



RESEARCH LETTER

10.1002/2017GL073606

Key Points:

- We develop a multivariate probabilistic model that uses precipitation to estimate the probability distribution of crop yields
- The proposed model shows how the probability distribution of crop yield changes in response to droughts
- During Australia's Millennium Drought precipitation and soil moisture deficit reduced the average annual yield of the five largest crops

Supporting Information:

- Supporting Information S1

Correspondence to:

A. AghaKouchak,
amir.a@uci.edu

Citation:

Madadgar S., A. AghaKouchak, A. Farahmand, and S. J. Davis (2017), Probabilistic estimates of drought impacts on agricultural production, *Geophys. Res. Lett.*, *44*, 7799–7807, doi:10.1002/2017GL073606.

Received 11 APR 2017

Accepted 15 JUL 2017

Accepted article online 19 JUL 2017

Published online 5 AUG 2017

Probabilistic estimates of drought impacts on agricultural production

Shahrbanou Madadgar¹, Amir AghaKouchak¹ , Alireza Farahmand¹, and Steven J. Davis² 

¹Department of Civil and Environmental Engineering, University of California, Irvine, California, USA, ²Department of Earth System Science, University of California, Irvine, California, USA

Abstract Increases in the severity and frequency of drought in a warming climate may negatively impact agricultural production and food security. Unlike previous studies that have estimated agricultural impacts of climate condition using single-crop yield distributions, we develop a multivariate probabilistic model that uses projected climatic conditions (e.g., precipitation amount or soil moisture) throughout a growing season to estimate the probability distribution of crop yields. We demonstrate the model by an analysis of the historical period 1980–2012, including the Millennium Drought in Australia (2001–2009). We find that precipitation and soil moisture deficit in dry growing seasons reduced the average annual yield of the five largest crops in Australia (wheat, broad beans, canola, lupine, and barley) by 25–45% relative to the wet growing seasons. Our model can thus produce region- and crop-specific agricultural sensitivities to climate conditions and variability. Probabilistic estimates of yield may help decision-makers in government and business to quantitatively assess the vulnerability of agriculture to climate variations. We develop a multivariate probabilistic model that uses precipitation to estimate the probability distribution of crop yields. The proposed model shows how the probability distribution of crop yield changes in response to droughts. During Australia's Millennium Drought precipitation and soil moisture deficit reduced the average annual yield of the five largest crops.

1. Introduction

The frequency and concurrence of weather and climate extremes such as heatwaves, droughts, and heavy rainfalls have been increasing worldwide [Easterling *et al.*, 2000; Alexander *et al.*, 2006; Mazdiyasi and AghaKouchak, 2015], and this trend and the associated negative impacts on human activities are expected to further increase under climate change [Field *et al.*, 2012; Diffenbaugh and Giorgi, 2012; Kharin *et al.*, 2007; Hao *et al.*, 2013; Timmermann *et al.*, 1999; Cai *et al.*, 2014]. Agriculture is particularly sensitive to climate variability and changes in extremes [Parry *et al.*, 2004; Howden *et al.*, 2007; Reilly *et al.*, 2003; Schlenker and Lobell, 2010], and understanding the environmental determinants of crop yield and agricultural productivity is central to evaluations of regional and global vulnerabilities to climate change [Asseng *et al.*, 2013; Rosenzweig *et al.*, 2014].

The effects of environmental conditions on regional crop production may be estimated by using statistical methods [Nicholls, 1997; Jaynes *et al.*, 2003; Prasad *et al.*, 2006; Lobell and Field, 2007; Lobell *et al.*, 2011], dynamical crop simulation models [Bannayan *et al.*, 2003; Jones and Thornton, 2003; Fischer *et al.*, 2005; Lobell and Ortiz-Monasterio, 2007], and combined statistical-dynamical models [Lobell *et al.*, 2005; Yu *et al.*, 2014]. Past studies have applied these different approaches to examine the relationships between crop production and climate variability [Alexandrov and Hoogenboom, 2000; Porter and Semenov, 2005; Erda *et al.*, 2005; Lobell and Field, 2007; Thornton *et al.*, 2009; Lobell *et al.*, 2011], precipitation [e.g., Doorenbos *et al.*, 1979; Rosenzweig *et al.*, 2002; Lobell *et al.*, 2007; Roudier *et al.*, 2011], soil moisture [Lal, 1974; Narasimhan and Srinivasan, 2005; Ramakrishna *et al.*, 2006], air temperature [e.g., Wheeler *et al.*, 2000; Lobell *et al.*, 2007; Schlenker and Roberts, 2009; Welch *et al.*, 2010; Roudier *et al.*, 2011], and solar radiation [e.g., Monteith, 1972; Koti *et al.*, 2005].

However, the various methods that have been previously used to assess the effects of environmental factors on agricultural productivity are either deterministic or offer probabilistic results via a single crop yield distribution function that incorporates all the possible climate conditions experienced during a growing season [see, e.g., Goodwin and Ker, 1998; Hansen and Jones, 2000; Porter and Semenov, 2005; Tebaldi and Lobell, 2008; Ramirez *et al.*, 2003; Roudier *et al.*, 2011]. In contrast, stakeholders such as farmers, insurers, and

policymakers might prefer a model that produces crop yield distributions based on a specific environmental condition (e.g., precipitation amount) that is expected (or predicted) for a given growing season. For example, if a seasonal drought prediction model forecasts precipitation will be at the 20th percentile of the historical record (well below average) in the upcoming growing season, stakeholders might want to know the corresponding distribution (i.e., uncertainty) of yields for different crops. Here we present a new model capable of producing such yield distributions which relies on a copula-based [Joe, 1997; Nelsen, 1999], multivariate statistical technique and the concept of conditional probability.

2. Methods

Our proposed model links drought information with crop yield data to provide a joint distribution in form of a two-dimensional probability space. In turn, the joint distribution is used to obtain a distribution of crop yield for any given set of environmental conditions (e.g., different percentiles of precipitation or soil moisture). Unlike the univariate probability distributions, a joint distribution provides many possible distributions for a wide range of variability in a secondary yet dependent variable. Given any projected environmental condition, one can thus develop the corresponding crop yield distribution and find the probability that crop yields will or will not exceed a certain level.

2.1. Copula-Based Model

We use copula functions [Joe, 1997; Nelsen, 1999] to find the joint probability distribution of the annual crop yields and the selected drought indicators (i.e., Standardized Precipitation Index (SPI) and Soil-moisture Index (SSI)). The joint probability distribution integrates weather information (e.g., precipitation or soil moisture) and crop yield data based on their dependency structure. A copula function is defined as the multivariate distribution functions (C), of two or more uniformly distributed variables on the interval 0, 1 [Nelsen, 1999; Salvadori et al., 2007]:

$$F_{X_1 \dots X_n}(x_1, \dots, x_i, \dots, x_n) = C[F_{X_1}(x_1), \dots, F_{X_i}(x_i), \dots, F_{X_n}(x_n)] = C(u_1, \dots, u_i, \dots, u_n) \quad (1)$$

where C is the cumulative distribution function (CDF) of copula and $F_{X_i}(x_i)$ (also denoted by u_i) is the non-exceedance probability of x_i , i.e., the marginal distribution. Note that C joins the CDF of random variables (i.e., u_i), while $F_{X_1 \dots X_n}$ joins the original random variables (i.e., x_i).

Copulas have flexible structures in joining random variables (i.e., x_j) with different types of marginal distributions (i.e., u_j). This is a unique feature that has inspired several copula applications in hydrological studies [e.g., De Michele et al., 2005; Shiau, 2006; Li et al., 2013; Khedun et al., 2014; Madadgar and Moradkhani, 2015; Grimaldi et al., 2016; Salvadori et al., 2007; Salvadori et al., 2011; Nazemi and Elshorbagy, 2012]. Unlike copulas, other multivariate distributions such as Gaussian and Gamma distributions [Kelly and Krzysztofowicz, 1997; Sharma, 2000; Yue et al., 2001] require all random variables coming from similar distributions. Marginal distributions in a copula application (i.e., u_i) are not limited to the commonly used parametric distributions and can be treated empirically [Chui and Wu, 2009; Piani and Haerter, 2012].

Here we use the two main Copula families that have been used in the literature: elliptical and Archimedean [Embrechts et al., 2003; Nelsen, 1999]. Among different functions, t and Gaussian copulas from the elliptical family, and Clayton [1978] and Frank [1979] copulas from Archimedean family (Table 1) are more frequently used. This study adopts bivariate copulas, as listed in Table 1, to estimate the joint probability distribution between the drought indicators (x) and crop yields (y). Thus, equation (1) reduces to the following two-dimensional form:

$$F_{XY}(x, y) = C[F_X(x), F_Y(y)] \quad (2)$$

In this study, we are interested in conditional probability of crop production exceeding a certain amount ($Y > y$) at different climatic conditions ($X = x$); i.e., $F_{Y|X}(Y > y | X = x)$. The conditional probability density function of $f_{Y|X}(y | x)$ is expressed as follows [Madadgar and Moradkhani, 2013; Mazdiyasi et al., 2017]:

$$f_{Y|X}(y | x) = c[F_X(x), F_Y(y)] \cdot f_Y(y) \quad (3)$$

where c is the probability density function (PDF) of the continuous copula function and $f_Y(y)$ is the PDF of marginal distribution for crop yield. Once the conditional PDF for a particular drought condition is

Copula	Function	Domain
Gaussian	$C(u_1, u_2) = \int_{-\infty}^{\Phi^{-1}(u_2)} \int_{-\infty}^{\Phi^{-1}(u_1)} \frac{1}{2\pi(1-\rho^2)} \exp\left\{-\frac{x_1^2 + x_2^2 - 2\rho x_1 x_2}{2(1-\rho^2)}\right\} dx_1 dx_2$ $u_1 = \Phi(x_1), u_2 = \Phi(x_2)$ <p>ρ: Linear correlation coefficient Φ: Standard normal cumulative distribution function</p>	$x_1, x_2 \in R$
t	$C(u_1, u_2) = \int_{-\infty}^{t_v^{-1}(u_2)} \int_{-\infty}^{t_v^{-1}(u_1)} \frac{1}{2\pi(1-\rho^2)^{\frac{1}{2}}} \exp\left\{1 + \frac{x_1^2 + x_2^2 - 2\rho x_1 x_2}{v(1-\rho^2)}\right\}^{-(v+2)/2} dx_1 dx_2$ $u_1 = t_v(x_1), u_2 = t_v(x_2)$ <p>ρ: Linear correlation coefficient t_v: Cumulative distribution function of t distribution with v degree of freedom</p>	$x_1, x_2 \in R$
Clayton	$C(u_1, u_2) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$ <p>θ: Measure of dependency between u_1 and u_2.</p>	$\theta \in (0, \theta)$
Frank	$C(u_1, u_2) = \frac{1}{\theta} \ln\left(\frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1}\right)$ <p>θ: Similar to Clayton copula</p>	$\theta \in R$

obtained from equation (3), the probability of crop yield exceeding a certain amount, i.e., $F_{Y|X}(Y > y | X = x)$, is calculated as the area under $f_{Y|X}(y | x)$ for $Y > y$.

To select the best copula function for each combination of drought indicators and crop yields, we apply the parametric bootstrapping goodness-of-fit test [Genest and Rémillard, 2008; Sadegh et al., 2017]. More details on the test statistics and copula selection procedure are available in the supporting information and in Multivariate Copula Analysis Toolbox (MvCAT) [Sadegh et al., 2017]. In a group of copulas, the one with the smallest test statistic (S) and greatest p value can be considered as the best alternative [Sadegh et al., 2017]. We tested the t, Gaussian, Clayton, and Frank copula functions for all combinations of drought

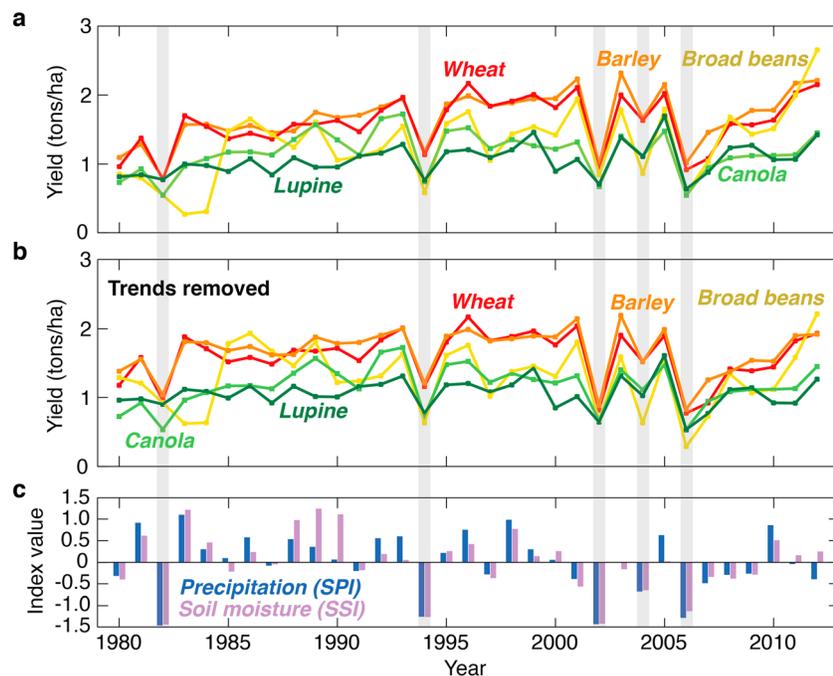


Figure 1. Time series of major rain-fed crop yields in Australia (a) before and (b) after removing the increasing trend over 1980–2012 and (c) comparing the detrended time series with drought indices based on precipitation (SPI, blue bars) and soil moisture (SSI, purple bars) over the same period. The grey vertical shading across the panels indicates the driest years.

Table 2. Pearson Correlation Coefficient Between the Crop Yields and the Selected Drought Indicators (SPI and SSI) During 1980–2012

Crop	SPI	SSI
Wheat	0.68	0.66
Broad beans	0.40	0.40
Canola	0.64	0.60
Lupine	0.54	0.46
Barley	0.67	0.62

indicators and crop yields and found the Clayton copula have the smallest *S* and the greatest *p* value among others (see Table S1 in the supporting information).

2.2. Study Area and Data for Model Demonstration

Australia has suffered several droughts in the past few decades [Mpelasoka *et al.*, 2008; Horridge *et al.*, 2005; Low *et al.*, 2015; Aghakouchak *et al.*, 2014] with significant environmental and socioeconomic impacts [Alston, 2012]. Here we demonstrate our copula-based model in the analysis of five major rain-fed crops cultivated in Australia: wheat, broad beans, canola, lupine, and barley [Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), 2013]. Annual crop yields during the analysis period 1980–2012 come from the Food and Agriculture Organization (FAO) of the United Nations [FAOSTAT, 2015]. The growing season for wheat, canola, and barley in Australia is May to October, and the season for broad beans and lupine is June to November [ABARES, 2013].

We evaluate weather conditions based on two drought indicators: Standardized Precipitation Index (SPI) [McKee *et al.*, 1993] for meteorological drought and Standardized Soil-moisture Index (SSI) [Hao and AghaKouchak, 2013] for agricultural drought. The SPI and SSI indicate the deviation of accumulated precipitation and soil moisture, respectively, during the growing season as compared to long-term climatology [Hao and AghaKouchak, 2014]. We used SPI and SSI records assessed by the Global Integrated Drought Monitoring and Prediction System (GIDMaPS) [Hao *et al.*, 2014; <http://drought.eng.uci.edu/>], which uses precipitation and soil moisture observations from NASA’s Modern-Era Retrospective Analysis for Research and Applications-Land (MERRA-Land) [Rienecker *et al.*, 2011; Reichle *et al.*, 2011; Bosilovich *et al.*, 2011]. The GIDMaPS data are available at a 1/2° × 2/3° spatial resolution. In this study, we used the standardized average precipitation and soil moisture over the rain-fed regions in Australia for the 6 month growing season of each selected crop.

3. Results

Figure 1a shows the agricultural production of major rain-fed crops in Australia during 1980–2012. Overall, improvements in agricultural practices, investments, and technological advances over this time period have led to steadily increasing crop yields but the sharp dips in crop yields occur during severe and extreme droughts (as highlighted by gray vertical shading in Figure 1). The Mann-Kendall trend test [Mann, 1945; Kendall, 1975] confirms a statistically significant positive trend (at $\alpha = 0.05$) in all crop yields except canola

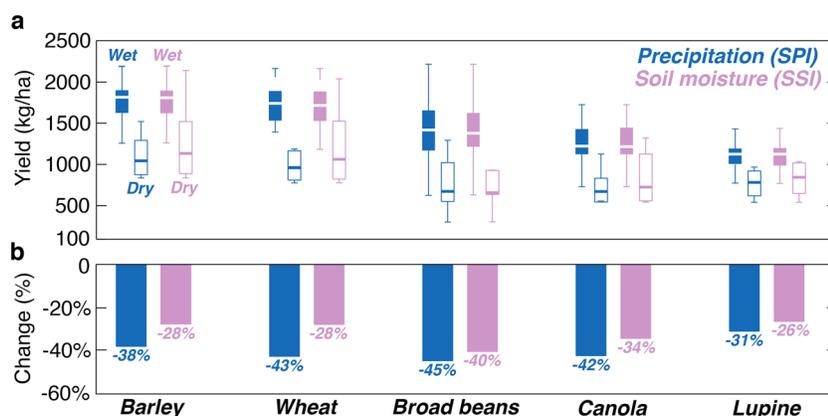


Figure 2. (a) Yield distributions of major rain-fed crops under different drought conditions based on precipitation (SPI, blue boxes and bars) and soil moisture (SSI, purple boxes and bars). The filled boxes show the yield distribution in years with wet/normal index values (i.e., > 0.5) and unfilled boxes show the distribution in years with dry index values (< -0.5). In each case, (b) the bars show the related average percent change in annual yield under the dry conditions relative to wet/normal conditions using either the precipitation or soil moisture indices (Figure S1 in the supporting information show a similar figure but with the original crop yield data).

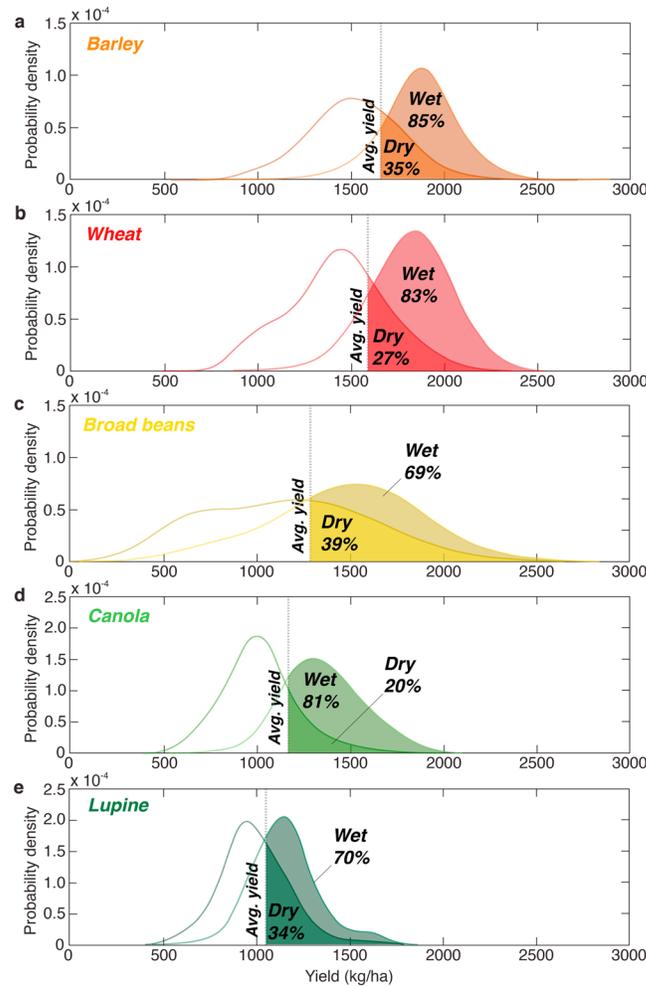


Figure 3. Conditional probability distributions of major detrended crop yields under dry and wet conditions. The shaded areas and percentages indicate the probability of crop yields exceeding its annual average (vertical dashed line). The conditional probabilities are defined as $\Pr(\text{Yield} > y \mid \text{SPI} = x)$ —Figure S2 in the supporting information shows a similar figure but with the original crop yield data.

(SPI or SSI < -0.5) as compared to normal/wet conditions (SPI or SSI > -0.5). These thresholds of dry and wet/normal are consistent with those used by the U.S. Drought Monitor (<http://droughtmonitor.unl.edu/>). The corresponding bars in Figure 2b depict the average percent reduction in crop yields in dry seasons, ranging from roughly 25% for lupine, barley, and wheat (with respect to soil moisture deficit) to 45% for broad beans (with respect to precipitation deficit). Changes due to precipitation and soil moisture deficits (blue and red bars, respectively) are similar in all cases, where all the five crop yields seem more sensitive to precipitation than soil moisture. Figure S1 in the supporting information shows similar results using the original crop yield data as opposed to detrended data. Given the similarity of observed responses to the two drought indicators (Figures 1 and 2), we present probabilistic model results based on precipitation (i.e., SPI) variations. However, soil moisture or any other environmental indicator could be readily substituted if such alternatives were shown to be better correlated with crop yields.

Figure 3 shows modeled conditional probability density functions of crop yields in wet (SPI = 0.5; blue) and dry (SPI = -0.5; red) conditions for each of the major rain-fed crops in Australia. In the case of each crop, yields are substantially larger during wet years, while cross comparing the PDFs shows that barley and wheat yields have rather similar distributions than other crops (consistent with historical yield records 1980–2012 shown in Figure 1). Further, lupine and canola production varies less than that of other crops, and broad

(see Table S2 in the supporting information for p values of the test). To ensure the observed trend is not going to affect the results, we conducted the data analysis on both original crop yield data and a detrended time series. We present the latter here; the analysis of original yields is presented in the supporting information.

Figure 1b shows the detrended crop yield time series and compares them with precipitation (SPI) and soil moisture (SSI) over the period 1980 to 2012 (Figure 1c). As observed, crop production dramatically reduces during severe droughts, where such sensitivity to substantial moisture deficit (i.e., precipitation or soil moisture) after a few wet years can lead to significant economic losses [Dijk et al., 2013; Chiew et al., 1998; Mpelasoka et al., 2008] as human expectations and management policies might have set by the high productivity during the precedent wet years.

The analysis of correlation coefficients shows that precipitation (SPI) exhibits a stronger association with the annual yield of each crop than does soil moisture (SSI; see Table 2). Yields of wheat and broad beans are the most and least correlated (i.e., sensitive to) crops with the selected drought indicators, respectively (Figure 1).

The boxplots in Figure 2a show the substantial historical decreases in major rain-fed crop yields in dry conditions

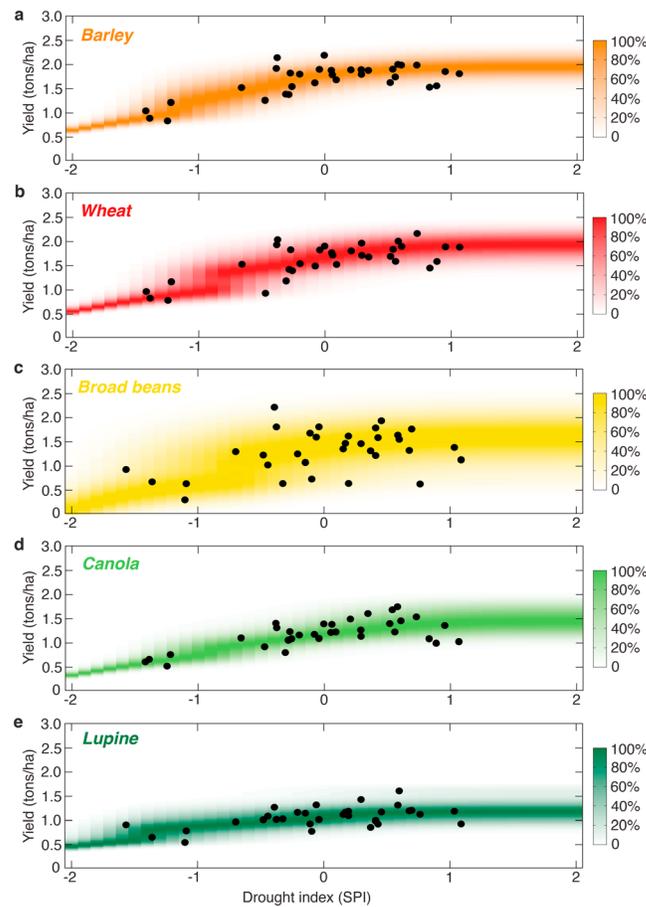


Figure 4. Comparing estimated crop yield distribution (normalized between 0 and 100%) with the observed annual production for each of the major rain-fed crops in Australia. Each panel shows where the observed annual crop yields locate with respect to the crop yield distribution for different observed SPI values.

where the observed annual crop yields locate within the crop yield distribution. There is one probability density function (PDF) in z axis at any SPI value which is represented by pixel colors. The colors represent normalized probability density function at given SPI, with 100% for the highest density and 0 for the lowest density. As seen, the majority of observed annual yields (filled dots) fall in the high-density region of PDFs in all panels. As a result, the estimated distributions are considered reliable for the major rain-fed crops in Australia.

For verification purposes, we also employed a 1 year out cross-validation procedure and applied three metrics, listed in Table S3 in the supporting information, to evaluate the performance of the proposed model in simulating the crop yield distribution [Laio and Tamea, 2007; Müller et al., 2005]. In 1 year out cross validation, the proposed model is trained with the entire record except 1 year. The trained model is then used to simulate the crop yield distribution of the year excluded from the training period. This procedure is repeated for all years during the analysis period. The metrics and verification results including Q-Q plots are listed in Figure S3 and Tables S3 and S4 in the supporting information. The results confirm the reliability of the proposed model in simulated crop distributions.

4. Discussion and Conclusions

As demonstrated, our copula-based model can produce probability distributions of crop yields given different projected weather conditions. In southwest Australia, where severe droughts (e.g., 1982, 1994, 2002, 2004, and 2006) led to major reductions in the yields of rain-fed crops [Dijk et al., 2013; Chiew et al., 1998;

bean production varies the most in the selected wet/dry conditions. The shaded areas in Figure 3 indicate the probability of yields exceeding annual average production for each crop over 1980–2012 (the vertical dashed line). For example, the probability of annual wheat production exceeding its average yield (~1602 kg/ha) is 27% in dry conditions (SPI = -0.5) and 83% in wet conditions. For broad beans with annual average yield of 1292 kg/ha, those probabilities change from 39% to 69%, respectively. For canola, the chance of producing above average yield (i.e., >1174 kg/ha) declines from 81% in wet conditions to 20% in dry conditions (i.e., 61% reduction in the probability of producing above average yield). Generally, drought risk on the annual production of broad beans is less than the other four crops (compare the exceedance probabilities in dry and wet conditions). Figure S2 in the supporting information shows similar results using the original crop yield data as opposed to detrended data (Figure 3). As shown, the results are quite consistent with both original and detrended crop yield data.

Figure 4 compares the estimated crop yield distribution with observed annual production for each of the major rain-fed crops in Australia. Each panel shows

Mpelasoka et al., 2008] (see Figure 1), the model indicates that a shift from wet ($SPI > -0.5$) to dry ($SPI < -0.5$) conditions causes yields of the five most important rain-fed crops to decrease by 25–45%. Unlike previous models, our model can provide a distinct crop yield distribution and the probability of achieving any target yield under any given weather conditions (e.g., 20th or 50th percentile of average precipitation). Further, the model is general and can be reformulated to use any other yield-related climatic variables and can readily compute the probability that yields will or will not exceed a target of interest. Future work will expand the number of climate/land surface variables included in the model and use it to more comprehensively assess regional and crop-specific sensitivities to drought, including perhaps short-term risk assessments of the future. The model can be used with climatic inputs aggregated over different temporal scales (e.g., 3 month and 6 month) as long as there is a relationship between climatic variables and crop production information. For example, the observed climate records used in this study could in theory be replaced by forecasts from climate/regional models—even if such forecasts are not available for entire growing season.

The model's ability to assess yield probabilities based on the best available weather forecasts fills a gap in the tools and information previously available to policymakers operating at both local and regional scales to manage water resources, plan drought responses, set long-term agriculture and water policies, and build up responsive and resilient food systems [Moschini and Hennessy, 2001; Chen and Chang, 2005]. On the business side of agriculture, having region- and crop-specific yield probabilities under different environmental conditions could inform better crop choices and improve the efficiency and effectiveness of farm policy interventions such as crop insurance and price or supply supports [Cuéllar et al., 2014; Barnett and Mahul, 2007].

Acknowledgments

This work was partially supported by National Science Foundation (NSF) INFEWS grant EAR 1639318. All the data sets used in this study are publically available. The drought data used in this study are available from the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; <http://drought.eng.uci.edu/>). The annual crop yields were obtained from the Food and Agriculture Organization (FAO) of the United Nations.

References

- Aghakouchak, A., D. Feldman, M. J. Stewardson, J.-D. Saphores, S. Grant, and B. Sanders (2014), Australia's drought: Lessons for California, *Science*, 343(6178), 1430–1431.
- Alexander, L. V., et al. (2006), Global observed changes in daily climate extremes of temperature and precipitation, *J. Geophys. Res.*, 111, D05109, doi:10.1029/2005JD006290.
- Alexandrov, V. A., and G. Hoogenboom (2000), The impact of climate variability and change on crop yield in Bulgaria, *Agric. For. Meteorol.*, 104(4), 315–327.
- Alston, M. (2012), Rural male suicide in Australia, *Soc. Sci. Med.*, 74(4), 515–522.
- Asseng, S., et al. (2013), Uncertainty in simulating wheat yields under climate change, *Nat. Clim. Change*, 3(9), 827–832.
- Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (2013), *Australian Crop Report*, Australian Bureau of Agricultural and Resource Economics and Sciences, Department of Agriculture, Fisheries and Forestry, Canberra.
- Bannayan, M., N. M. J. Crout, and G. Hoogenboom (2003), Application of the CERES-Wheat model for within-season prediction of winter wheat yield in the United Kingdom, *Agron. J.*, 95, 114–125.
- Barnett, B. J., and O. Mahul (2007), Weather index insurance for agriculture and rural areas in lower-income countries, *Am. J. Agric. Econ.*, 89(5), 1241–1247.
- Bosilovich, M. G., F. R. Robertson, and J. Chen (2011), Global energy and water budgets in MERRA, *J. Clim.*, 24(22), 5721–5739.
- Cai, W., et al. (2014), Increasing frequency of extreme El Niño events due to greenhouse warming, *Nat. Clim. Change*, 4(2), 111–116.
- Chen, C. C., and C. C. Chang (2005), The impact of weather on crop yield distribution in Taiwan: Some new evidence from panel data models and implications for crop insurance, *Agr. Econ.*, 33(5), 503–511.
- Chiew, F. H. S., T. C. Piechota, J. A. Dracup, and T. A. McMahon (1998), El Niño/Southern Oscillation and Australian rainfall, streamflow and drought: Links and potential for forecasting, *J. Hydrol.*, 204(1–4), 138–149.
- Chui, C., and X. Wu (2009), Exponential series estimation of empirical copulas with application to financial returns, in *Nonparametric Econometric Methods, Advances in Econometrics*, vol. 25, edited by Q. Li and J. S. Racine, pp. 263–290, Emerald Group Publishing Limited, Bingley, U. K.
- Clayton, D. G. (1978), A model for association in bivariate life tables and its application in epidemiological studies of familial tendency in chronic disease incidence, *Biometrika*, 65, 141–151.
- Cuéllar, M. F., D. Lazarus, W. P. Falcon, and R. L. Naylor (2014), Institutions, interests, and incentives in American food and agriculture policy, in *The Evolving Sphere of Food Security*, pp. 87–107, Oxford Univ. Press, U. K.
- De Michele, C., G. Salvadori, M. Canossi, A. Petaccia, and R. Rosso (2005), Bivariate statistical approach to check adequacy of dam spillway, *J. Hydrol. Eng.*, 10(1), 50–57.
- Diffenbaugh, N. S., and F. Giorgi (2012), Climate change hotspots in the CMIP5 global climate model ensemble, *Clim. Change*, 114(3–4), 813–822.
- Dijk, A. I., H. E. Beck, R. S. Crosbie, R. A. Jeu, Y. Y. Liu, G. M. Podger, B. Timbal, and N. R. Viney (2013), The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society, *Water Resour. Res.*, 49, 1040–1057, doi:10.1002/wrcr.20123.
- Doorenbos, J., A. H. Kassam, and C. I. M. Bentvelsen (1979), *Yield Response to Water*, Issue 33 of FAO Irrigation and Drainage Paper, Food and Agriculture Organization of the United Nations, Rome.
- Easterling, D. R., G. A. Meehl, C. Parmesan, S. A. Changnon, T. R. Karl, and L. O. Mearns (2000), Climate extremes: Observations, modeling, and impacts, *Science*, 289(5487), 2068–2074.
- Embrechts, P., F. Lindskog, and A. J. McNeil (2003), Modelling dependence with copulas and applications to risk management, in *Handbook of Heavy Tailed Distributions in Finance*, edited by S. T. Rachev, chap. 8, pp. 329–384, Elsevier Science, Amsterdam.
- Erda, L., X. Wei, J. Hui, X. Yinlong, L. Yue, B. Liping, and X. Liyong (2005), Climate change impacts on crop yield and quality with CO₂ fertilization in China, *Philos. Trans. R. Soc. London, Ser. B*, 360(1463), 2149–2154.
- FAOSTAT (2015), *Food and Agriculture Organization of the United Nations Statistics Division*, FAO, Rome.

- Field, C. B., et al. (2012), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*, Cambridge Univ. Press, New York.
- Fischer, G., M. Shah, F. N. Tubiello, and H. van Velhuizen (2005), Socio-economic and climate change impacts on agriculture: An integrated assessment, 1990–2080, *Philos. Trans. R. Soc. London, Ser. B*, 360(1463), 2067–2083.
- Frank, M. J. (1979), On the simultaneous associativity of $F(x,y)$ and $x + y - F(x,y)$, *Aequationes Math.*, 19, 194–226.
- Genest, C., and B. Rémillard (2008), Validity of the parametric bootstrap for goodness-of-fit testing in semiparametric models, *Annales de l'Institut Probabilités et Statistiques*, 44(6), 1096–1127.
- Goodwin, B. K., and A. P. Ker (1998), Nonparametric estimation of crop yield distributions: Implications for rating group-risk crop insurance contracts, *Am. J. Agric. Econ.*, 80, 139–153.
- Grimaldi, S., A. Petroselli, G. Salvadori, and C. De Michele (2016), Catchment compatibility via copulas: A non-parametric study of the dependence structures of hydrological responses, *Adv. Water Resour.*, 90, 116–133.
- Hansen, J. W., and J. W. Jones (2000), Scaling-up crop models for climate variability applications, *Agric. Syst.*, 65(1), 43–72.
- Hao, Z., A. AghaKouchak, and T. J. Phillips (2013), Changes in concurrent monthly precipitation and temperature extremes, *Environ. Res. Lett.*, 8(3) 034014.
- Hao, Z., and A. AghaKouchak (2013), Multivariate standardized drought index: A parametric multi-index model, *Adv. Water Resour.*, 57, 12–18.
- Hao, Z., and A. AghaKouchak (2014), A multivariate multi-index drought modeling framework, *J. Hydrometeorol.*, 15, 89–101.
- Hao, Z., A. AghaKouchak, N. Nakhjiri, and A. Farahmand (2014), Global integrated drought monitoring and prediction system, *Sci. Data*, 1, 140001, 1–10, doi:10.1038/sdata.2014.1.
- Horridge, M., J. Madden, and G. Wittwer (2005), The impact of the 2002–2003 drought on Australia, *J. Policy Model.*, 27(3), 285–308.
- Howden, S. M., J. F. Soussana, F. N. Tubiello, N. Chhetri, M. Dunlop, and H. Meinke (2007), Adapting agriculture to climate change, *Proc. Natl. Acad. Sci. U.S.A.*, 104(50), 19,691–19,696.
- Jaynes, D. B., T. C. Kaspar, T. S. Colvin, and D. E. James (2003), Cluster analysis of spatiotemporal corn yield patterns in an Iowa field, *Agron. J.*, 95(3), 574–586.
- Joe, H. (1997), *Multivariate Models and Dependence Concepts*, Chapman & Hall, London.
- Jones, P. G., and P. K. Thornton (2003), The potential impacts of climate change on maize production in Africa and Latin America in 2055, *Global Environ. Change*, 13(1), 51–59.
- Kelly, K. S., and R. Krzysztofowicz (1997), A bivariate meta-Gaussian density for use in hydrology, *Stochastic Hydrol. Hydraul.*, 11(1), 17–31.
- Kendall, M. G. (1975), *Rank Correlation Methods*, 4th ed., Charles Griffin, London.
- Kharin, V. V., F. W. Zwiers, X. Zhang, and G. C. Hegerl (2007), Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations, *J. Clim.*, 20, 1419–1444.
- Khedun, C. P., A. K. Mishra, V. P. Singh, and J. R. Giardino (2014), A copula-based precipitation forecasting model: Investigating the interdecadal modulation of ENSO's impacts on monthly precipitation, *Water Resour. Res.*, 50, 580–600, doi:10.1002/2013WR013763.
- Koti, S., K. R. Reddy, V. R. Reddy, V. G. Kakani, and D. Zhao (2005), Interactive effects of carbon dioxide, temperature, and ultraviolet-B radiation on soybean (*Glycine max* L.) flower and pollen morphology, pollen production, germination, and tube lengths, *J. Exp. Bot.*, 56(412), 725–736.
- Laio, F., and S. Tamea (2007), Verification tools for probabilistic forecasts of continuous hydrological variables, *Hydrol. Earth Syst. Sci.*, 11, 1267–1277.
- Lal, R. (1974), Soil temperature, soil moisture and maize yield from mulched and unmulched tropical soils, *Plant Soil*, 40(1), 129–143.
- Li, C., V. P. Singh, and A. K. Mishra (2013), Monthly river flow simulation with a joint conditional density estimation network, *Water Resour. Res.*, 49, 3229–3242, doi:10.1002/wrcr.20146.
- Lobell, D. B., and C. B. Field (2007), Global scale climate–crop yield relationships and the impacts of recent warming, *Environ. Res. Lett.*, 2(1) 014002.
- Lobell, D. B., K. N. Cahill, and C. B. Field (2007), Historical effects of temperature and precipitation on California crop yields, *Clim. Change*, 81(2), 187–203.
- Lobell, D. B., J. I. Ortiz-Monasterio, G. P. Asner, P. A. Matson, R. L. Naylor, and W. P. Falcon (2005), Analysis of wheat yield and climatic trends in Mexico, *Field Crops Res.*, 94, 250–256.
- Lobell, D. B., W. Schlenker, and J. Costa-Roberts (2011), Climate trends and global crop production since 1980, *Science*, 333(6042), 616–620.
- Lobell, D. B., and J. I. Ortiz-Monasterio (2007), Impacts of day versus night temperatures on spring wheat yields: A comparison of empirical and CERES model predictions in three locations, *Agron. J.*, 99, 469–477.
- Low, K. G., S. B. Grant, A. J. Hamilton, K. Gan, J. D. Saphores, M. Arora, and D. L. Feldman (2015), Fighting drought with innovation: Melbourne's response to the Millennium Drought in Southeast Australia, *Wiley Interdiscip. Rev. Water*, 2, 315–328.
- Mann, H. B. (1945), Non-parametric tests against trend, *Econometrica*, 13, 163–171.
- Madadgar, S., and H. Moradkhani (2013), A Bayesian framework for probabilistic seasonal drought forecasting, *J. Hydrometeorol.*, 14, 1685–1705.
- Madadgar, S., and H. Moradkhani (2015), Improved Bayesian multimodeling: Integration of copulas and Bayesian model averaging, *Water Resour. Res.*, 50, 9586–9603, doi:10.1002/2014WR015965.
- Mazdiyasi, O., and A. AghaKouchak (2015), Substantial increase in concurrent droughts and heatwaves in the United States, *Proc. Natl. Acad. Sci. U.S.A.*, 112(37), 11,484–11,489.
- Mazdiyasi, O., et al. (2017), Increasing probability of mortality during Indian heat waves, *Sci. Adv.*, 3(6), e1700066, doi:10.1126/sciadv.1700066.
- McKee, T. B., N. J. Doesken, and J. Kleist (1993), The relationship of drought frequency and duration to time scales, in *Proceedings of the Eighth Conference on Applied Climatology*, Am. Meteorol. Soc., pp. 179–184, Boston, Mass.
- Monteith, J. L. (1972), Solar radiation and productivity in tropical ecosystems, *J. Appl. Ecol.*, 9, 747–766.
- Moschini, G., and D. A. Hennessy (2001), Uncertainty, risk aversion, and risk management for agricultural producers, in *Handbook of Agricultural Economics*, vol. 1, edited by E. Duflo and A. Banerjee, pp. 88–153, Elsevier Science, Amsterdam.
- Mpelasoka, F., K. Hennessy, R. Jones, and B. Bates (2008), Comparison of suitable drought indices for climate change impacts assessment over Australia towards resource management, *Int. J. Climatol.*, 28(10), 1283–1292.
- Müller, W. A., C. Appenzeller, F. J. Doblas-Reyes, and M. A. Liniger (2005), A debiased ranked probability skill score to evaluate probabilistic ensemble forecasts with small ensemble sizes, *J. Clim.*, 18(10), 1513–1523.
- Narasimhan, B., and R. Srinivasan (2005), Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring, *Agric. For. Meteorol.*, 133(1–4), 69–88.
- Nazemi, A., and A. Elshorbagy (2012), Application of copula modelling to the performance assessment of reconstructed watersheds, *Stoch. Environ. Res. Risk Assess.*, 26(2), 189–205.

- Nelsen, R. B. (1999), *An Introduction to Copulas*, Springer, New York.
- Nicholls, N. (1997), Increased Australian wheat yield due to recent climate trends, *Nature*, *387*, 484–485.
- Parry, M. L., C. Rosenzweig, A. Iglesias, M. Livermore, and G. Fischer (2004), Effects of climate change on global food production under SRES emissions and socio-economic scenarios, *Global Environ. Change*, *14*(1), 53–67.
- Piani, C., and J. O. Haerter (2012), Two dimensional bias correction of temperature and precipitation copulas in climate models, *Geophys. Res. Lett.*, *39*, L20401, doi:10.1029/2012GL053839.
- Porter, J. R., and M. A. Semenov (2005), Crop responses to climatic variation, *Philos. Trans. R. Soc. London, Ser. B*, *360*(1463), 2021–2035.
- Prasad, A. K., L. Chai, R. P. Singh, and M. Kafatos (2006), Crop yield estimation model for Iowa using remote sensing and surface parameters, *Int. J. Appl. Earth Obs. Geoinf.*, *8*(1), 26–33.
- Ramakrishna, A., H. M. Tam, S. P. Wani, and T. D. Long (2006), Effect of mulch on soil temperature, moisture, weed infestation and yield of groundnut in northern Vietnam, *Field Crop. Res.*, *95*(2–3), 115–125.
- Ramirez, O. A., S. Misra, and J. Field (2003), Crop-yield distributions revisited, *Am. J. Agric. Econ.*, *85*(1), 108–120.
- Reichle, R. H., R. D. Koster, G. J. M. De Lannoy, B. A. Forman, Q. L. Sarith, P. P. Mahanama, and A. Touré (2011), Assessment and enhancement of MERRA land surface hydrology estimates, *J. Clim.*, *24*, 6322–6338.
- Reilly, J., et al. (2003), U.S. agriculture and climate change: New results, *Clim. Change*, *57*(1–2), 43–67.
- Rienecker, M. M., et al. (2011), MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, *J. Clim.*, *24*, 3624–3648.
- Rosenzweig, C., F. N. Tubiello, R. Goldberg, E. Mills, and J. Bloomfield (2002), Increased crop damage in the US from excess precipitation under climate change, *Global Environ. Change*, *12*(3), 197–202.
- Rosenzweig, C., et al. (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.
- Roudier, P., B. Sultan, P. Quirion, and A. Berg (2011), The impact of future climate change on West African crop yields: What does the recent literature say?, *Global Environ. Change*, *21*(3), 1073–1083.
- Salvadori, G., C. De Michele, and F. Durante (2011), On the return period and design in a multivariate framework, *Hydrol. Earth Syst. Sci.*, *15*, 3293–3305.
- Sadegh, M., et al. (2017), Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework, *Water Resour. Res.*, *53*, 5166–5183, doi:10.1002/2016WR020242.
- Salvadori, G., C. De Michele, N. T. Kottegoda, and R. Rosso (2007), *Extremes in Nature: An Approach Using Copulas*, Springer, Berlin.
- Schlenker, W., and M. J. Roberts (2009), Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change, *Proc. Natl. Acad. Sci. U.S.A.*, *106*(37), 15,594–15,598.
- Schlenker, W., and D. B. Lobell (2010), Robust negative impacts of climate change on African agriculture, *Environ. Res. Lett.*, *5*(1) 014010.
- Sharma, A. (2000), Seasonal to interannual rainfall probabilistic forecasts for improved water supply management: Part 3—A nonparametric probabilistic forecast model, *J. Hydrol.*, *239*(1–4), 249–258.
- Shiau, J. T. (2006), Fitting drought duration and severity with two-dimensional copulas, *Water Resour. Manage.*, *20*(5), 795–815.
- Tebaldi, C., and D. B. Lobell (2008), Towards probabilistic projections of climate change impacts on global crop yields, *Geophys. Res. Lett.*, *35*, L08705, doi:10.1029/2008GL033423.
- Thornton, P. K., P. G. Jones, G. Alagarswamy, and J. Andresen (2009), Spatial variation of crop yield response to climate change in East Africa, *Global Environ. Change*, *19*(1), 54–65.
- Timmermann, A., J. Oberhuber, A. Bache, M. Esch, M. Latif, and E. Roeckner (1999), Increased El Niño frequency in a climate model forced by future greenhouse warming, *Nature*, *398*(6729), 694–697.
- Welch, J. R., J. R. Vincent, M. Auffhammer, P. F. Moya, A. Dobermann, and D. Dawe (2010), Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures, *Proc. Natl. Acad. Sci. U.S.A.*, *107*(33), 14,562–14,567.
- Wheeler, T. R., P. Q. Craufurd, R. H. Ellis, J. R. Porter, and P. V. V. Prasad (2000), Temperature variability and the yield of annual crops, *Agric. Ecosyst. Environ.*, *82*, 159–167.
- Yu, Q., L. Li, Q. Luo, D. Eamus, S. Xu, C. Chen, E. Wang, J. Liu, and D. C. Nielsen (2014), Year patterns of climate impact on wheat yields, *Int. J. Climatol.*, *34*(2), 518–528.
- Yue, S., T. B. M. J. Ouarda, and B. Bobée (2001), A review of bivariate gamma distributions for hydrological application, *J. Hydrol.*, *246*(1–4), 1–18.