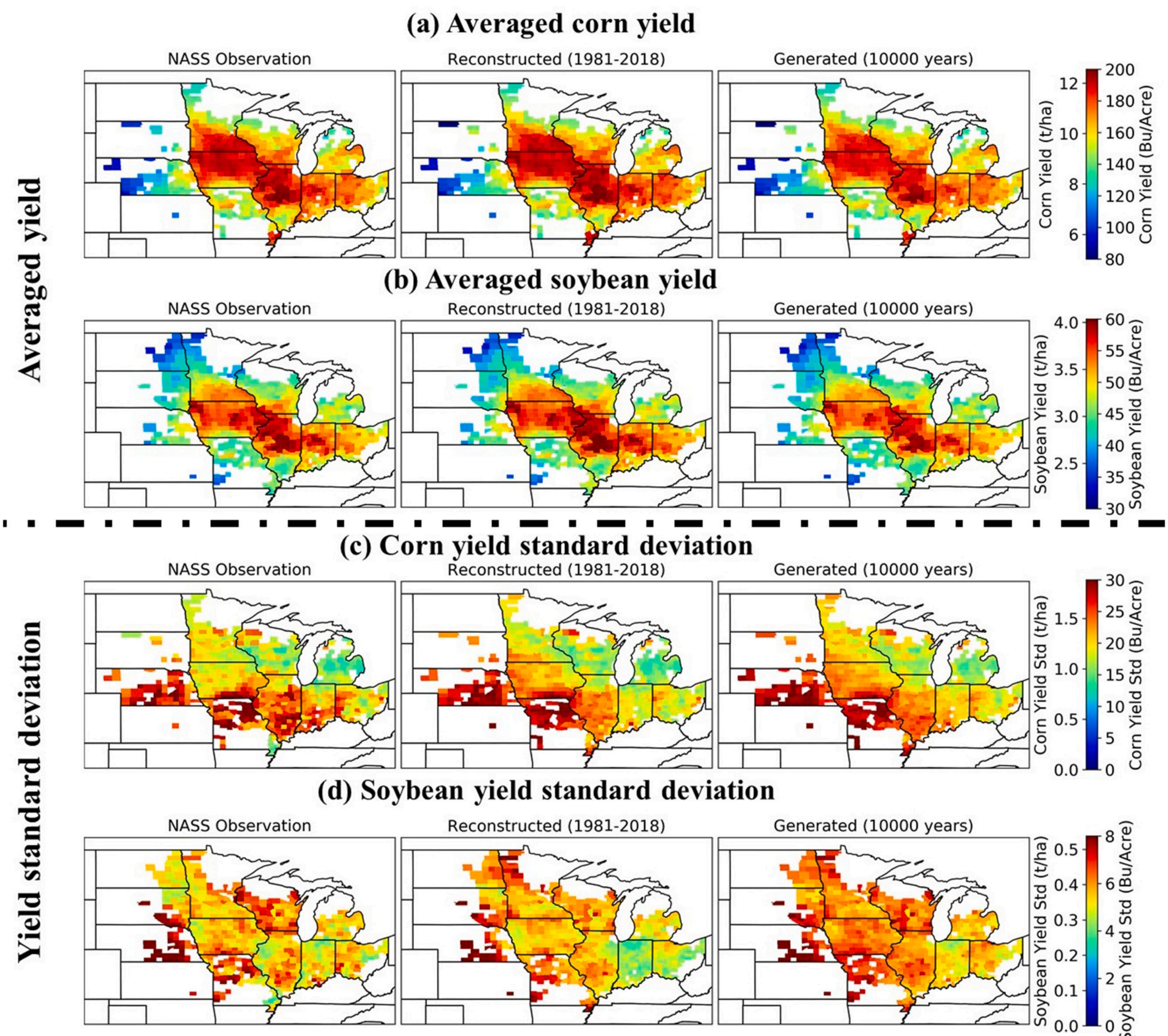

Fig. 5. Comparing the mean and standard deviation (std) of trend-adjusted (i.e., trend-adjusted to 2018) rainfed observed (1981–2018) and simulated (for both 1981–2018 and 10,000 generated years) yield for both corn and soybean.

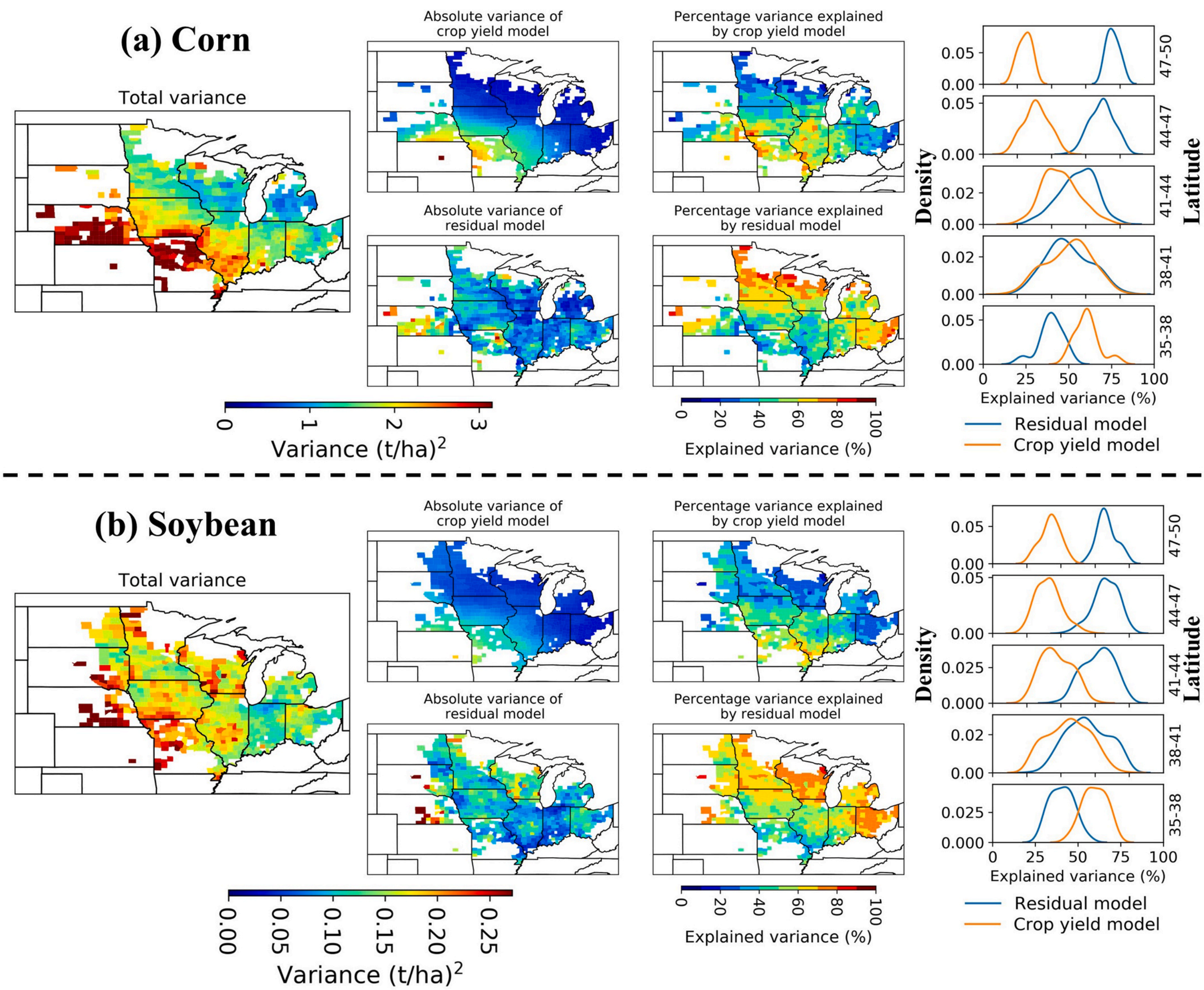

Fig. 6. Partitioning the total crop yield variance into variance explained by the statistical crop yield model and the crop yield residual model for both corn and soybean based on the generated crop yield dataset. The variances of crop yield model and residual model were calculated based on the yield generated from crop yield model (Var($Yield_c$)) and crop yield residual model (Var($Yield_r$)), respectively. The total variance (Var($Yield_c + Yield_r$)) was calculated based on the sum of yields generated from crop yield model and the crop yield residual model. The plots in right panels of (a) and (b) show the distributions of percentage of crop yield variance explained by crop yield model and crop yield residual model within different latitude fitted using the gaussian kernel density estimates.

3.3.2. Estimating crop yield risk under current and future climate scenarios

Based on the 10,000-year crop yield simulations, the county-specific crop yield risk level under current climate conditions was calculated. Specifically, the return periods corresponding to 25% yield reduction (Fig. 7) and the yield under different risk levels (i.e., with return periods ranging from 5 to 100 years, Fig. S5) over the U.S. Midwest were obtained for each county for corn and soybean, respectively. The return period corresponding to 25% yield reduction is smaller in the southwest and northwest periphery of Midwest compared to the core part of the corn belt for both corn and soybean (Fig. 7), indicating crop production is riskier in those regions. Counties in the southwest periphery usually have hotter summers with higher interannual variability of precipitation, therefore crops planted in those counties are more likely to be exposed to heat and severe drought stresses during the critical growth stages. Meanwhile, crop production in the northwest periphery is more likely to suffer from unexpected cold waves and frost damage before harvest and excessive rainfall due to volatile precipitation patterns, which may cause higher yield reduction risk in these regions (Li et al., 2019b).

The crop yield risk will increase under future climate scenario compared with current climate when considering the CO_2 effects but without technical improvements for RCP 8.5 (Fig. 8) scenario in 2050. For both corn and soybean, the averaged crop yield will decrease and yield variability will increase under the future climate scenario (Fig. 8a and b). The crop yield risk will increase more for corn than that for soybean under future climate scenario. The overall crop yield reduction is about 30% and 10% for corn and soybean, respectively, with CO_2 effects but without technical improvement, with higher yield loss in the southwest part and lower yield loss in the northeast part for both corn and soybean (Fig. 8c and d). The standard deviation (Fig. 8e and f) and coefficient of variation (Fig. 8i and j) of yield will increase in the U.S. Midwest with climate change. The change of crop yield coefficient of variation is higher in the southwest Midwest compared to other regions, and is higher for corn than for soybean (Fig. 8g and h).

The overall crop yield of the U.S. Midwest under different risk levels were obtained from the 10,000-year county scale crop yield simulations weighted by the crop area from NASS Quick Stats. The Midwestern crop yield reduction risk under both current and future climate scenarios was calculated (Fig. 9). For both corn and soybean, the yield reduction increased rapidly with the increase of return period when the return period was shorter, while the increase of crop yield reduction rate slowed down when the return period was longer. Under extreme years (i.e., return period about 100-years), about one fifth of the yield was lost for corn and soybean. Specifically, two severe droughts occurred in 2012 and 1988, resulting in huge crop yield loss in the U.S. Corn Belt. By comparing the simulated yield in these two years (trend adjusted) with the generated crop yield reduction-return period curves, we estimated the return period and its uncertainty in these two extreme years (Fig. 9). The uncertainty was obtained from the standard deviation of the predicted yield in these extreme years with 10,000-year crop yield residual data generated from the residual model. The return period of 2012 is about 30 years for corn and about 12 years for soybean, respectively; while for 1988, the return period is about 21 years for corn and about 7 years for soybean, respectively. For the future climate scenario, the reduction of corn and soybean yield will become larger compared with current conditions (Fig. 9a and d) with the increase of temperature and decrease of precipitation during the growing season for RCP 8.5 at 2050 when the CO_2 fertilization effect and technology improvement were not considered. For example, the yield loss for corn at a 50-year return period will be 58.8% under RCP 8.5; while for soybean, the yield loss will be 35.0% at a 50-year return period under RCP 8.5. The yield reduction will be reduced with the increase of [CO_2] (Fig. 9b and e) for soybean, and may be inverted with the technical improvements for both corn and soybean (Fig. 9c and f). For example, when considering the CO_2 fertilization effect but not considering the technology improvement, the yield loss for corn and soybean at a 50-year return period will be 57.4% and 28.8% under RCP 8.5, respectively. While considering both the CO_2 fertilization effect and technology improvement, the yield loss for corn at a 50-year return period will be 19.5% under RCP 8.5. But for soybean, the yield reduction may be inverted and the yield may increase 5.0% at a 50-year return period under RCP 8.5.

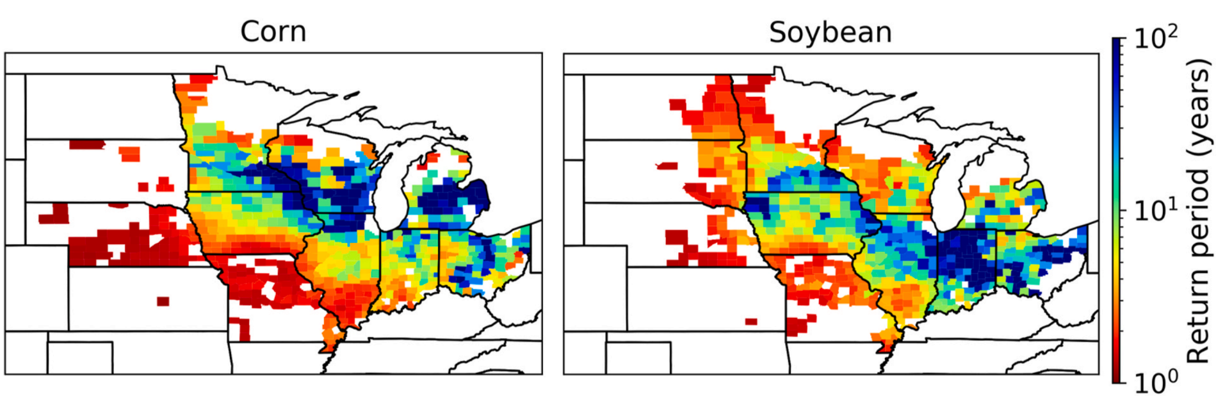

Fig. 7. Crop yield risk measures based on the return periods for corn and soybean corresponding to 25% yield reduction under current climate conditions based on the generated crop yield dataset.

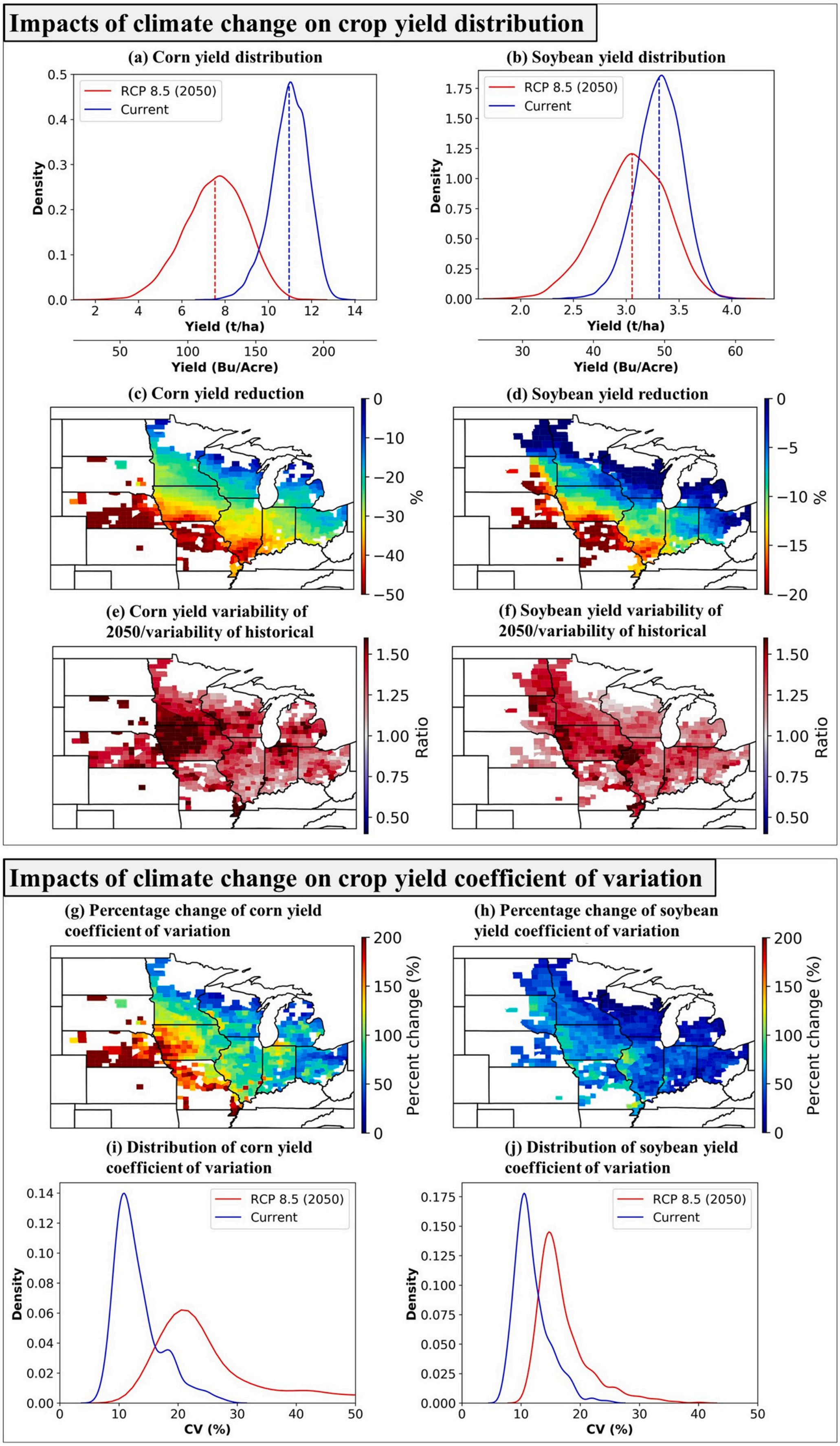

Fig. 8. Difference between the crop yield predicted in current climate and 2050 for the RCP 8.5 scenario (with CO_2 effects but without technical improvements effects). (a) and (b) are the distributions of the U.S. Midwest crop yield (calculated based on the predicted county-scale yield weighted by the planting area of 2018) under current and future climate (RCP 8.5 at 2050) scenarios for corn and soybean, respectively; (c) and (d) are the spatial distribution of yield difference between current and future climate scenarios for corn and soybean, respectively; (e) and (f) are the ratio of predicted crop yield standard deviation in 2050 for the RCP 8.5 scenario and historical climate scenarios for corn and soybean, respectively; (g) and (h) are the change of yield coefficient of variation in 2050 RCP 8.5 comparing with current climate scenarios for corn and soybean, respectively; (i) and (j) are the distribution of yield coefficient of variation (each county) in historical climate and 2050 for the RCP 8.5 scenario scenarios for corn and soybean, respectively. The distributions of data in (a), (b), (i), and (j) were fitted using the gaussian kernel density estimates.

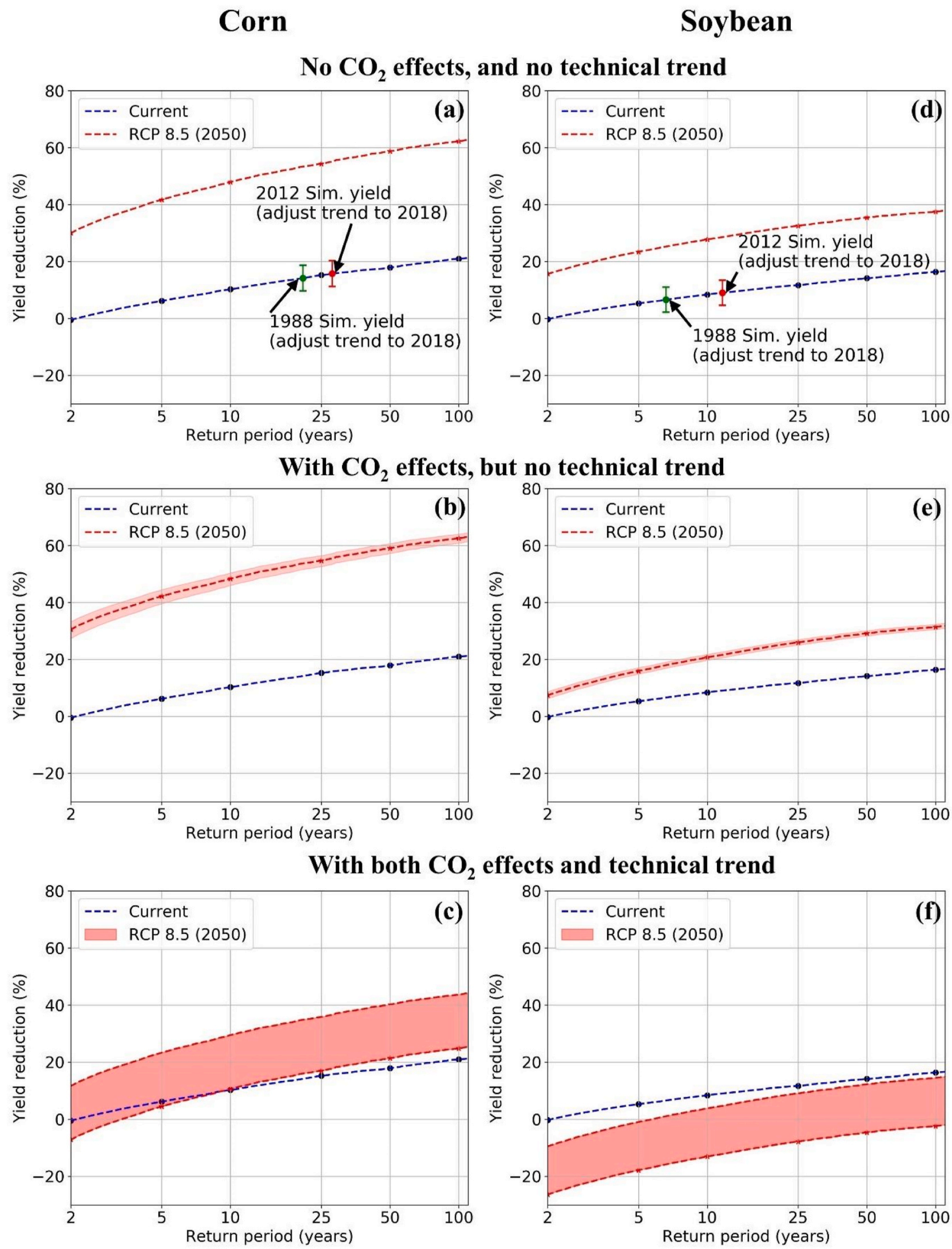

Fig. 9. The estimated rainfed corn and soybean yield reduction (the baseline is 2018) in the U.S. Midwest under different return periods in historical climate and 2050 for the RCP 8.5 scenario. Positive value means yield decrease and negative value means yield increase compared to averaged crop yield (adjusted yield trend to 2018) generated from the current climate condition. The x-axis of all the subplots were in base 10 logarithmic scale. The error bars in (a) and (b) show the standard deviation of crop yield prediction in 1988 and 2012. (a)–(c) and (d)–(f) are the yield reduction without both the [CO_2] effects and technical improvement effects, with the [CO_2] effects but without technical improvement effects, with both [CO_2] effects and technical improvement effects for corn and soybean, respectively. In (b) and (e), the shaded regions were obtained based on the 90% confidence intervals of [CO_2] effects on corn and soybean yield; The shaded regions in (c) and (f) were obtained assuming the technical improvement on yield is consistent with the current or half as current.

4. Discussion

In this study, we developed a generic framework to evaluate rainfed corn and soybean yield risk in the U.S. Midwest for both current and future climate scenarios by integrating the extended EOF based synthetic climate patterns generation and a well-validated statistical crop yield model. Although this study only focused on the risk assessment of corn and soybean yield in the U.S. Midwest, the framework proposed here can also be easily applied to other regions and other crops with long term (i.e., >30 years) climate and crop yield observations.

We noted some limitations in this study regarding the data availability and models. For the data, we only used 39 years of crop yield data for crop yield model building and 124 years of climate data for synthetic climate pattern generation. Although these are the longest and best climate and crop yield data publicly available and the data period covered some historical extreme years (i.e., 1988 and 2012), it is still somewhat limited for risk assessment. For the crop yield model, we used a statistical model with only climate data as predictors. There is a caveat that the statistical model may not be the best option for extrapolation under future climate conditions. However, the impact of this issue was largely mitigated by focusing on relatively short-term future climate conditions until 2050. Besides, our statistical crop model had a strong prediction performance with validation R^2 of 0.79 and 0.75 for corn and soybean, respectively. This suggests that our model can capture the responses of crop yield to climate variability, ensuring the application of the proposed framework for climate-induced rainfed crop yield risk assessment. We also noted the CO_2 fertilization and technical improvement effects were considered in our framework just using a simple statistical approach as a first-order approximation, which may lead to uncertainties in our risk assessment results. In the following discussion, we synthesized our results to answer the questions raised in the introduction section of the paper.

4.1. How much interannual variability of corn and soybean yield is explained by the climate variability, and how does this vary spatially?

Using our framework, we found that about 45% and 40% of crop yield interannual variability in corn and soybean can be explained by the climate in the U.S. Midwest (Fig. 6). The remaining portion of crop yield variability can be explained by the residual model and its covariations with the climate-based crop yield model, which may indicate the influence of pest, diseases and its covariations with climate, and other natural disasters (e.g., hail and wind storm) on crop yield loss. The percentages of corn and soybean yield interannual variability explained by climate variability from our study are consistent with previous studies (Lobell and Field, 2007; Ray et al., 2015), which found that interannual yield variability explained by climate variability was ~41% and 36% in the U.S. and 39% and 35% at the global scale for corn and soybean, respectively. The variance of crop yield that can be explained by climate variables decreased from the southern part to the northern part of the Midwest for both corn and soybean. This could be because it may be easier for crops to suffer from the heat stress in the southern part of Midwest than the northern part (Schlenker and Roberts, 2006; Zhu et al., 2019). In the higher temperature regions, small increases in temperature may cause a degree of "heat stress". While in the northern part, the normal condition is still below the "maximum-rate or optimal temperature" for crop growth. So even though the temperature increases a little bit, it is still under the thermal optimum in the northern part of the region. Another possibility is that the planting dates have changed more in the north growing region than in the southern growing region, which may also result in different overall effects of climate change on yield (Egli and Cornelius, 2009).

4.2. What is the risk level of the 1988 and 2012 droughts in terms of the corn and soybean yield loss?

Based on our framework, we calculated the risk level for the two major droughts that happened in the U.S. Midwest regions for rainfed corn and soybean. For corn, the return periods are about 21 and 30 years for 1988 and 2012, respectively; while for soybean, the return periods are about 7 and 12 years for 1988 and 2012, respectively. The crop yield return period is larger in 2012 than 1988 for both corn and soybean, and is larger for corn than soybean in both two extreme years. The spatial pattern of the return period in these two extreme years is different for

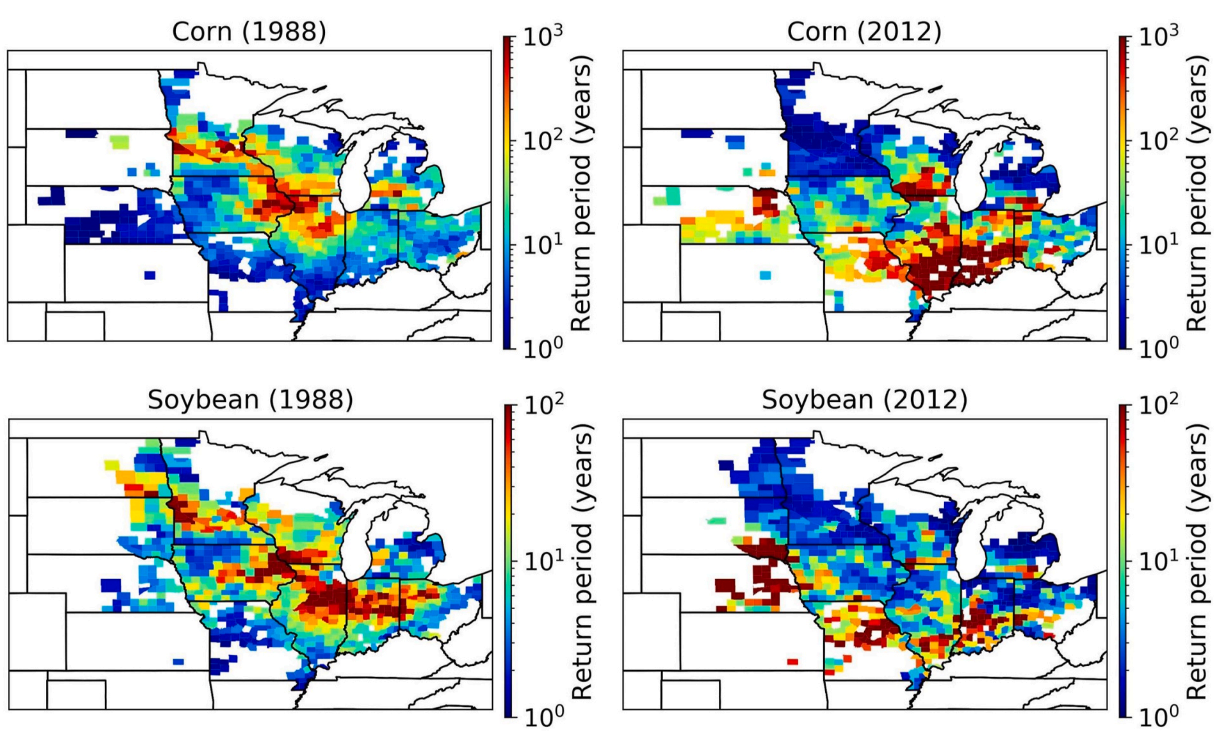

Fig. 10. Return period for corn and soybean yield reduction in the drought year 1988 and 2012.

both corn and soybean (Fig. 10). For the 1988 drought, the return period of both corn and soybean is larger in the northern part of the Midwest; while for the 2012 drought, the return period is larger in the southern part for both corn and soybean. This is consistent with the drought severity patterns during these two extreme years (Zhou et al., 2020).

4.3. What are the impacts of climate change on the crop yield risk in the U.S. Midwest?

From our framework, when considering the climate change and CO_2 fertilization effect but without the technical improvement, the averaged crop yield will decrease and yield variability will increase for most parts of the Midwest under RCP 8.5 scenario in 2050 for both corn and soybean (Fig. 8). The crop yield reduction is about 30% and 10% for corn and soybean with CO_2 effects but without technical improvement, respectively, which is consistent with previous studies (Cai et al., 2009; Lobell and Asseng, 2017), with higher yield loss in the southwest part and lower yield loss in the northeast part for both corn and soybean. For the northeast part, the growth period will be extended with higher temperature, and may compromise the influence of crop yield loss caused by the reduction of precipitation (Southworth et al., 2000); while in the southwest part, with the increase of temperature and decrease of precipitation, the frequency of heat stress and drought will increase (Southworth et al., 2000). The crop yield variance and crop yield risk will increase for both corn and soybean under RCP 8.5, and corn will experience higher yield loss compared with soybean especially in the southwest part of the Midwest.

4.4. Practical implications of this study

We adopted two crop yield risk measures analyzed in this paper, i.e., (1) return period and (2) coefficient of variation. Both risk measures have significant implications for different aspects of the risk management policies and practices in agriculture. First, the return period of disastrous events is critical to determine the future premium rate for the U.S. federal Multi-Peril Crop Insurance (MPCI), and consequently is essential for crop (re)insurance companies to assess the risk level of their crop insurance portfolios. The U.S. MPCI program is the biggest crop insurance program in the world, which has an annual premium size of $10 billion. The correctly determined premium rates help to protect U.S. farmers at a reasonable cost of government subsidy (Goodwin and Smith, 1995; Shields, 2015). The current premium rating system is only based on the previous loss experience in a short time window (less than 30 years for yield protection policies, less than 20 years for revenue protection policies), which, as many have argued (Coble et al., 2010), can be misleading due to rare disastrous events such as the 2012 Midwest drought in the recent history. The return period analysis in this paper, especially how these return periods will change under the future climatic conditions, will be essential for both policy makers and crop (re)insurance companies to understand and manage crop insurance risks.

Coefficient of variation, on the other hand, captures not only the left-tail behavior but also the overall variations of crop yield. Better knowledge of such variations helps to optimize the agriculture supply chain. For example, when one selects among the locations for building a new food processing or ethanol plant, the region with low coefficient of variation is preferred, as the low interannual variation saves the adjustment and transportation cost to secure the stable feedstock supply. Furthermore, understanding how yield variation can evolve under future climate conditions enables the agriculture supply chain companies to redesign their storage and transportation structure to mitigate supply-side risks incurred by future climate change. For example, an increasing crop yield variation might suggest an investment in storage facilities or transportation capacity be profitable in the future.

5. Conclusion

In conclusion, by combining a stochastic climate pattern generation method and a statistical crop yield model, we proposed a general framework for climate induced crop yield risk assessment and applied it in the U.S. Midwest in both current and future climate scenarios. Based on our framework, we found that (1) about 45% of corn and 40% of soybean yield interannual variability can be explained by the climate, and explained interannual yield variance by climate variables decreased from the southern to the northern part in the Midwest; (2) the southwest and northwest regions of the U.S. Midwest has higher yield loss risk compared with other regions; (3) the crop yield loss risk will increase under future climate scenario for both corn and soybean, with averaged yield decrease and yield variability increase. The results of this study can be used for the crop insurance policy establishment in this region, as well as the assessment of crop yield risk under climate change.

Author contributions

Wang Zhou: Conceptualization, Methodology, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization; **Kaiyu Guan:** Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing; **Bin Peng:** Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing; **Zhuo Wang:** Methodology, Writing - Review & Editing; **Rong Fu:** Methodology, Writing - Review & Editing; **Bo Li:** Methodology, Writing - Review & Editing; **Elizabeth A. Ainsworth:** Methodology, Writing - Review & Editing; **Evan DeLucia:** Writing - Review & Editing; **Lei Zhao:** Writing - Review & Editing; **Zhangliang Chen:** Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Authors acknowledge the support from the Faculty Fellowship on Climate Risk, Gies College of Business at the University of Illinois at Urbana Champaign, National Science Foundation (NSF) Career Award (1847334), and seed funding from the Center for Advanced Studies at UIUC.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wace.2021.100369.

References

Alter, R.E., Douglas, H.C., Winter, J.M., Eltahir, E.A.B., 2018. Twentieth century regional climate change during the summer in the Central United States attributed to agricultural intensification. Geophys. Res. Lett. 45, 1586–1594. https://doi.org/10.1002/2017GL075604.

Benami, E., Jin, Z., Carter, M.R., et al., 2021. Uniting remote sensing, crop modelling and economics for agricultural risk management. Nature Reviews Earth & Environment. https://doi.org/10.1038/s43017-020-00122-y.
Bindu, K.H., Hima Bindu, K., Raghava, M., Dey, N., Raghavendra Rao, C., 2019. Introduction to coefficient of variation. Coefficient of Variation and Machine Learning Applications 1–26.
Björnsson, H., Venegas, S.A., 1997. A manual for EOF and SVD analyses of climatic data. CCGCR Report 97 (1), 112–134.
Burchfield, E., Matthews-Pennanen, N., Schoof, J., Lant, C., 2020. Changing yields in the Central United States under climate and technological change. Climatic Change 159, 329–346. https://doi.org/10.1007/s10584-019-02567-7.
Cai, X., Wang, D., Laurent, R., 2009. Impact of climate change on crop yield: a case study of rainfed corn in central Illinois. Journal of Applied Meteorology and Climatology 48 (9), 1868–1881. https://doi.org/10.1175/2009JAMC1880.1.
Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. Nat. Clim. Change 4 (4), 287–291. https://doi.org/10.1038/nclimate2153.
Coble, Keith H., Knight, Thomas O., Goodwin, Barry K., Miller, Mary Frances, Rejesus, Roderick M., Duffield, George, 2010. A Comprehensive Review of the Rma Aph and Combo Rating Methodology: Final Report. Report prepared for the USDA Risk Management Agency by Sumaria Systems*, Inc.*, US Department of Agriculture, Risk Management Agency, Washington, DC.
Crane-Droesch, A., Marshall, E., Rosch, S., Riddle, A., Cooper, J.C., Wallander, S., 2019. Climate Change and Agricultural Risk Management into the 21st Century.
Daly, C., Smith, J.I., Olson, K.V., 2015. Mapping atmospheric moisture climatologies across the conterminous United States. PloS One 10 (10), e0141140. https://doi.org/10.1371/journal.pone.0141140.
Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Pasteris, P. P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int. J. Climatol. 28 (15), 2031–2064.
Deryng, D., Conway, D., Ramankutty, N., Price, J., Warren, R., 2014. Global crop yield response to extreme heat stress under multiple climate change futures. Environ. Res. Lett.: ERL [Web site] 9 (3), 034011. https://doi.org/10.1088/1748-9326/9/3/034011.
Egli, D.B., Cornelius, P.L., 2009. A regional analysis of the response of soybean yield to planting date. Agron. J. 101 (2), 330–335.
Goodwin, B.K., Ker, A.P., 1998. Nonparametric estimation of crop yield distributions: implications for rating group-risk crop insurance contracts. Am. J. Agric. Econ. 80 (1), 139–153. https://doi.org/10.2307/3180276.
Goodwin, Barry K., Smith, Vincent H., 1995. The Economics of Crop Insurance and Disaster Aid. American Enterprise Institute.
Hammer, G.L., Dong, Z., McLean, G., Doherty, A., Messina, C., Schussler, J., Zinselmeier, C., Paszkiewicz, S., Cooper, M., 2009. Can changes in canopy and/or root system architecture explain historical maize yield trends in the U.S. corn belt? Crop Sci. 49, 299–312. https://doi.org/10.2135/cropsci2008.03.0152.
Hijmans, R.J., Graham, C.H., 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Global Change Biol. 12 (12), 2272–2281.
Hodges, J.L., 1958. The significance probability of the smirnov two-sample test. Arkiv för Matematik 3 (5), 469–486.
Jin, Z., Zhuang, Q., Wang, J., Archontoulis, S.V., Zobel, Z., Kotamarthi, V.R., 2017. The combined and separate impacts of climate extremes on the current and future US rainfed maize and soybean production under elevated CO. Global Change Biol. 23 (7), 2687–2704. https://doi.org/10.1111/gcb.13617.
Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Wheeler, T.R., 2017. Brief history of agricultural systems modeling. Agric. Syst. 155, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014.
Kang, Y., Khan, S., Ma, X., 2009. Climate change impacts on crop yield, crop water productivity and food security – a review. Prog. Nat. Sci.: communication of state key laboratories of China 19 (12), 1665–1674. https://doi.org/10.1016/j.pnsc.2009.08.001.
Kim, D.H., Yoo, C., Kim, T.-W., 2011. Application of spatial EOF and multivariate time series model for evaluating agricultural drought vulnerability in Korea. Adv. Water Resour. 34 (3), 340–350. https://doi.org/10.1016/j.advwatres.2010.12.010.
Kogan, F.N., 1995. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. Bull. Am. Meteorol. Soc. 76 (5), 655–668.
Li, Y., Guan, K., Peng, B., Franz, T.E., Wardlow, B., Pan, M., 2020. Quantifying irrigation cooling benefits to maize yield in the US Midwest. Global Change Biol. 26, 3065–3078. https://doi.org/10.1111/gcb.15002.
Li, Y., Guan, K., Yu, A., Peng, B., Zhao, L., Li, B., Peng, J., 2019a. Toward building a transparent statistical model for improving crop yield prediction: modeling rainfed corn in the U.S. Field Crop. Res. 234, 55–65. https://doi.org/10.1016/j.fcr.2019.02.005.
Li, Y., Guan, K., Schnitkey, G.D., DeLucia, E., Peng, B., 2019b. Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. Global Change Biol. 25 (7), 2325–2337. https://doi.org/10.1111/gcb.14628.
Li, Y., Ye, W., Wang, M., Yan, X., 2009. Climate change and drought: a risk assessment of crop-yield impacts. Clim. Res. 39, 31–46. https://doi.org/10.3354/cr00797.
Lobell, D.B., Asseng, S., 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environ. Res. Lett. 12 (1), 015001.
Lobell, D.B., Field, C.B., Cahill, K.N., Bonfils, C., 2006. Impacts of future climate change on California perennial crop yields: model projections with climate and crop uncertainties. Agric. For. Meteorol. 141 (2–4), 208–218. https://doi.org/10.1016/j.agrformet.2006.10.006.
Lobell, D.B., Burke, M.B., 2010. On the use of statistical models to predict crop yield responses to climate change. Agric. For. Meteorol. 150 (11), 1443–1452.
Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett.: ERL [Web site] 2 (1), 014002. https://doi.org/10.1088/1748-9326/2/1/014002.
Lobell, D.B., Field, C.B., 2008. Estimation of the carbon dioxide (CO2) fertilization effect using growth rate anomalies of CO 2 and crop yields since 1961. Global Change Biol. 14, 39–45. https://doi.org/10.1111/j.1365-2486.2007.01476.x.
Lobell, D.B., Roberts, M.J., Schlenker, W., Braun, N., Little, B.B., Rejesus, R.M., Hammer, G.L., 2014. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science* (80) 344, 516–519. https://doi.org/10.1126/science.1251423.
Long, S.P., Ainsworth, E.A., Leakey, A.D.B., Nösberger, J., Ort, D.R., 2006. Food for thought: lower-than-expected crop yield stimulation with rising CO2 concentrations. Science 312 (5782), 1918–1921. https://doi.org/10.1126/science.1114722.
Maiorano, A., Martre, P., Asseng, S., Ewert, F., Müller, C., Rötter, R.P., Ruane, A.C., Semenov, M.A., Wallach, D., Wang, E., Alderman, P.D., Kassie, B.T., Biernath, C., Basso, B., Cammarano, D., Challinor, A.J., Doltra, J., Dumont, B., Rezaei, E.E., Gayler, S., Kersebaum, K.C., Kimball, B.A., Koehler, A.K., Liu, B., O'Leary, G.J., Olesen, J.E., Ottman, M.J., Priesack, E., Reynolds, M., Stratonovitch, P., Streck, T., Thorburn, P.J., Waha, K., Wall, G.W., White, J.W., Zhao, Z., Zhu, Y., 2017. Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles. Field Crop. Res. 202, 5–20. https://doi.org/10.1016/j.fcr.2016.05.001.
Mallya, G., Zhao, L., Song, X.C., Niyogi, D., Govindaraju, R.S., 2013. 2012 midwest drought in the United States. J. Hydrol. Eng. 18 (7), 737–745.
Massey, F.J., 1951. The Kolmogorov-smirnov test for goodness of fit. J. Am. Stat. Assoc. 46 (253), 68–78.
Meehl, G.A., Tebaldi, C., 2004. More intense, more frequent, and longer lasting heat waves in the 21st century. Science 305 (5686), 994–997. https://doi.org/10.1126/science.1098704.
Ortiz-Bobea, A., Tack, J., 2018. Is another genetic revolution needed to offset climate change impacts for US maize yields? Environ. Res. Lett. 13, 124009 https://doi.org/10.1088/1748-9326/aae9b8.
Papoulis, A., Unnikrishna Pillai, S., 2002. Probability, Random Variables, and Stochastic Processes. Tata McGraw-Hill Education, p. 852.
Pease, J.W., 1992. A comparison of subjective and historical crop yield probability distributions. J. Agric. Appl. Econ. 24 (2), 23–32.
Peng, B., Guan, K., Pan, M., Li, Y., 2018. Benefits of seasonal climate prediction and satellite data for forecasting U.S. Maize yield. Geophys. Res. Lett. 45 (18), 9662–9671. https://doi.org/10.1029/2018GL079291.
Peng, B., Guan, K., Tang, J., Ainsworth, E.A., Asseng, S., Bernacchi, C.J., Zhou, W., 2020. Towards a multiscale crop modelling framework for climate change adaptation assessment. Nature plants 6 (4), 338–348. https://doi.org/10.1038/s41477-020-0625-3.
Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6, 5989. https://doi.org/10.1038/ncomms6989.
Rippey, B.R., 2015. The U.S. drought of 2012. Weather and Climate Extremes 10, 57–64. https://doi.org/10.1016/j.wace.2015.10.004.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. U.S.A. 111 (9), 3268–3273. https://doi.org/10.1073/pnas.1222463110.
Schlenker, W., Roberts, M.J., 2006. Nonlinear effects of weather on corn yields*. Rev. Agric. Econ. 28 (3), 391–398. https://doi.org/10.1111/j.1467-9353.2006.00304.x.
Scholz, F.W., Stephens, M.A., 1987. K-sample anderson-darling tests. J. Am. Stat. Assoc. 82 (399), 918.
Sherrick, B.J., Zanini, F.C., Schnitkey, G.D., Irwin, S.H., 2004. Crop insurance valuation under alternative yield distributions. Am. J. Agric. Econ. 86 (2), 406–419.
Shields, Dennis A., 2015. Federal Crop Insurance: Background. US Congressional Research Service Report 40532, Washington DC.
Southworth, J., Randolph, J.C., Habeck, M., Doering, O.C., Pfeifer, R.A., Rao, D.G., Johnston, J.J., 2000. Consequences of future climate change and changing climate variability on maize yields in the midwestern United States. Agric. Ecosyst. Environ. 82 (1–3), 139–158.
Stojanovski, P., Dong, W., Wang, M., Ye, T., Li, S., Mortgat, C.P., 2015. Agricultural risk modeling challenges in China: probabilistic modeling of rice losses in hunan province. International Journal of Disaster Risk Science 6 (4), 335–346. https://doi.org/10.1007/s13753-015-0071-4.
Tao, F., Rötter, R.P., Palosuo, T., Gregorio Hernández Díaz-Ambrona, C., Mínguez, M.I., Semenov, M.A., Kersebaum, K.C., Nendel, C., Specka, X., Hoffmann, H., Ewert, F., Dambreville, A., Martre, P., Rodríguez, L., Ruiz-Ramos, M., Gaiser, T., Höhn, J.G.,

Salo, T., Ferrise, R., Bindi, M., Cammarano, D., Schulman, A.H., 2018. Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. Global Change Biol. 24, 1291–1307. https://doi.org/10.1111/gcb.14019.

Tubiello, F.N., Amthor, J.S., Boote, K.J., Donatelli, M., Easterling, W., Fischer, G., Gifford, R.M., Howden, M., Reilly, J., Rosenzweig, C., 2007. Crop response to elevated CO2 and world food supply. Eur. J. Agron. 26, 215–223. https://doi.org/10.1016/j.eja.2006.10.002.

USDA, 2020. Crop Production 2019 Summary. https://www.nass.usda.gov/Publications/Todays_Reports/reports/cropan20.pdf.

Wang, T., Hamann, A., Spittlehouse, D., Carroll, C., 2016. Locally downscaled and spatially customizable climate data for historical and future periods for north America. PloS One 11 (6), e0156720. https://doi.org/10.1371/journal.pone.0156720.

Weare, B.C., Nasstrom, J.S., 1982. Examples of extended empirical orthogonal function analyses. Mon. Weather Rev. 110 (6), 481–485.

Wouter Botzen, W.J., 2013. Managing Extreme Climate Change Risks through Insurance. Cambridge University Press, p. 432.

Zhou, L., Meng, Y., Abbaspour, K.C., 2019. A new framework for multi-site stochastic rainfall generator based on empirical orthogonal function analysis and Hilbert-Huang transform. J. Hydrol. 575, 730–742. https://doi.org/10.1016/j.jhydrol.2019.05.047.

Zhu, P., Zhuang, Q., Archontoulis, S.V., Bernacchi, C., Müller, C., 2019. Dissecting the nonlinear response of maize yield to high temperature stress with model-data integration. Global Change Biol. 25 (7), 2470–2484. https://doi.org/10.1111/gcb.14632.

Zhou, W., Guan, K., Peng, B., Shi, J., Jiang, C., Wardlow, B., Zhang, J., 2020. Connections between the hydrological cycle and crop yield in the rainfed U.S. Corn Belt. J. Hydrol. 590, 125398 https://doi.org/10.1016/j.jhydrol.2020.125398.

Zhou, W., Guan, K., Peng, B., Tang, J., Jin, Z., Jiang, C., Grant, R., Mezbahuddin, S., 2021. Quantifying carbon budget, crop yields and their responses to environmental variability using the ecosys model for U.S. Midwestern agroecosystems. Agric. For. Meteorol. 307, 108521 https://doi.org/10.1016/j.agrformet.2021.108521.