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- 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

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Probabilistic estimates of drought impacts on agricultural production

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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; *Mazdiyasni 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]:

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

where C is the cumulative distribution function (CDF) of copula and $F_{X_i}(x_i)$ (also denoted by u_i) is the nonexceedance 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_i) with different types of marginal distributions (i.e., u_i). 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:

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

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., $F_{Y|X}(Y > y \mid X = x)$. The conditional probability density function of $f_{Y|X}(y \mid x)$ is expressed as follows [*Madadgar and Moradkhani*, 2013; *Mazdiyasni et al.*, 2017]:

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

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

Table 1. Summary of the Bivariate Copula Functions Used in This Study

Copula	Function	Domain
Gaussian	$C(u_1,u_2)=\int_{-\infty}^{\Phi^{-1}(u_2)}\int_{-\infty}^{\Phi^{-1}(u_1)}\frac{1}{2\pi(1-\rho^2)}\exp\left\{-\frac{{x_1}^2+{x_2}^2-2\rho x_1x_2}{2(1-\rho^2)}\right\}dx_1dx_2$ $u_1=\Phi(x_1)u_2=\Phi(x_2)$ ρ: Linear correlation coefficient Φ: Standard normal cumulative distribution function	$x_1, x_2 \in R$
t	$C(u_1,u_2)=\int_{-\infty}^{{t_v}^{-1}(u_2)}\int_{-\infty}^{{t_v}^{-1}(u_1)}\frac{1}{2\pi(1-\rho^2)^{\frac{1}{2}}}\exp\left\{1+\frac{{x_1}^2+{x_2}^2-2\rho x_1x_2}{v(1-\rho^2)}\right\}^{-(v+2)/2}dx_1dx_2$ $u_1=t_v(x_1)\ ,\quad u_2=t_v(x_2)$ ρ: Linear correlation coefficient t_v: Cumulative distribution function of t distribution with v degree of freedom	$x_1, x_2 \in R$
Clayton	$C(u_1,u_2)=({u_1}^{-\theta}+{u_2}^{-\theta}-1)^{-1/\theta}$ θ: Measure of dependency between u_1 and u_2.	$\theta \in (0, \theta)$
Frank	$C(u_1,u_2)=\frac{1}{\theta}\ln\left(\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}\right)$ θ: Similar to Clayton copula	$\theta \in R$

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

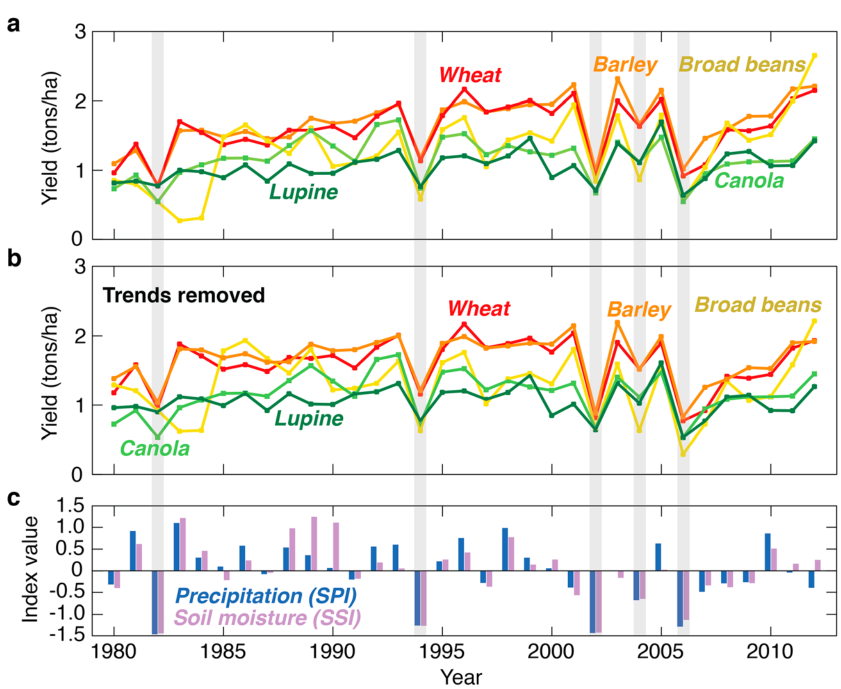

Figure 1. Time series of major rain-fed crop yields in Australia (a) before and (b) after removing the increasing trend over 1980–2012 and (c) comparing the detrended time series with drought indices based on precipitation (SPI, blue bars) and soil moisture (SSI, purple bars) over the same period. The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

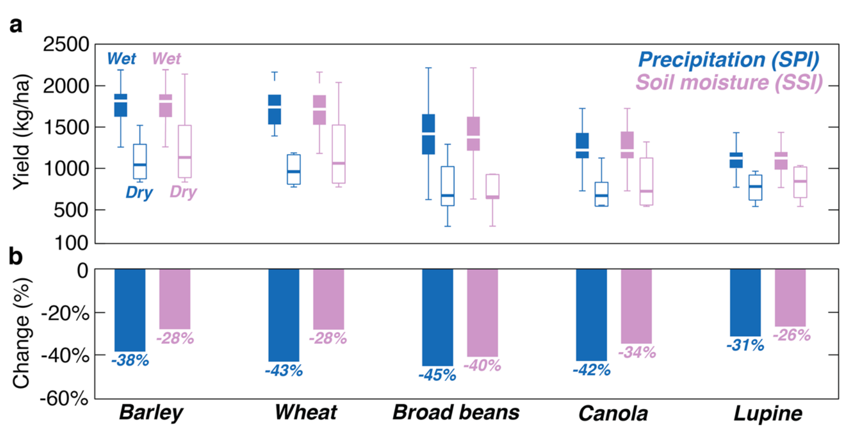

Figure 2. (a) Yield distributions of major rain-fed crops under different drought conditions based on precipitation (SPI, blue boxes and bars) and soil moisture (SSI, purple boxes and bars). The filled boxes show the yield distribution in years with wet/normal index values (i.e., > -0.5) and unfilled 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).

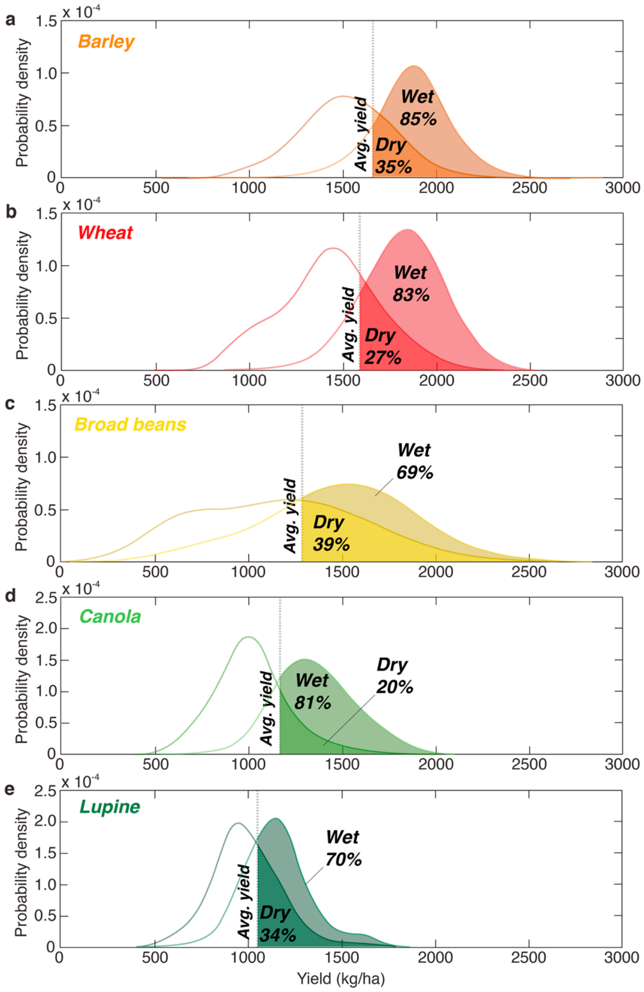

Figure 3. Conditional probability distributions of major detrended crop yields under dry and wet conditions. The shaded areas and percentages indicate the probability of crop yields exceeding its annual average (vertical dashed line). The conditional probabilities are defined as Pr (Yield $> y$ | SPI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

(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 (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

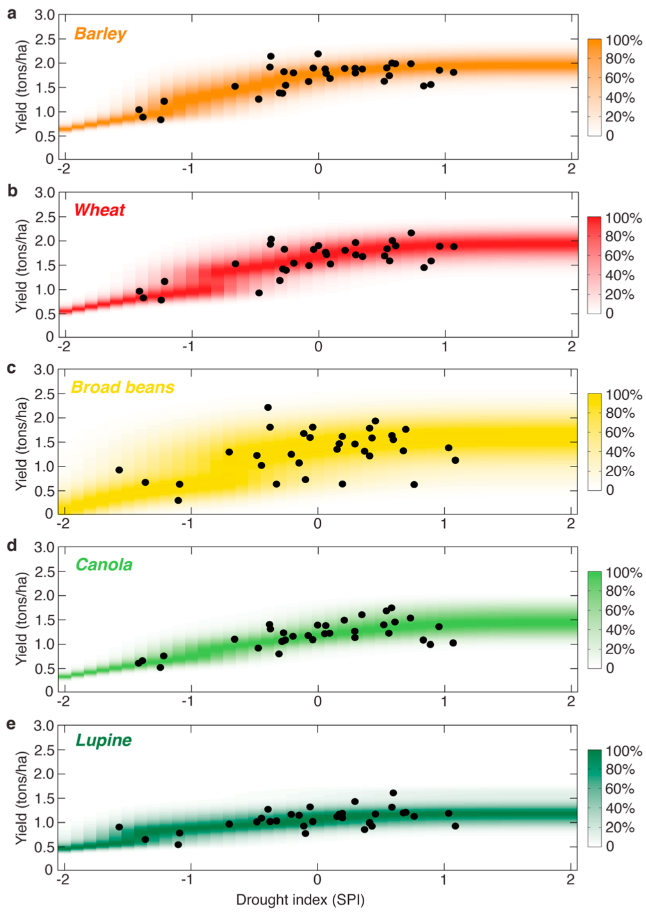

Figure 4. Comparing estimated crop yield distribution (normalized between 0 and 100%) with the observed annual production for each of the major rain-fed crops in Australia. Each panel shows where the observed annual crop yields locate with respect to the crop yield distribution for different observed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

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 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;

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

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