Title

Integrating an Agro-Meteorological Indicator for Assessing Drought Impacts on Agricultural Production

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Integrating an Agro-Meteorological Indicator for Assessing Drought Impacts on Agricultural Production

THESIS

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MASTER OF SIENCE

in Environmental Engineering

by

Lei Li

Thesis Committee:
Professor Amir AghaKouchak, Chair
Professor Kuo-Lin Hsu
Professor Xiaogang Gao

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Last my thanks would go to my beloved family for their loving considerations and great confidence in me all through these years.

ABSTRACT OF THE THESIS

Integrating an Agro-Meteorological Indicator for Assessing Drought Impacts on Agricultural Production

By

Lei Li

Master of Environmental Engineering

University of California, Irvine, 2015

Professor Amir AghaKouchak, Chair

In the study, we analyzed variability of three univariate and multivariate drought indicators and yields of five of the largest rain-fed crops in Australia including wheat, broad beans, canola, lupins and barley. Using multivariate copulas, this study relates changes in climate variability to changes in crops production during 1980-2012. In the analysis period, the five chosen crops indicate a modest association with the selected drought indicators: Standardized Precipitation Index (SPI); Standardized Soil Moisture Index (SSI), and Multivariate Standardized Drought Index (MSDI). The latter combines precipitation and soil moisture and provides a measure of agro-meteorological drought. A model is developed to describe the relationship between drought and crop production using copulas. The model offers the likelihood of crop yield given an observed or predicted SPI, SSI or MSDI.

INTRODUCTION

Potential impacts of climate variability and change on crop yields have been pursued for decades worldwide. Temperature (e.g. Wheeler *et al.*, 2000), precipitation (e.g. Rosenzweig *et al*., 2002) and solar radiation (e.g. Monteith, 1972) significantly affect agricultural production in both positive and negative ways. A quantitative understanding of the relative impacts of the variability in climate on crop yield can help develop effective adaptation strategies to cope with climate change and variability.

Different approaches have been applied in previous studies, such as statistical regression method (e.g. Peltonen-Sainio *et al.*, 2010) and process-based crop simulation models (e.g. Lobell and Ortiz-Monasterio, 2007). Statistical regression method evaluates the impact of climate change on agricultural productivities through regressing crop yields to different weather conditions. This empirical method has been applied in numerous crop-climate relationship studies since the 1960s (e.g., Wolfgang, 1973). The classic regression models developed by Thompson (1969,1970,1975,1985,1986,1988) has far-reaching implications in the study of relationship between climate variables and crop yields. In the 1990s, Nicholls (1997) suggested to use first difference regression method, which calculated first differences (year-to-year variations) of yield and relevant weather variables to assess the relationship between crop yields and climate variables. The study demonstrated the method would reduce the influence of artificial trends and could lead to skillful forecasts. Lobell and Field (2007) adopted Nicholls's approach to evaluate the response of global yields for wheat, maize and barley in a warming world. Osborne and Wheeler (2013) jointly examined the relationship of yield and climate variability for rice, wheat and maize from 1961 to 2010 using first difference method. In addition to time series approach based on the data at a single location, panel methods based on different locations and time are adopted in the recent studies. Schlenker *et al*. (2010) used a panel analysis of historical yields of five staple crops grown in South Africa and Zimbabwe and weather data during 1961-2002. Lobell *et al*. (2011a) combined crop yield, crop locations, growing seasons and monthly temperature and rainfall in a panel analysis to assess the impact of climate trends on yields of four crops at the country scale for the period of 1980 to 2008.

Another type of approach found in numerous studies on assessment of climate-crop yield relationship is process-based crop simulation model. This approach, linking meteorological variables with crop growth processes, is capable of simulating yields under constant management with climate records as the input of these models. Crop Environment Resource Synthesis (CERES) model (Richie *et al.*, 1985; Hodges *et al*., 1987; Chipanshi *et al*., 1997; Hundal and Kaur, 1997; Rosenthal *et al*., 1998; Bannayan *et al*., 2003; Nain *et al*., 2004) and Agricultural Production Systems Simulator (APSIM) model (McCown *et al.*, 1996; Keating *et al.* 2003) are the common adopted models to investigate the potential effects of climate changes on crop production. Most of the models applied for simulating crop yields are crop-specific models. For instance, APSIM model consists of a suite of modules for different crops. APSIM-Wheat is the common adopted module in the wheat yield-climate relationship simulation studies. To date, APSIM system contains modules for 28 different crops (See crops on http://www.apsim.info/Documentation/Model,CropandSoil/CropModuleDocumentation.aspx).

However, both process-based crop simulation and statistical modeling approaches are subject to substantial uncertainties. Therefore, recent studies (Lobell *et al*., 2005; Yu *et al*., 2014) often combine different methods for evaluating the effects of climate change and variability on variables would put on agricultural production.

Heat stress has been reported to have a significant impact on crop outputs throughout the world. Lobell *et al*. (2011b) presented statistical evidence to indicate that maize productions in United States and Africa had negative response to accumulation of temperature above 30°C. In addition, based on processed-based crop simulation models, Lobell *et al.* (2012) also found that wheat growth in northern India suffered significant acceleration of senescence from extreme heat. Moreover, another crop simulation study over Europe-wide indicated that high temperature and drought in the growing season could reduce the crop productivity (Ciais *et al*., 2005).

Beside the heat stress, variability in precipitation and soil moisture would also affect production of crop yields. Recently, Luo and Wen (2014) attempt to examine the effects of observed climate on three most grown crops in Australia by adopting robust statistical regression method. They indicate that growing season rainfall was significantly, non-linearly correlated with crop yields in New South Wales, Australia.

In order to assess climatic contributions to crop yields, the association between crop yields and climate variables over the past few decade needs to be evaluated. A good understanding of the relationship between rainfall and rain-fed agricultural production in the past would help to cope with future climate variability.

Here, a retrospective analysis is applied in the study. We investigate the relationship between variations of crop yields in rain-fed area in Australia and precipitation and soil moisture variability in the growing areas of the crops by comparing year-to-year variations in historical data during 1980-2012. We choose five of the largest rain-fed crops grown in Australia including wheat, broad beans, canola, lupins and barley in the study (ABARES, 2013). The rain-fed agricultural regions of Australia locate in the temperate areas shown in Figure 1.1.

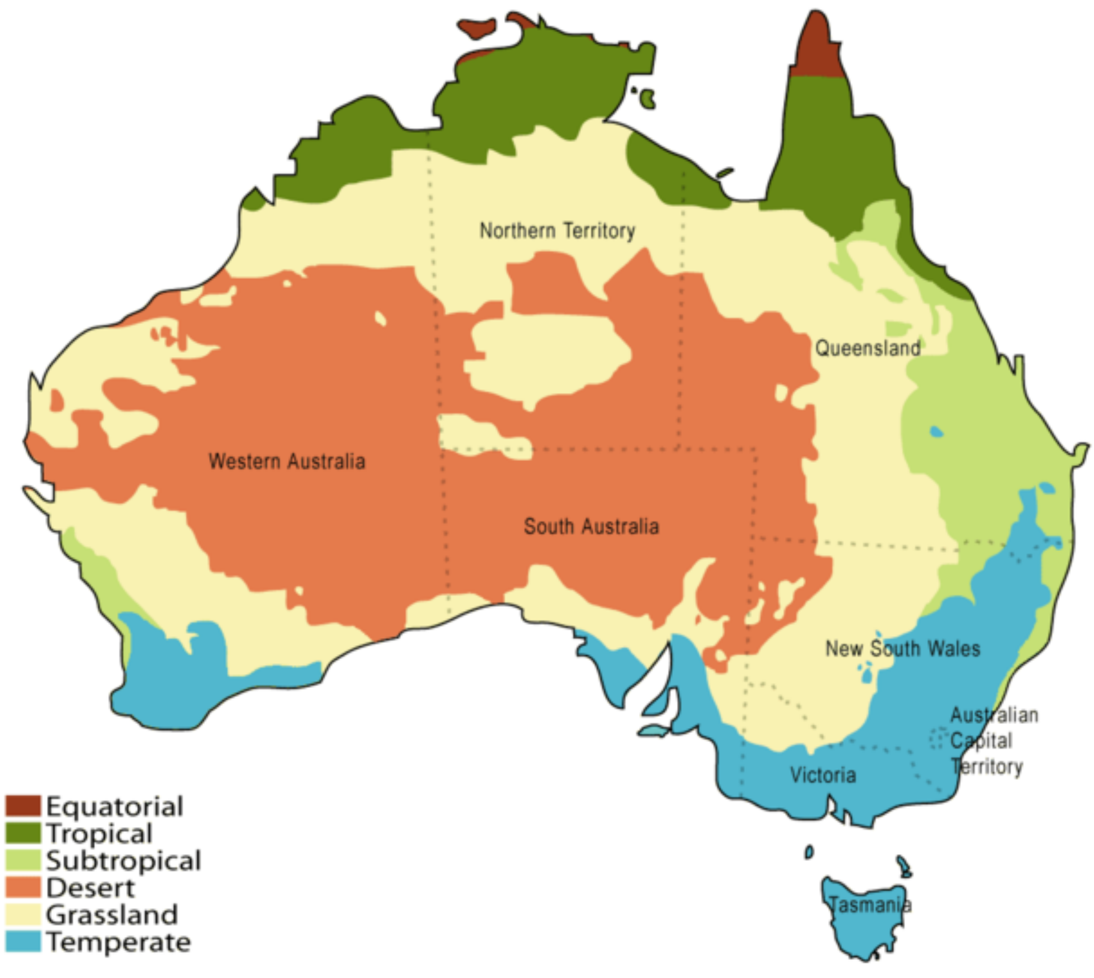

Figure 1.1|Australia Climate Map The Australian Bureau of Meteorology climate classification (Data from bom.gov.au.)

The objectives of this study are:

(1) Compare the historical variations of yields for five broad-acre rain-fed crops grown in Australia and Standardized Precipitation Index (SPI), Standardized Soil moisture Index (SSI), and Multivariate Standardized Drought Index (MSDI) over Australia's agricultural areas.

(2) Adopt a copula-based approach to model the dependence structure between the crop yield and three climate indices for probabilistic yield assessment.

METHOD

2.1 Data Description

To compare the variations of precipitation and soil moisture with rain-fed crop yields, standardized indices including Standardized Precipitation Index (SPI) (McKee *et al.*, 1993), Standardized Soil moisture Index (SSI) (Hao and AghaKouchak, 2013), and Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak, 2014) are adopted in the study. The SPI and SSI are mathematically based on the cumulative probabilities of given precipitation and soil moisture with historical data. They are capable to represent the amount of rainfall and soil moisture over a given time scale. The MSDI, combining the SPI and SSI, incorporates precipitation and soil moisture using the joint distribution function of the two variables. In this study, the SPI, SSI and MSDI for the period of 1980-2012 are obtained from Global Integrated Drought Monitoring and Prediction System (GIDMaPS; Hao *et al.*, 2014; http://drought.eng.uci.edu/). The original precipitation and soil moisture data are derived from National Aeronautics and Space Administration's (NASA) land-only version of Modern-Era Retrospective Analysis for Research and Applications (MERRA-Land) data.

Rather than use annual averages for the climate variables, we used precipitation and temperature of the growing season (Table 2.1). Furthermore, precipitation and temperature are extracted for the rain-fed agricultural areas in Australia (shown in Fig 2.1).

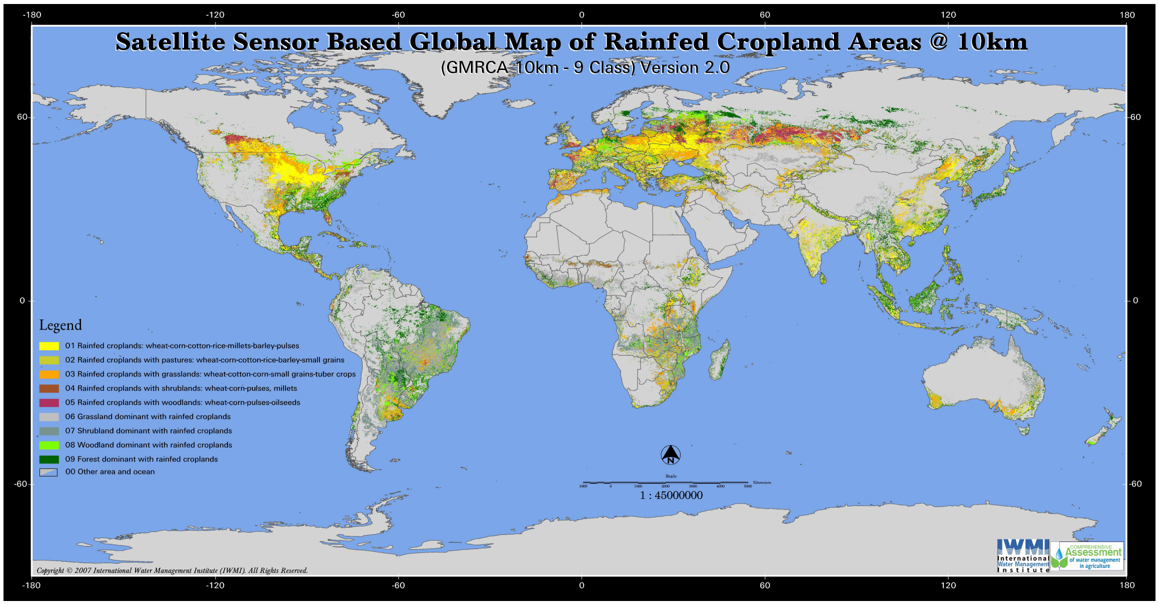

Figure 2.1|Satellite Sensor Based Global Map of Rain-fed Cropland Areas (obtained from http://waterdata.iwmi.org/)

The annual crop yields for 1980-2012 were obtained from the Food and Agriculture Organization (FAO) of the United Nations. The five crops used in this study are broadly grown in the rain-fed areas of Western and South-Eastern Australia. Wheat, Canola and Barley usually seed in May and harvest in October, while the growing season of Broad beans and Lupins are from June to November (ABARES, 2013). We use 6-month scale climate indices to cover the growing season of five different crops chosen in the study respectively (Table 2.1).

Table 2.1| Growing Season of The Crops and The Specific Climate Indices

Crops	Growing Season	SPI/SSI/MSDI
Wheat	May-October	6-month, October
Broad beans	June-November	6-month, November
Canola	May-October	6-month, October
Lupins	June-November	6-month, November
Barley	May-October	6-month, October

2.2 Dependence Analysis

2.2.1 Copula

To model the relationship between the drought indicators and yields of rain-fed crops, the approach of copulas is applied in the study. In statistics, copulas are functions used to link two or more univariate distributions to form multivariate joint distribution (Sklar, 1959,1973). Each copula function of random variables is constructed with marginal distributions that are uniform parametrically. The approach is useful and convenient for examining the dependence structure between the variables by estimating multivariate joint distribution independently of the marginal distribution functions (Nelsen, 2006). To model the joint distributions of different couples of drought indicators and yields of rain-fed crops, we adopted a bivariate copula fitted to the historical data and estimated the parameters of each copula function of different combinations.

For the case of bivariate problem, we consider two continuous random variables X and Y, describing drought indicator and crop yield respectively. Assume $\boldsymbol{F_X}(x)$ and $\boldsymbol{F_Y}(y)$ denote the marginal cumulative distribution functions of X and Y. The values of variables are firstly transformed into values in the interval $\mathbb{I} = [0,1]$ through probability integral transform method. Then, the joint distribution of X and Y can be described with a copula C as:

$$\boldsymbol{F_{XY}}(x, y) = \boldsymbol{C}(\boldsymbol{F_X}(x), \boldsymbol{F_Y}(y)) \tag{1}$$

There is a range of copula families for modeling dependence structure between the stochastic variables, for example, Gaussian copula, the Student's t-copula and the class of Archimedean copulas (Nelsen, 2006). The Archimedean copulas (e.g. Clayton, 1978; Gumbel, 1960; Frank, 1979) are capable of building joint distribution function of random variables with only one parameter. Thus, the families of Archimedean copulas are widely adopted for dependence structure modeling. Here, a Frank copula (Frank, 1979) from Archimedean class is adopted to model the dependence structure between the drought indicators and yields of rain-fed crops. The bivariate Frank copula can be expressed as:

$$\boldsymbol{C}_{\boldsymbol{\theta}}(\boldsymbol{u},\boldsymbol{v}) = \frac{1}{\theta} ln\left(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{e^{-\theta} - 1}\right) \quad (2)$$

where θ is the parameter, and $\boldsymbol{u}$ and $\boldsymbol{v}$ are the marginal distributions of transformed variables which are uniform on $\mathbb{I} = [0,1]$. In this study, $\boldsymbol{u}$ and $\boldsymbol{v}$ denote the marginal distributions of drought indicators and yields of rain-fed crops, respectively.

2.2.2 Parameter Estimation

Maximum likelihood estimation (MLE) is a prominent approach used in parameter estimation for different copulas. Assume two random variables X and Y describing drought indicator and crop yield respectively with their joint distribution function $\boldsymbol{F}_{\boldsymbol{XY}}(x,y)$ and marginal probability density functions $\boldsymbol{f}(x)$ and $\boldsymbol{f}(y)$. The joint density function can be written as:

$$\boldsymbol{f}_{\boldsymbol{XY}}(x,y) = \frac{\partial^2 \boldsymbol{F}_{\boldsymbol{XY}}(x,y)}{\partial x \partial y} \boldsymbol{f}(x)\boldsymbol{f}(y) \quad (3)$$

MLE estimates the parameter θ by maximizing log-likelihood:

$$\log \boldsymbol{\mathcal{L}}(\theta; x, y) = \log \boldsymbol{f}_{\boldsymbol{XY}}(x, y|\theta) \quad (4)$$

In this study, combining equation (1), (2), (3) and (4), the parameter θ in each copula function of different combinations of drought indicators and crop yields can be estimated through MLE approach.

2.2.3 Measure of Association

The association between stochastic variables can be measure in different ways. Pearson linear correlation coefficient, which is a traditional index of association, evaluates the degree of two random variables linearly correlated. However, in most cases, the association between stochastic variables is nonlinear. In the case of nonlinear association between variables, concordance measurement is usually been considered. Assume two random variables X and Y, if the observed values of X and Y increase/decrease simultaneously, the two variables are concordance. Spearman's correlation coefficient and Kendall's correlation coefficient are the usual method to estimate the concordance of two random variables. The copula-based association measurement remains invariable with the strictly monotonously increasing transformation (Nelsen, 2006). The two coefficients are related to the copula functions, regardless of the marginal distributions of variables. Schweizer and Wolf (1981) described the two correlation coefficients in terms of copula functions. To evaluate the concordance of different drought indicators with rain-fed crop yields used in this study, we apply Kendall's correlation coefficient based on the copula framework, which is useful and convenience to be employed in the measurement of association between variables.

In this study, we use the Kendall τ rank correlation coefficient for a bivariate Frank copula expressed as:

$$\boldsymbol{\tau = 1 + 4[D(\theta) - 1]/\theta} \tag{5}$$

where $\boldsymbol{D(\theta)}$ is a so-called "Debye" function defined using the integration variable t as:

$$\boldsymbol{D(\theta) = \frac{1}{\theta}\int_0^\theta \frac{t}{exp(t) - 1}dt} \tag{6}$$

The values of the coefficient range from -1 to 1. Two variables are in accordance with each other when the value is close to 1. When the value is close to -1, it indicates that the two variables have a negative correlation with each other. The variables are independent if the value of the coefficient equals to 0.

RESULTS

3.1 Time series analysis

Figure 3.1 displays the comparison of year-to-year variability of Australia wheat yield with three drought indicators for the period of 1980-2012. From the observation of the figure, we note that both the yield of Australia wheat and three drought indicators have been highly variable in recent decades. Such fluctuations indicate that Australia crop production is closely related to climate variations.

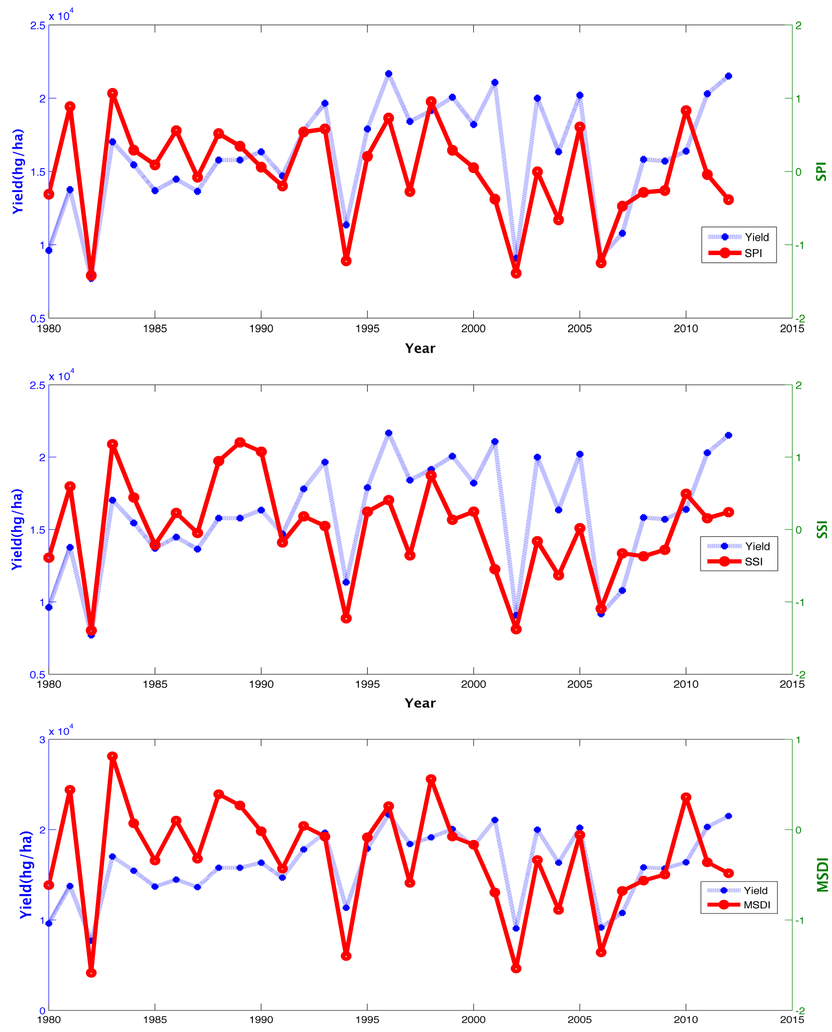

Figure 3.1| Time Series of SPI (top), SSI (middle), MSDI (bottom) and wheat yield in Australia, 1980-2012

As it is shown in Figure 3.1, the variation pattern of the observed yield of Australia wheat during 1980 to 2012 is similar to different drought indicators (SPI/SSI/MSDI). All of the three drought indicators have good relationship with the crop yield. This similar change pattern of wheat yield and three drought indicators suggest that one can use these drought indices to predict the rain-fed crop yields. Similarly, we investigated the other four common crops namely broad beans, canola, lupins and barley in Australia rain-fed areas.

Figure 3.2 displays time series of yields (blue line) of (a) wheat, (b) broad beans, (c) canola, (d) lupins and (e) barley grown in the rain-fed areas of Australia and their corresponding growing season SPI (red line) during 1980 to 2012. All of the crops' yields show good relationship with SPI, especially for canola and lupins. As it is shown in the figure, while the value of SPI increasing/decreasing, the yields change accordingly. The consistency between variability of SPI and crop yields in inter-annual time series is apparent. Only in 2012, the change in yields is not in line with climate variability. The crop yield increases despite a decline in precipitation. Other than climatic factors, crop production could also be influenced by some human activities such as land management for increasing the yields and improvement of cultivar in recent years. Crop productions are closely associated with the effective precipitation during the growing season. The obvious physical relationship between SPI and crop production is clearly identified in Figure 3.2. In general, the variability in yields is in line with the SPI, which indicates that it is possible to apply SPI to reflect the trend of rain-fed crop yields.

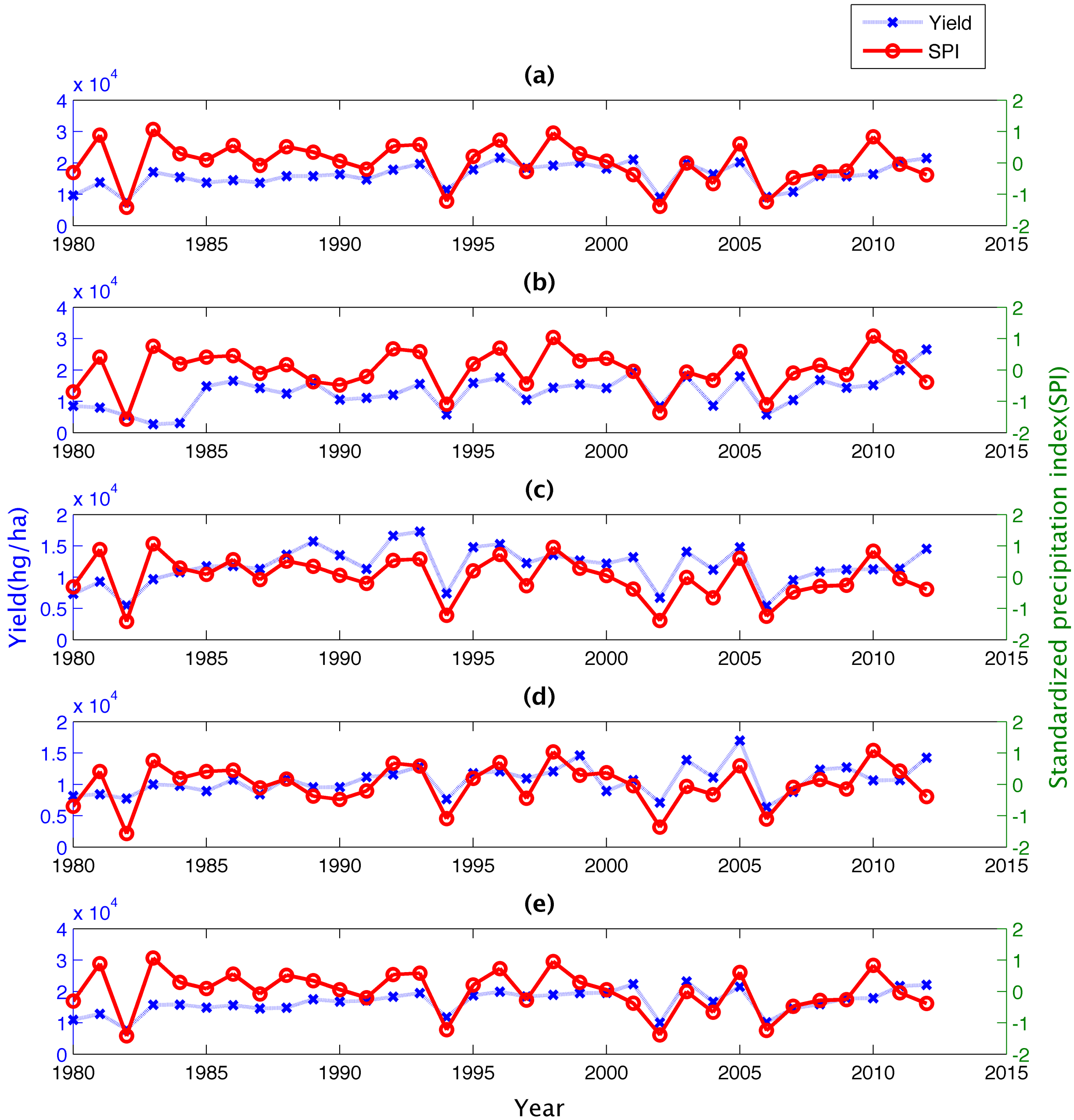

Figure 3.2| Time Series (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields in Australia against SPI, 1980-2012

Soil moisture is another important factor that correlated closely to crop growth. The metabolism of crop plants is closely related to the water contained in soil, and this is what the SSI reflects. If the SSI decreases a lot, it means the soil contains little water for plant to utilize. This results in a slow metabolism of plant, and brings less crop production. Moreover, plant cannot live under a certain level of soil moisture. Therefore, the condition of soil moisture is one of the key factors to influence the production of crops.

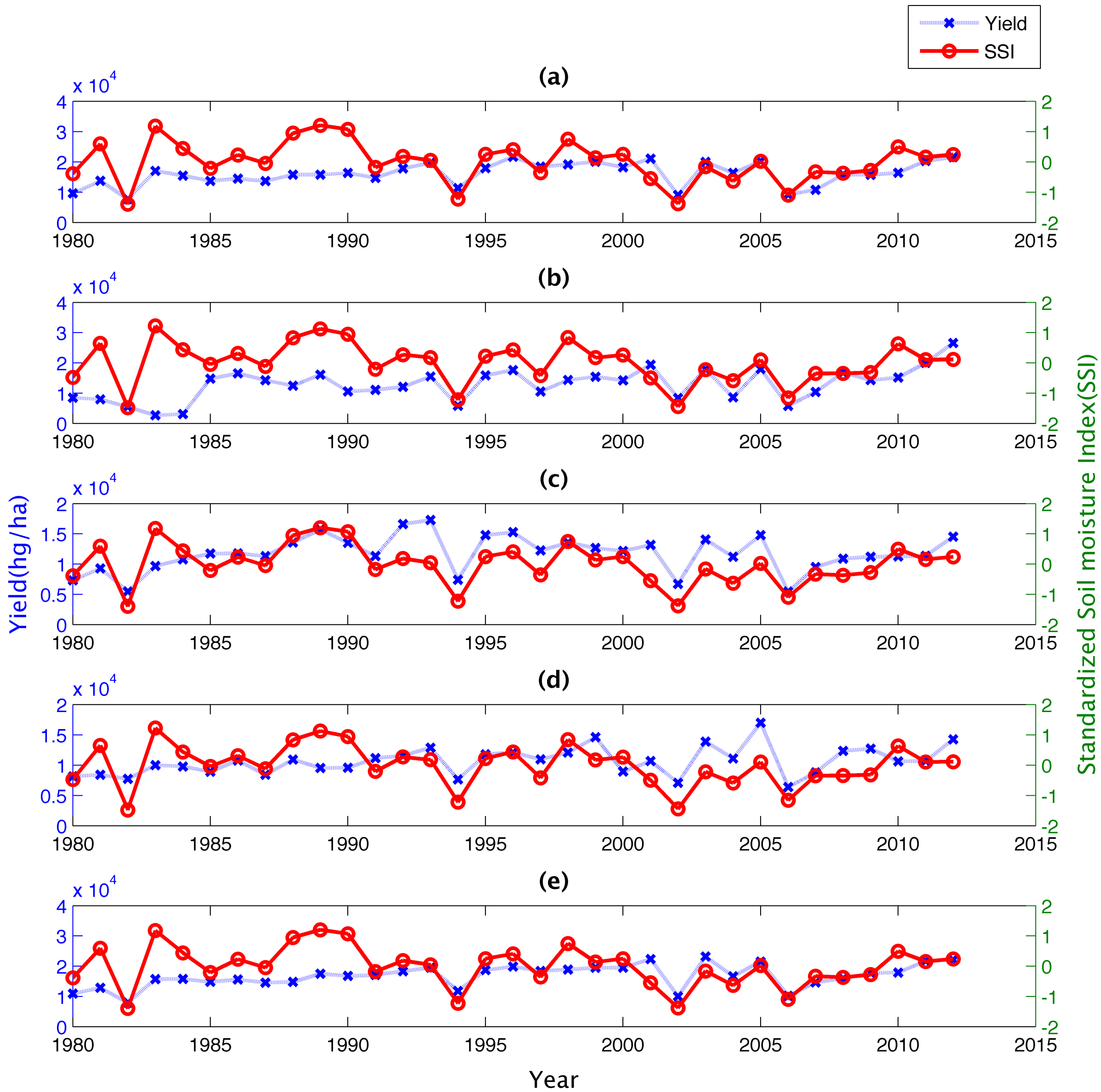

Figure 3.3| Time Series of Australia (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields and SSI, 1980-2012

Figure 3.3 compares time series of yields (blue line) of (a) wheat, (b) broad beans, (c) canola, (d) lupins and (e) barley grown in the rain-fed areas in Australia and their corresponding growing season the SSI (red line) during 1980 to 2012. It is also shown good relationships between all of the five crop yields and the SSI as the figure displays. We note that in the figure, the yield of canola(c) shows the strongest association with the SSI among the five crops chosen in the study. In most years, the yield of canola changes in the same way when the SSI increases or decreases. The overall trend of yields for the five rain-fed crops is substantially close to the trend of the SSI. It suggests that, besides precipitation, Australia's rain-fed crop yields could also have a strong relationship with the soil moisture conditions in the growing area. Furthermore, it could be evidence that application of climate indices on reflecting the trend of some rain-fed crop yields in Australia was feasible.

As precipitation and soil moisture jointly influence the agricultural production and the SPI and the SSI are both have good relationship with different crop yields during recent decades, the MSDI, combining the SPI and SSI, incorporates precipitation and soil moisture using the joint distribution function of the two variables, are of great importance to be considered in the climate-yield relationship research.

Figure 3.4 displays time series of yields (blue line) of (a) wheat, (b) broad beans, (c) canola, (d) lupins and (e) barley grown in the rain-fed areas in Australia and their corresponding growing season MSDI (red line) during 1980 to 2012. The MSDI exhibit a very similar change patterns as the plots of the SPI shown in Figure 3.2. It reveals that the MSDI also have good consistency with the crop yields. The good satisfactory agreements between different rain-fed crops and the three drought indicators suggest that one can use these drought indices to predict the rain-fed crop yields.

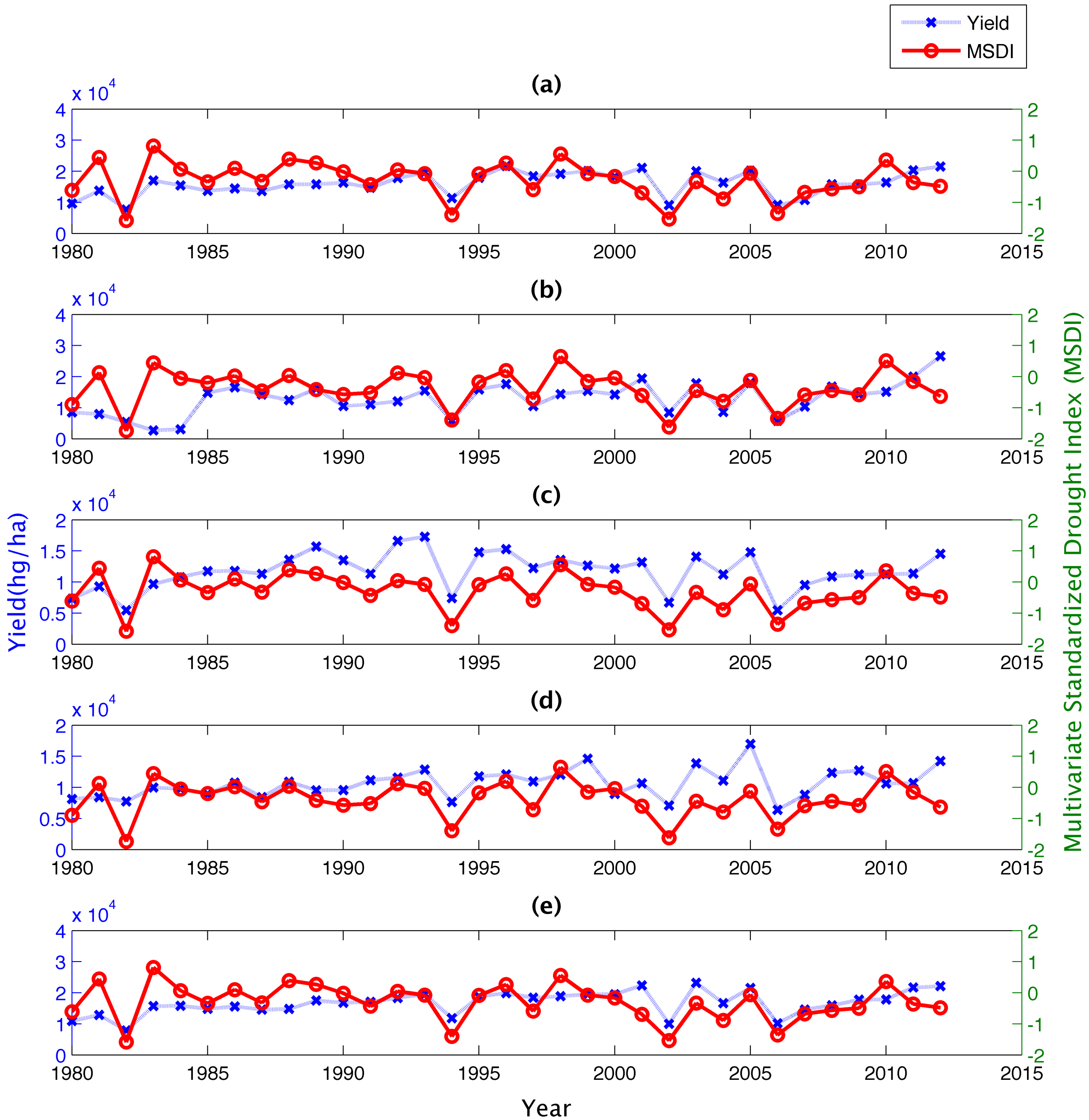

Figure 3.4| Time Series of Australia (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields and MSDI, 1980-2012

In general, from observation of Figure 3.2, 3.3, 3.4, the consistency between variability of SPI/SSI/MSDI and crop yields in inter-annual time series is apparent. The SPI and the MSDI have very similar change pattern with crop yields. These results are based on the observation of the plots of time series during 1980-2012. To evaluate the relationship more accurately, a statistical analysis is shown in the next section.

3.2 Dependence analysis

To statistically investigate the dependence structure between each climate index and crop yield, we fit a Frank copula from Archimedean classes to data in this study and jointly analyze the association with different couples of drought indicators and Australia rain-fed crop yields.

We estimated the parameter of each copula for different couples of Australia rain-fed crop yields and drought indicators using Copulafit programed in Matlab. By introducing the estimated parameters into Equation (2) in section 2.2.1, we obtained joint distributions of different couples of crop yields and drought indicators. Figure 3.5,3.6,3.7 displays contour lines of joint distributions of yield of (a) wheat, (b) broad beans, (c) canola, (d) lupins and (e) barley grown in the rain-fed areas of Australia during the period of 1980 to 2012 and SPI, SSI, MSDI, respectively. The joint distributions based on copula show dependence structure between drought indicators and crop production. Given a specific joint probability and precipitation, one can obtain yield of different crops.

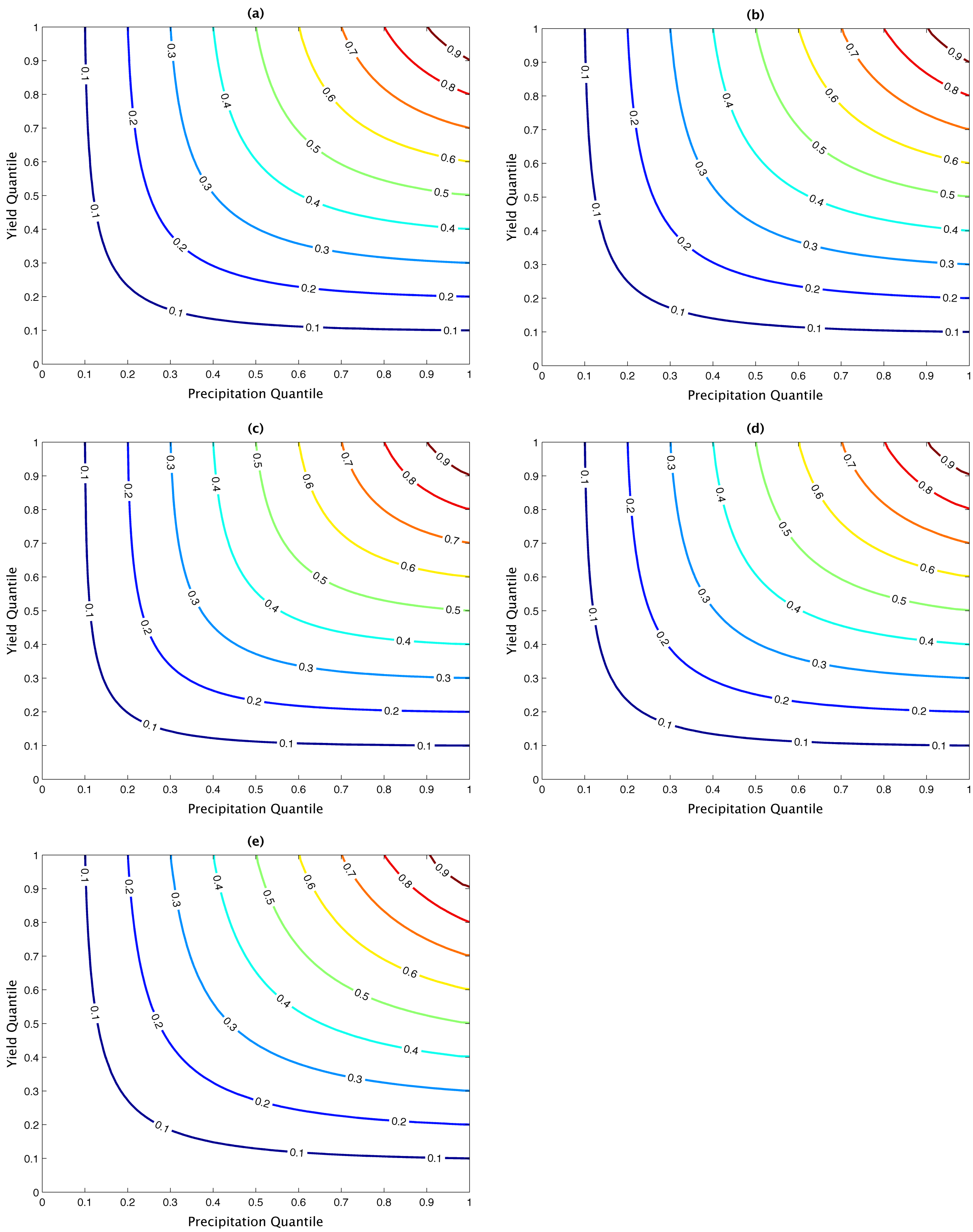

Figure 3.5| Joint Distributions of Australia (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields and SPI, 1980-2012

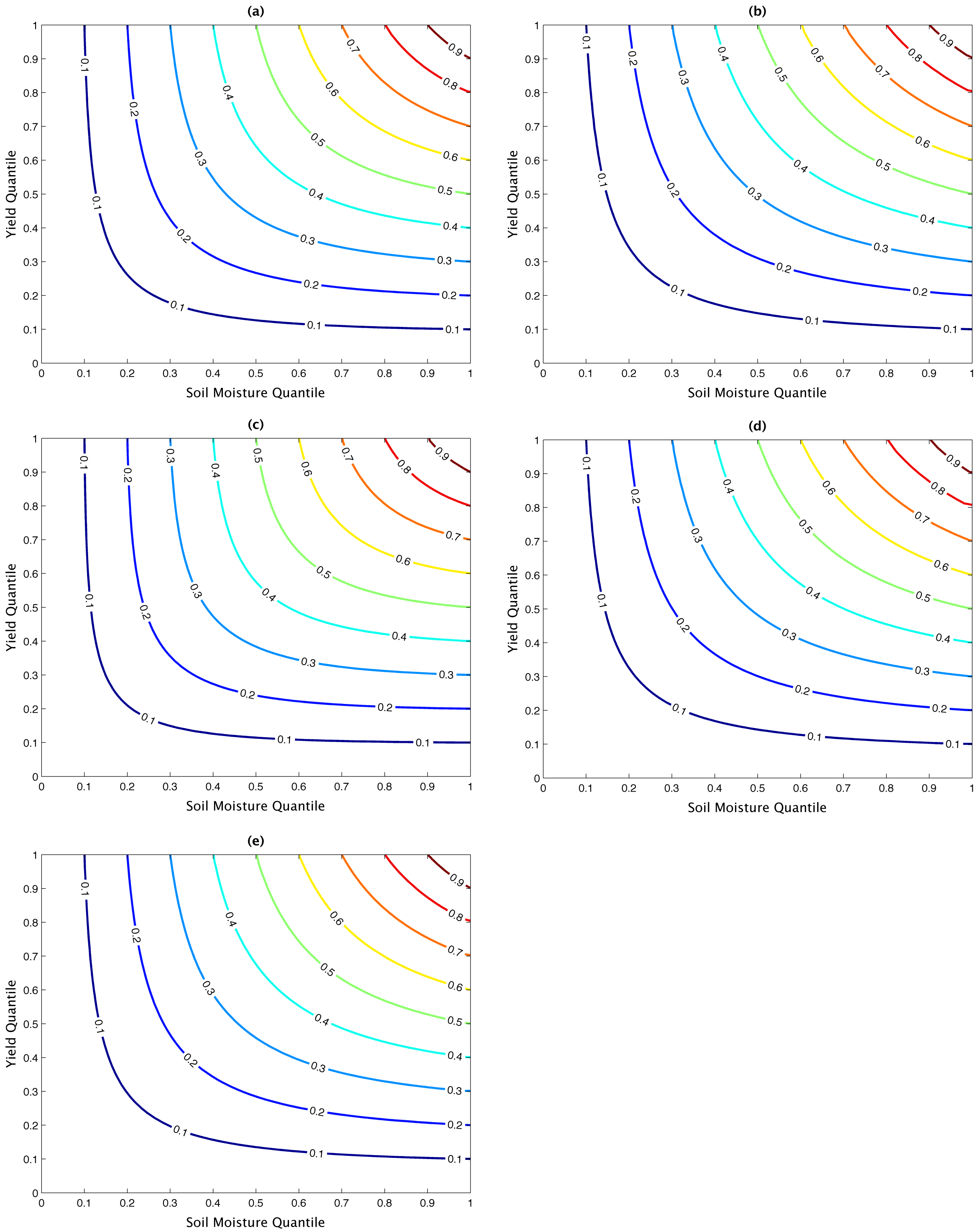

Figure 3.6| Joint Distributions of Australia (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields and SSI, 1980-2012

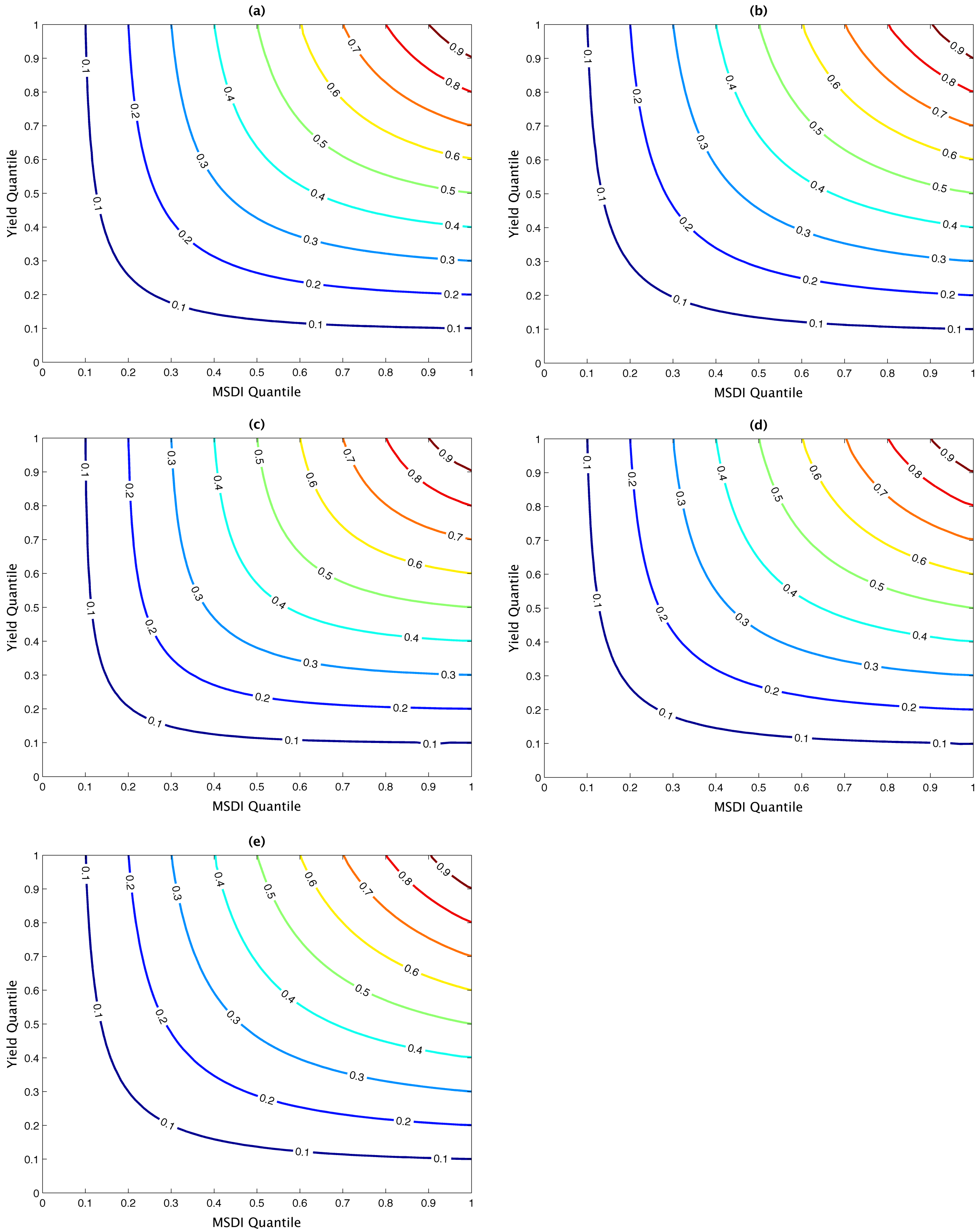

Figure 3.7| Joint Distributions of Australia (a) Wheat, (b) Broad beans, (c) Canola, (d) Lupins, (e) Barley Yields and MSDI, 1980-2012

SUMMARY AND CONCLUSIONS

Although precipitation and soil moisture are not the only factors that could decide food production, they do play critical role in crops' growth. By analyzing the time series of yields of five crops grown in the rain-fed areas in Australia and three drought indicators (SPI/SSI/MSDI) during the period of 1980-2012, we notice that both the yield of Australia wheat and three drought indicators have been highly variable in recent decades. All of the three drought indicators have good relationship with yields of the five rain-fed crops. The similar change pattern in the inter-annual historical observed records indicates the close association between the drought indicators and rain-fed crop production in Australia.

Using multivariate copulas, the study relates changes in climate variability to changes in crops production during 1980-2012. By fitting a Frank copula to the bivariate data, we obtained the joint distribution of each drought indicator and crop yield. The copula-based joint distributions show dependence structure between drought indicators and crop productions. The model describes the relationship between drought and crop production using copulas and offers the likelihood of crop yield given an observed or predicted SPI, SSI or MSDI.

The Kendall's rank correlation coefficient of each couples of drought indicators and yields of rain-fed crops in this study shows association with the three drought indicators. SPI and MSDI show the strongest concordance with all of the five rain-fed crops according to the relatively high correlation coefficient in this study.

The proposed model can be used to assess the probability of crop yield exceeding a certain threshold if precipitation or soil moisture is known. Knowing both precipitation and soil moisture, hence MSDI, one can derive probability of exceedance of crop yield for thresholds of interest (e.g., above average yield or yield above 75^{th} percentile).

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