Climate and the Spatial-Temporal Distribution of Winter Wheat Yields:

Evidence from the U.S. Pacific Northwest

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Introduction

The past decade has seen a resurgence of interest in modeling crop yields as a function of weather and other variables, and using those models to project possible impacts of climate change on crop yields (Chen et al. 2004; Schlenker et al. 2005; McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009; Lobell, Schlenker and Costa-Roberts 2011; Fisher et al. 2012; Deschenes and Greenstone 2012; Tack, Harri and Coble 2012; Roberts, Schlenker and Eyer 2012). Virtually all of this literature has focused on what can be interpreted as predictions of mean yields for some spatial unit such as a county or an agro-ecozone.

In this paper, our main goal is to contribute to the development of methods for analysis of climate impacts on yield distributions, using the partial-moment model of Antle (2010). We discuss why this model is useful for analysis of changes in distributional characteristics, such as asymmetry and excess kurtoses (i.e., "fat tails"). We demonstrate how to use this model to investigate the distributions of county-average winter wheat yields in the Pacific Northwest region of the U.S., using a 32-year panel data set. We use the model to test further several hypotheses Antle (2010) proposed about the asymmetric effects of exogenous variables on output distribution moments, and about the value of partial moments to characterize asymmetry. Then we investigate how the yield distribution may be impacted by future climate, using down-scaled data from 14 Global Climate Models (GCMs) that are part of the fifth phase of the Coupled Model Inter-comparison Project (CMIP5). In addition, our analysis contributes to the literature on the distributions of county-level yields that has emerged from the literature on crop insurance and the issue of the normality of yield distributions.

Winter wheat in the PNW is an interesting case in that warming might arguably have a positive yield impact, at least for relatively small temperature increases, but these beneficial effects of warming could be constrained by water availability which can come from rainfalls or irrigation in a semi-arid environment. Climate projections for the PNW show increases in mean annual temperature of between 2-8^{o}C by the end of the 21st century, a reduction in the amount of precipitation falling as snow, and substantial changes to regional hydrology. Warming is likely to be accentuated in summer, but the seasonality of precipitation is likely to be amplified, and together with some winter warming could have beneficial impacts on winter wheat. Winter wheat is the major crop in PNW and about 16% of total U.S. production in 2010 was produced in this region (USDA 2013). Washington is one of the largest winter wheat producing states, and produced 118 million bushels (about 8% of total U.S. production) of winter wheat in 2010 (USDA 2013).

The next section presents some further brief comments on the recent literature. Then we present the model specification we use, followed by a description of the data and econometric results. Next we present projects of future yield distributions, followed by concluding remarks.

Previous Studies

Previous studies have found mixed results of temperature, growing season degree-days and precipitation effects on mean crop yields, depending on crops and regions (Lobell, Schlenker and Costa-Roberts 2011; Schenker and Roberts 2009; Fisher et al. 2012; Deschenes and Greenstone 2012; Reilly et al. 2003). One notable study by Schenker and Roberts (2009) found yields in U.S. increase with temperature up to 29^{o}C for corn, 30^{o}C for soybeans and 32^{o}C for cotton, but that temperatures above these thresholds reduce yields. Using a quadratic yield-temperature function and country-level data, Lobell, Schlenker and Costa-Roberts (2011) found larger negative effects of temperature and positive effects of precipitation in warmer countries for major crops (maize, rice, wheat and soybean), up to corresponding temperature and precipitation thresholds.

Some studies have addressed changes in the variability of crop production in response to inter-annual variability in temperature and precipitation and found that the mean climate conditions and their variability appear to contribute in a statistically significant way to not only mean crop yields but to their variability, although the magnitude of this effect varies across crops and locations (Chen et al. 2004; McCarl, Villavicencio, and Wu 2008). For U.S. maize yield, increased weather variability increases yield variability and decreases mean yield (Urban et al. 2012).

Modeling yields distributions using higher moments has a long history, but Tack, Harri and Coble (2012) appear to be one of the few studies that have done this to investigate impacts of climate change. They used Antle's (1983) moment-based approach combined with maximum entropy techniques to simulate how the distributions of county-average yields are affected by temperature and precipitation using cotton yield data from 1972 to 2005 for counties in Arkansas, Mississippi and Texas. However, a simple climate scenario of 1^{o}C uniform increase in temperature is not enough to present the robustness of results to climate uncertainty (Urban et al. 2012; Roberts, Schlenker and Eyer 2012).

There is a long history of econometric models of crop yields. Most such models characterize yield in a production function framework, specifying output or yield as a function of inputs and other farm characteristics, with effects of weather relegated to an error term. In contrast, the literature investigating effects of climate on yields takes a different approach, often specifying yield as a function of weather variables (typically, annual or seasonal mean temperature, total precipitation, and some other variables). In a number of studies, most management variables are not represented explicitly, a procedure which can be justified to some degree by interpreting the model as a "reduced form," but which may also lead to bias problems caused by mis-specification (Ortiz-Bobea and Just 2013). The literature on modeling yield distributions saw key contributions by Just and Pope (1978) who proposed a heteroskedastic additive-error (location-scale) model, and Antle (1983) who proposed a more general moment-based model of the mean, variance and higher-order moments. Other notable contributions include the model using the Beta distribution by Nelson and Preckle (1989) and the combination of that model with the Just and Pope's model by Du, Hennessy and Yu (2012). Antle (2010) showed how the moment-based model can be decomposed into partial moments to provide a more detailed representation of asymmetry and how it is affected by inputs and other exogenous factors. Also relevant is the literature on modeling crop yield distributions for analysis of crop insurance, and the related literature which has addressed whether crop yield distributions are normally distributed (Just and Weninger 1999; Koundouri and Kourogenis 2011).

The Moment-Based Model for County Average Yields

We begin by emphasizing that the model we are presenting here is designed to represent the distribution of county-averaged yields across counties in the space and time dimension. This distribution must be distinguished from the distribution of farm-level yields, say, within a spatial unit such as a county or an agro-ecozone. Moreover, because the county-level dataset we use is a continuous panel over 32 years, we are able to incorporate the time dimension into the analysis, something that cannot be done with most farm-level data that are cross-sectional surveys covering one or a few growing seasons.

Following Antle (2010), the production function is defined as $y = f(z,w)$, y is yield, z represents farm-specific bio-physical and economic characteristics, and w represents other stochastic factors that we interpret here as weather. The variables z and w are jointly distributed in a population of land units (call them farms in a county) for a specified time interval (call it a growing season) according to $\phi(z, w \mid \chi)$, where χ is interpreted as the parameters of the joint distribution of z and w, and can be interpreted as the representing the *micro-climate* for each county in each time period along with the distribution of other bio-physical and economic characteristics of the location. The micro-climates vary over space and time, themselves being realizations of a *macro-climate*. Thus, the county-average yield Y_{jt} is itself a random variable that varies according to the county's observable physical and economic characteristics, its micro-climate realizations, and other unobservable random processes. Following this logic, we hypothesize that the county-average yield follows a distribution $\Gamma(Y \mid X_{jt})$ where X_{jt} represents observable characteristics of the county j in period t. We define the mean of this distribution as $\mu_1\left(X_{jt}\right)$ and the higher-order central moments as $\mu_i\left(X_{jt}\right)$ for $i > 1$. Likewise we can define the negative and positive partial higher moments as $n_i\left(X_{jt}\right)$ and $p_i\left(X_{jt}\right)$ as defined in Antle (2010) by taking expectations of negative and positive deviations from the mean.

We use the preceding logic to formulate a model for the spatial-temporal distribution of county-average yields. Following Antle (1983), we specify a "linear moment model" for which the mean function is

(1) $$Y_{jt} = X_{jt}\gamma_1 + u_{jt}\ ,\ j = 1, \ldots, N\ , t = 1, \ldots, T$$

where Y_{jt} is crop yield in the j^{th} county in period t, X_{jt} is a vector of independent explanatory variables, and u_{jt} is a disturbance term with a mean of zero. Note that from the preceding discussion, X_{jt} could include climate variables representing the micro-climate parameters χ, and these parameters could be means as well as higher moments of observed weather realizations over space and time within a county. Also note that while linear in the parameters, this model can include quadratic terms, interactions and other functions of explanatory variables, as in a "flexible" functional form. The i^{th} moment function for county-average yields is,

(2) $$u_{jt}^{i} = X_{jt}\gamma_i + v_{ijt}\ , E\left(v_{ijt}\right)=0, \text{ for } i \geq 2,\ j=1,?..\ ?N\ ,t=1,\ldots,T$$

A key feature of the moment-based model is that it contains a different parameter vector γ_i for each moment function, thus providing a general representation of the yield distribution without imposing arbitrary restrictions on its properties. However, the model specified with "full" moments as in (2) does restrict the way that conditioning variables X can influence asymmetry described as negative and positive deviations from a reference point such as the mean. To provide a more flexible way to characterize and estimate asymmetric effects of inputs on output distributions, Antle (2010) proposed a partial-moment model that is a generalization of the full-moment model. Based on equation (2), the partial-moment functions can be specified as,

(3) $$|u_{jt}|^{i} = X_{jt}\gamma_{in} + v_{ijt\delta}\ , E\left(v_{ijt\delta}\right)=0\ ,i \geq 2\ ,\ j=1,?..\ ?N\ ,t=1,\ldots,T \text{ for } u_{jt}<0$$

(4) $$|u_{jt}|^{i} = X_{jt}\gamma_{ip} + v_{ijtp}\ , E\left(v_{ijtp}\right)=0\ ,i \geq 2,\ j=1,?..\ ?N\ ,t=1,\ldots,T \text{ for } u_{jt}>0$$

The flexibility of the partial-moment specification comes at a statistical cost of more parameters to be estimated, but this flexibility may be particularly important for representation of odd-order moments (Antle 2010). Using this model, the hypothesis of symmetric effects of inputs on moments can be tested by testing if $\gamma_{in}=\gamma_{ip}$ for each moment i or for all moments jointly. If this hypothesis is rejected, then the model can be used to evaluate the different effects that exogenous variables have on the negative and positive tails of the distribution.

Because we use panel data, it is likely that the errors in equation (1) exhibit autocorrelation. Following the procedures described in Antle (1983), we use the standard transformation of the mean equation (1),

(5) $$Y_{jt} - \rho Y_{jt-1} = \mu_{1jt} - \rho \mu_{1jt-1} + \varepsilon_{jt} \ , j = 1, \ldots, N, t = 1, \ldots, T$$

and we assume

$$u_{jt} = \rho u_{jt-1} + \varepsilon_{jt} \quad , |\rho| < 1$$

$$E(\varepsilon_{jt}^h \varepsilon_{j't'}^l) = \begin{cases} 0, j \neq j', t \neq t' \\ \mu_{h+l,jt}, j = j', t = t' \end{cases}$$

Note that under this error structure and the moment function specification in (2), it follows that the moments of the errors u_{jt} are equal to the moments of the ε_{jt} at the sample means of the exogenous variables. Thus, the higher- moment functions can be estimated by transforming the mean equation and then applying the procedures described above to the resulting residuals. We note that in this specification, we assume away spatial autocorrelation; extension of this type of analysis to include spatial autocorrelation remains a topic for future research.

An important feature of this model is the use of residuals taken to powers and used as dependent variables to estimate higher moments. A potential problem with this procedure – like all econometric procedures using residuals – is that specification errors in the mean function can be transmitted to the higher moments. Tack, Harri and Coble (2012) proposed the alternative procedure of estimating zero-order moments to avoid this potential problem. Note, however, that while this approach makes sense for the entropy method they propose, which can be implemented with zero-order moments, their method does not provide a convenient way to summarize the effects of exogenous variables on behavioral-relevant properties of distributions, such as changes in dispersion or skewness. If one does want to compute conventional measures of dispersion or skewness, then estimating zero-order moments does not eliminate the bias problem. For example, one can compute the variance of a random variable as the difference between the zero-order second moment and the mean squared. Thus, if the mean is estimated with bias due to mis-specification, that error squared will be transmitted to the estimated variance. To address the mis-specification problem, our approach is two-fold: first, we use a "flexible" functional form for the mean function; and second, we test for the robustness of the higher-order moment functions to alternative specifications.

Data

County level winter wheat yields, planted acres and irrigated acres from 1979-2010 in PNW were collected via the National Agriculture Statistics Services (NASS). In order to control soil quality, we include soil characteristic variables, including soil erodibility K-factor, slope length, salinity, fraction flood-prone, wetlands, fraction sand, faction clay, moisture capacity and permeability, for 2002, obtained from Deschenes and Greenstone (2012) and Fish et al. (2012). We constructed the index of irrigation management as the proportion of irrigated acres to the total winter wheat planted. Lacking input data at the county level, we use real per capita income and population obtained from the Bureau of Economic Analysis, and a time trend, as proxies for technical efficiency and management.

Regarding weather variables, the standard agronomic approach for modeling temperature is to convert daily temperatures into degree-days, which represent heating units and is an important indicator to capture the nonlinear effect of temperature on crop yields (Thomas Hodges 1991; William Grierson 2002; Schlenker et al. 2005; Schlenker and Roberts 2009). Schlenker et al. (2006) and Deschenes and Greenstone (2012) use the definition of degree-days with the lower threshold equal to 8 °C and the upper threshold to 32 °C [1] and summed over the growing season to get the seasonal degree days. Following Schlenker et al. (2006), we define the level beyond 32°C as the harmful threshold for crop growth, but note that for winter wheat in the

[1] In other words, a day with a temperature below 8 ^{o}C results in zero degree days; a day with a temperature between 8 ^{o}C and 32 ^{o}C contributes the number of degrees above 8C; a day with a temperature above 32^{o}C degrees contributes 24 degree days.

PNW region such temperatures are rare. In the PNW, winter wheat is typically planted in September and October and harvested in July and August of the following year (USDA 2010). Based on crop growth processes, we defined the growing season as the reproductive period of winter wheat from November through April[2] and use mean growing season temperature, total growing season precipitation and growing season degree-days with temperature between 8^oC to 32^oC to represent the micro-climate of the county. These data were obtained from the CMIP5 Statistically Downscaled for Western USA (http://nimbus.cos.uidaho.edu/MACA/).

Another factor affecting crop growth in the PNW region is drought, defined as a pattern of temperature and precipitation that is unfavorable to crop growth. We constructed indices of extreme drought weather based on the information of Palmer drought severity index (PDSI), which uses a 0 as normal, with drought indicated by negative numbers. Using this index we constructed two dummies, $Moderate\ Drought = 1$ if $-2 \le PDSI < 0$, otherwise 0; and $Severe\ Drought = 1$ if $PDSI < -2$, otherwise 0.

Projected climate data

Nearly forty CMIP5 GCMs were evaluated for their ability to capture spatiotemporal characteristics of climate in the PNW (Rupp et al. 2013). Irrespective of model skill in simulating historic climate, GCM projections run with two emission scenarios (RCP45 and RCP85[3]) show substantial changes in seasonal climate of the PNW over the 21st century. As shown in Table 1. These changes include significant and unanimous increases in temperature, with most acute warming during the summer months. Slight increases (5%) in annual mean precipitation are projected, with over 75% of the models showing an increase in precipitation.

[2] We also test the model specification with growing season defined from November to June, and find consistent results to table 4 and table 5 in this paper.
[3] RCP85 refers to business-as-usual with an additional 8.5 W m^{-2} (~1370 ppm CO_2 equivalent) by 2100 and RCP45 refers to a particular experiment in which a "representative concentration pathway" (RCP) has been specified which leads to an approximate radiative forcing of 4.5 W m^{-2}(Riahi, Gruebler and Nakicenovic 2007).

However, models project that most of the increase in precipitation will be manifest during the cool season, with decreased precipitation during June to August. These projections are very similar to the previous generation of modeling results as documented by Mote and Salathe (2010).

Daily output from 14 of the CMIP5 models was statistically downscaled using the Multivariate Adaptive Constructed Analogs method (Abatzoglou and Brown 2012) to 4-km resolution using the same training dataset used in our historical analysis. Downscaling was completed for both historical forcing (1950-2005) and for future emission scenarios, RCP45 and RCP85, from 2006 to 2100. Growing season degree-days and drought index were calculated following the same procedure as previously mentioned.

Table 2 provides summary statistics of the data. To test whether higher moments of the micro-climate affect county-average yields, we also included the standard deviation of temperature over the growing season (precipitation variability cannot be calculated using the available data). Following other studies, we specify the model to be quadratic in mean temperature and total precipitation with interactions between these variables and the irrigation (Lobell, Schlenker and Costa-Roberts 2011; Schlenker and Roberts 2006; 2009; Roberts, Schlenker and Eyer 2012).

Estimation Results and Hypothesis Tests

Using the model and data described above, we can test a variety of hypotheses that are motivated by the agronomic, economics and climate change literatures.

Yield distributions are stationary and exhibit autocorrelation

To test the presence of unit root in panel data, we use Fisher-type tests (e.g., Augmented Dickey-Fuller unit-root tests and Phillips-Perron unit-root tests) to test for unit roots of variables in the mean equation, with the null hypothesis that all the panels contain a unit root (Choi 2001). As shown in table 3, Augmented Dickey-Fuller Unit-root test results show that all variables reject the null hypothesis of unit roots for all cross-sections of the panel, suggesting it is not necessary to difference the variable before being included in the estimation model. Although our data show that yields are stationary, there may be autocorrelation in the errors, e.g., due to the effects of soil moisture carry-over from the previous season. Wooldridge's test for autocorrelation in panel data (Drukker 2003; Wooldridge 2002) rejects the null hypothesis of no first-order autocorrelation with a F-value of 40.46 (p=0.000). Thus, we apply the moment-based model to the autocorrelation-transformed data as described above (equation (5)).

The mean and higher moments of county-level yield distributions are functions of climate variables

Table 4 shows estimates of the mean, second-, third- and fourth- order full moment functions. All full moment functions are statistically significant functions of the exogenous variables except for the third full moment (see further discussion below), and many climate variables are statistically significant. The upper part of table 6 presents the calculated marginal effects and elasticities of variables with quadratic and interaction term in full moment estimations. Controlling for soil characteristics, the mean equation estimates show that a higher mean temperature increases winter wheat yield to a threshold of 3.4 ^{o}C and then reduces it, with an elasticity of effect of 0.45 at the sample mean. An important implication is that higher average temperatures of more than1.4 ^{o}C would reduce yields, and as table 1 shows, mean temperature increases are projected to be larger than this as soon as the 2030s. The model shows that higher temperature variation also increases the crop yield. Although other studies show that variability of temperature increases the variance and reduces the mean yields (Urban et al. 2012; McCarl, Villavicencio, and Wu 2008), table 4 shows that this is not the case for winter wheat production in PNW. One explanation for this finding is that in this system where the mean temperature over the growing season is around 2^{o}C, an increase in temperature variation may shift outward the maximum potential yield, thus increasing the mean and also increasing the negative tail of the distribution as evidenced by the effect on the third full moment and on the partial moments.

Similar to the effect of temperature, winter wheat will increase along with the total precipitation over the growing season to a threshold of 178 cm and then decline, and these results are consistent with previous studies of the relationship between precipitation and mean crop yield (Roberts, Schlenker and Eyer 2012; Lobell, Schlenker and Costa-Roberts 2011; Schlenker and Roberts 2009). As expected, total precipitation and irrigation are substitutes. Controlling all other variables at their means, the marginal effects of precipitation on mean winter wheat yield is 0.07 and the elasticity is 0.18.

The results also show that crop yields decrease with extreme drought, although the mean effect is a relatively small, about 3 bushes per acre. In determining the mean crop yield, irrigation is another important factor. Controlling all other variables at their means, the marginal effect of irrigation on the mean crop yield is 31 with the elasticity of 0.37. Other variables including total population and per capita income are also statistically significant, suggesting that crop yield will increase if technology and management are improved. In addition, there is an inverted U-shape time trend to capture the effect of technological progress on crop yield.

For higher order moment equation estimations, the third moment function is not statistically significant with the overall p-value equals to 0.12. Therefore, we only interpret results of the second and fourth moment functions. As we discuss below, however, the third partial moments are statistically significant.

Total precipitation over the growing season has an inverted-U shape effect on the second and fourth moment of winter wheat yield distributions, by first increasing to some thresholds (86cm for the second and 89cm for the fourth moment) and then decreasing. With increased (reduced) “fat tails” by increased total precipitation (over a threshold), the probability of a county to have extreme yields, including low and high, will increase (decrease). Correspondingly, the variance of county yields will change.

Unsurprisingly, increased severe drought will increase the variability and “fatness” of the tails of the yield distribution. Following our argument above, the 2012 drought in Midwest is an example of how extreme weather destroyed or damaged yields of corn and soybeans, resulting extremely low yields and high variability of county yield distributions.

The second moment of winter wheat yield distribution is reduced by irrigation alone but will increase as precipitation goes up. The marginal effect of irrigation on the variance of winter wheat yield is about 43 considering the strong interaction effect, with a small elasticity of 0.12. In addition, mean temperature and moderate drought will also increase yield variability with the marginal effect of temperature equals to 3.7 and elasticity of 0.06.

The effects of climate variables on yield distributions are asymmetric

Table 5 shows estimates of the second, third and fourth partial moment functions along with the symmetry test results. The tests for equality of the negative and positive partial moment function parameters are all strongly rejected. Inspection of the parameters confirms that this is due to a logical pattern of effects of the climate variables. To account for the quadratic form of the model with the irrigation interaction, the marginal effects of temperature and precipitation were calculated for low and high values of the irrigation variable, and at the sample means of all variables (Table 6 and Figure 1). When irrigation is very low, the marginal effect of temperature on the lower tail is positive, but this effect decreases as irrigation increases. Unlike the case of temperature effects, increased irrigation reduces the positive marginal effects of precipitation on the upper tail but increases the positive effects on the lower tail, consistent with the substitution between irrigation and precipitation.

Higher temperatures and drought conditions increase the "fatness" of yield distribution tails

As shown in table 5, mean temperature is statistically significant on the fourth partial moment. Higher temperature increases the fatness of the lower tail, resulting in higher probability of low yields. However, this effect is reduced by the strong interaction effect with irrigation. As irrigation rate goes up, the marginal effect of temperature will decrease the fatness of the lower tail (please see the solid gray lines in figure 1). The relationship between higher temperature and increased "fat tails" could also be explained by the effect from the severe drought index. As weather gets extremely droughty, the yield distribution is more likely to have "fat tails" (results from table 4), and more specifically, the "fatness" is stronger in the lower tail as shown in table 5.

Projection under Future Climate Scenarios

Since our statistical model captures the yield distributions in response to weather variables to a reasonable degree, we proceed to predict the shape of yield distributions for two periods, 1980-2010 and 2006-2100, using CMIP5 projections for 14 GCMs and 2 emission scenarios (i.e., RCP45 and RCP85). By the end of this century, average temperature and total precipitation over the growing season are expected to increase in PNW, and inter-annual standard deviation of temperature is also expected to increase in most counties. Using parameters estimated from our statistical models, varying all climate variables and controlling all other variables at their sample means, figure 2 shows the predicted historical yields under climate effects[4]. Compared to the observed historical yields, our predicted yields have the same trend as the observed one.

Using projected future climate data from 14 GCMs, we predict the mean of winter wheat yield distribution under two emission scenarios (RCP45 and RCP85) as shown in figure 3. Generally speaking, the mean winter wheat yield is increasing under future climatic conditions; however, the magnitude depends on the GCMs and emission scenarios we choose. In most cases, the increasing trends under two emission scenarios are very close in the early period, while they are distinguished with each other by the end of this century for all cases and the mean winter wheat yield increases more under the higher emission scenario (RCP85), which projects a higher temperature and less precipitation (on average from table 1). Nevertheless, winter wheat production in PNW will benefit from future climate change partly because the current mean temperature is relatively low. Although all GCMs project increased temperature by 2100, it will continue to have positive effects on winter wheat production unless the combined effects of temperature and precipitation become unfavorable.

Following the same procedure, we predict values of the second and fourth full moment under future climate scenarios in figure 4 and figure 5, respectively[5]. On average, the variability of winter wheat yield is decreasing in some cases, while increasing in others. Compared to RCP45, the absolute values of changes in the second moment is much larger under RCP85, although the magnitude is depending on which GCM climate data we use. Figure 4 also shows that it is necessary to use climate data from multiple GCMs when looking in future. Using one or

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[4] For estimation purpose, we transferred our data to correct serial correlation for the mean equation. Thus, to get correct predicted values of the mean yield equation, we use equation (5) and estimated parameters to predict the mean yield as, $\hat{y}_{jt} = \hat{\rho} y_{jt-1} + \hat{\gamma}_1 (X_{jt} - \hat{\rho} X_{jt-1})$. If using the lagged predicted error $\hat{u}_{jt-1}$ from equation (1), we then can get the correct predicted mean yield, $\hat{y}_{jt} = X_{jt}\hat{\gamma}_1 + \hat{\rho}\hat{u}_{jt-1}$.

[5] Our estimation model of the third full moment is insignificant, thus, we only predict values of the second and fourth moment.

two GCMs or emission scenarios is not sufficient to capture the uncertainty of future climate change.

As shown in figure 5, predicted values of the fourth moment have a declining trend by the end of this century in most cases; however, they barely change when using climate data from GCM10 (i.e., inmcm4), which projects a large drop in precipitation and small increase in temperature (see table 1 for details). Even with a trend, the trend is flatter under RCP45 than that under the "business as usual" emission scenario (RCP85).

In conclusion, results from figure 3, 4 and 5 show that future climate change will re-shape the distribution of winter wheat yield in PNW, although the magnitude of this shift depends on which GCM climate data and emission scenario we use as inputs.

Concluding Remarks

In this paper, we first examine how historical climate conditions affect the distribution of winter wheat yield using the moment and partial moment based approaches developed by Antle (1983; 2010); and then predict how future climate change will re-shape the yield distribution using projected climate data from 14 GCMs and 2 emission scenarios.

The winter wheat yield distribution is substantially determined by climatic variables. Mean temperature and total precipitation affect not only mean yield, but also the second and fourth full and partial moments. Due to the asymmetric effects of climate variables on higher-order full and partial moments, we found higher temperatures and drought conditions are likely to increase the variability, skewness and fatness of the lower tail of winter wheat yield distribution and total precipitation would increase the upper tail, up to a threshold.

When predicting to the future, we found mean yield has an increasing trend across all GCMs and 2 emission scenarios. However, the direction of changes in second and fourth full moment is not certain, depending on which GCM climate data and emission scenario we use. This result raises a concern for assessing climate change impacts in a regional or global study: how many and which GCM and emission scenario should we use? Due to the uncertainty of future climate change implied by the climate projections, it would be an interesting extension to compare predicted results in this paper with that from other model groups, i.e., crop simulation models, particularly considering that GCMs have shown to under predict the magnitude of inter-annual to decadal variability for the PNW in general (Sheffield 2013; Rupp et al. 2013).

References

Antle, J. 1983. Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach. *Journal of Business and Economic Statistics* 1(3):192–201

Antle, J. 2010. Asymmetry, Partial Moments and Production Risk. *American Journal of Agricultural Economics* 92:1294–1309

Chen, C., B.A. McCarl, and D.E. Schimmelpfennig. 2004. Yield Variability as Influenced by Climate: A Statistical Investigation. *Climatic Change* 66:239–61.

Choi, I. 2001. Unit root tests for panel data. *Journal of International Money and Finance* 20: 249-272

Chow, G. C. 1960. Tests of Equality between Sets of Coefficients in Two Linear Regressions. *Econometrica* 28 (3): 591–605

Cochrane and Orcutt. 1949. Application of least squares regression to relationships containing autocorrelated error terms. *Journal of the American Statistical Association* 44: 32–61

Deschênes, O., and M.Greenstone. 2012. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply. *American Economic Review* 102(7): 3761-73

Drukker, D.M. 2003. Testing for serial correlation in linear panel-data models. *The Stata Journal* 3 (2):168–177

Du, X., D. Hennessy, and C. Yu. 2012. Testing Day's Conjecture that More Nitrogen Decreases Crop Yield Skewness. *American Journal of Agricultural Economics* 94(1):225-237

Fisher, A.C., W. M. Hanemann, M. J. Roberts, and Wolfram Schlenker. 2012. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment. *American Economic Review* 102(7): 3749-60

Just, R. E., and Q. Weninger. 1999. Are Crop Yields Normally Distributed? *American Journal of Agricultural Economics* 81(2): 287–304. Chen et al.

Just, R.E., and R.D. Pope. 1978. Stochastic Specification of Production Function and Economic Implications. *Journal of Econometrics* 7:67–6.

Koundouri, P., and N. Kourogenis. 2011. On the Distribution of Crop Yields: Does the Central Limit Theorem Apply? *American Journal of Agricultural Economics* 93(5): 1341-1357

Lobell, D.B., W.M. Schlenker, and J. Costa-Roberts. 2011. Climate trends and global crop production since 1980. *Science* 333(6042):616

McCarl, B.A., X. Villavicencio, and X. Wu. 2008. Climate Change and Future Analysis: Is Stationary Dying? *American Journal of Agricultural Economics* 90(5): 1241-1247.

Mote, P.W., & E.P. Salathe´. 2010. Future climate in the Pacific Northwest. *Climatic Change* 102(1_2): 29_50. doi:. 10.1007/s10584-010-9848-z.

Nelson,C. H.,and P.V. Preckel. 1989. The Conditional Beta Distribution as a Stochastic Production Function. *American Journal of Agricultural Economics* 71: 370–378

Ortiz-Bobea, A., and R.E. Just. 2013. Modeling the Structure of Adaptation in Climate Change Impact Assessment. *American Journal of Agricultural Economics* 95 (2): 244-251.

Reilly, J, et al. 2003. U.S. agriculture and climate change: new results. *Climatic Change* 57:43–67

Riahi, K., A. Gruebler, N. Nakicenovic. 2007. Scenarios of long-term socio-economic and environmental development under climate stabilization. *Technol Forecast Soc Chang* 74(7):887–935

Roberts, M., W.M. Schlenker, J.Eyer. 2012. Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change. *American Journal of Agricultural Economics*: 1-8

Rupp, D.E., J.T. Abatzoglou, K.C. Hegewisch and P.W. Mote. 2013. Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest US. Working paper.

Schlenker, W., and M.J. Roberts. 2006. Nonlinear Effects of Weather on Corn Yields. *Review of Agricultural Economics* 28(3): 391-398

Schlenker, W., and M.J. Roberts. 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *PNAS* 106(37): 15594-15598

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2006. The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *Review of Economics and Statistics* 88(1): 113-125

Sheffield, J. 2013. North American Climate in CMIP5 Experiments: Part II: Evaluation of 20th Century Intra-seasonal to Decadal Variability.Working paper.

Tack, J,.A. Harri, K. Coble. 2012. More Than Mean Effects: Modeling the effects of Climate on the Higher Order Moments of Crop Yields. *American Journal of Agricultural Economics* 94(5):1037-1054

Urban, D., M. Roberts, W. M. Schlenker, D.B. Lobell. 2012. Projected temperature changes indicate significant increase in interannual variability of U.S. maize yields. *Climatic Chang*e 112(2): 525-533

USDA, 2010. Field crops usual planting and harvesting dates. National Agricultural Statistics Service, United States Department of Agriculture, Agricultural Handbook number 628

USDA, 2013. Crop production 2012 summary. National Agricultural Statistics Service, United States Department of Agriculture, ISSN: 1057-7823

Wooldridge, J. M. 2002. Econometric Analysis of Cross Section and Panel Data. Cam- bridge, MA: MIT Press.

Table 1 Average changes in precipitation and temperature in PNW climate

GCM	Model name	% Precipitation (Seasonal)			Temperature Change(^{o}C)		
				RCP45			
		2030s	2050s	2090s	2030s	2050s	2090s
1	bcc-csm1-1	89.7	100.9	92.7	1.4	2.1	2.7
2	BNU-ESM	103.9	113.9	105.5	2.0	3.3	3.9
3	CanESM2	95.1	105.5	105.6	2.3	3.4	4.3
4	CNRM-CM5	101.1	100.9	114.3	1.6	2.4	3.0
5	CSIRO-Mk3-6-0	91.2	87.6	92.2	1.3	3.2	3.7
6	GFDL-ESM2G	103.2	102.3	107.4	0.9	2.4	2.5
7	GFDL-ESM2M	108.2	98.0	100.3	1.2	1.4	1.8
9	HadGEM2-ES	95.0	96.1	92.6	1.6	3.3	4.3
8	HadGEM2-CC	96.5	89.3	93.3	1.6	3.0	3.9
10	inmcm4	100.1	93.5	90.3	0.6	1.2	1.9
11	MIROC5	99.7	97.3	94.2	1.4	2.4	3.1
12	MIROC-ESM	102.8	105.3	104.6	1.9	3.5	4.3
13	MIROC-ESM-CHEM	97.3	102.3	108.3	1.8	3.5	4.3
14	MRI-CGCM3	102.9	100.9	100.7	0.9	1.3	2.2
Average		**99.1**	**99.6**	**100.1**	**1.5**	**2.6**	**3.3**
				RCP85			
1	bcc-csm1-1	89.9	103.5	90.6	1.9	3.2	5.1
2	BNU-ESM	101.4	114.3	109.8	2.2	4.3	6.5
3	CanESM2	94.3	104.8	112.8	2.4	4.5	7.1
4	CNRM-CM5	106.5	106.3	100.7	1.7	3.1	5.3
5	CSIRO-Mk3-6-0	94.6	88.1	91.9	1.5	3.8	6.1
6	GFDL-ESM2G	105.0	107.7	104.3	1.4	2.7	4.6
7	GFDL-ESM2M	96.4	97.3	97.1	1.5	2.6	3.9
9	HadGEM2-ES	94.7	84.1	82.9	2.0	4.2	7.2
8	HadGEM2-CC	95.5	88.5	89.2	1.8	4.5	6.9
10	inmcm4	96.3	86.9	94.6	0.9	2.0	3.3
11	MIROC5	99.5	101.8	102.9	1.5	3.0	4.8
12	MIROC-ESM	99.2	101.4	109.2	1.9	4.2	6.8
13	MIROC-ESM-CHEM	101.8	106.8	106.1	2.0	4.4	6.9
14	MRI-CGCM3	98.8	103.6	98.3	1.0	1.9	3.7
Average		**98.1**	**99.7**	**99.3**	**1.7**	**3.5**	**5.6**

Note: All changes are benchmarked to average temperature and precipitation for 1950-2005. We use the average overgrowing seasons in 2011-2040, 2041-2070 and 2071-2100 as the mean for 2030s, 2050s and 2090s. Then we calculate the changes in temperature and precipitation across all 14 GCMs for each emission scenario and timeline.

Table 2 Statistics and descriptions of variables

Variable	Mean	Std. Dev.	Min	Max
Winter wheat yield (bushes/acre)	68.86	24.19	0.00	136.80
Mean temperature (^{o}C)	2.03	3.18	-7.65	9.22
Standard deviation (SD) of temperature	3.19	0.71	0.84	5.17
Total precipitation (cm)	69.56	59.85	7.10	348.25
Growing season degree-days	54.75	45.99	0.00	316.60
Irrigation rate	0.33	0.38	0.00	1.00
Total population (1000 persons)	81.50	183.59	0.68	1937.16
Per capita income (1000 dollars)	19.57	8.52	5.20	70.46
Moderate Drought	0.35	0.48	0	1
Severe Drought	0.15	0.35	0	1
Salinity	0.01	0.02	0.00	0.13
Fraction flood-prone	0.20	0.23	0.00	1.00
Wetlands	0.04	0.05	0.00	0.33
Soil erodibility K-factor	0.32	0.10	0.00	0.50
Slope length	361.82	204.74	0.00	1200.56
Fraction sand	0.02	0.04	0.00	0.25
Fraction clay	0.10	0.16	0.00	1.00
Moisture capability	0.18	0.03	0.09	0.32
Permeability	1.77	1.01	-0.69	5.70

Note: values of climate variables are reported corresponding to the growing season from November to April and degree-days are calculated with temperature between 8^{o}C to 32^{o}C; Per capita income is deflated using consumer price index.

Table 3 Fisher-type Panel Unit Root Tests

Variable	Augmented Dickey-Fuller Unit-root Tests Z-statistic	Phillips-Perron Fuller Unit-root Tests Z-statistic	N	T
Winter wheat yield	-12.92***	-22.20***	104	25
	(0.000)	(0.000)		
Mean temperature	-28.07***	-29.99***	119	32
	(0.000)	(0.000)		
SD of temperature	-18.94***	-37.81***	119	32
	(0.000)	(0.000)		
Total precipitation	-30.16***	-38.50***	119	32
	(0.000)	(0.000)		
Growing season degree-days	-17.87***	-40.53***	119	32
	(0.000)	(0.000)		
Irrigation rate	-3.34***	-14.74***	104	23
	(0.0004)	(0.000)		
Total population	-22.38***	6.17	119	32
	(0.000)	(1.0000)		
Per capita income	-2.18**	-2.46***	119	32
	(0.0147)	(0.0069)		

Ho: all panels contain unit roots; Ha: at least one panel is stationary. p-values are in parentheses; * p<0.1, ** p<0.05 and *** p<0.01

Table 4 Estimation Results of the 1st, 2nd, 3rd and 4th Full-moment Functions

Variable	μ_1	μ_2	μ_3	μ_4
Mean temperature^2	-0.136***	-0.675	6.262	-600.4
	(0.0339)	(0.525)	(17.72)	(558.3)
Mean temperature	0.915***	7.381**	-178.8	6907.5
	(0.270)	(3.649)	(127.7)	(4331.0)
SD of temperature	1.205*	5.837	-746.8*	10438.5
	(0.640)	(12.36)	(440.6)	(15753.8)
Total precipitation	0.332***	0.844*	26.49	1338.7**
	(0.0394)	(0.489)	(17.67)	(600.4)
Total precipitation^2	-0.000932***	-0.00489**	-0.104	-7.483**
	(0.000162)	(0.00236)	(0.0885)	(3.081)
Irrigation $\times$ Total precipitation	-0.400***	1.411**	-58.57**	1189.7
	(0.0527)	(0.675)	(25.82)	(848.0)
Irrigation $\times$ Mean temperature	0.245	-2.833	227.1	-4917.6
	(0.391)	(4.809)	(161.9)	(5126.5)
Growing season degree-days	0.0125	-0.172	9.748*	-208.6
	(0.0102)	(0.183)	(5.814)	(172.3)
Moderate Drought	-0.0219	20.69*	-56.11	10668.0
	(0.580)	(11.60)	(411.6)	(14203.2)
Severe Drought	-2.836***	52.95***	-59.00	32468.7**
	(0.759)	(14.58)	(487.0)	(14712.6)
Irrigation rate	58.60***	-49.16**	2067.4**	-34842.4
	(2.725)	(23.83)	(822.7)	(24500.7)
Total population	0.0212***	-0.0694	-0.0717	-134.6*
	(0.00785)	(0.0609)	(2.224)	(77.93)
Per capita income	0.628***	3.471	-117.7	4278.6
	(0.207)	(2.198)	(83.96)	(3096.1)
Time trend	0.332**	2.038	56.25	1240.4
	(0.130)	(2.627)	(97.83)	(3661.8)
Time trend^2	-0.0108**	-0.0929	0.530	-102.2
	(0.00426)	(0.0857)	(3.207)	(119.4)
Constant	-10.19**	-30.38	9032.4**	-191325.0
	(5.102)	(117.0)	(4260.1)	(150382.2)
Soil variables	Y	Y	Y	Y
N	2107	2107	2107	2107
adj. R-sq	0.375	0.043	0.010	0.024
r2	0.382	0.0542	0.0214	0.0349
F	48.95	4.370	1.343	2.538
p	0.0000	0.0000	0.123	0.0001

Note: standard errors are in parentheses; * p<0.1, ** p<0.05 and *** p<0.01

Table 5 Estimation Results of the 2nd, 3rd and 4th Partial-moment Functions

	μ_2		μ_3		μ_4	
	N[a]	P[b]	N	P	N	P
Mean temperature^2	-0.781	-1.236	-25.66	-29.25	-901.3	-759.2
	(0.733)	(0.798)	(24.70)	(22.71)	(925.1)	(687.2)
Mean temperature	12.22**	1.878	472.5***	-60.06	17689.2***	-3963.9
	(5.037)	(5.255)	(174.2)	(165.1)	(6730.4)	(5629.0)
SD of temperature	29.63	-16.49	1066.9	-550.7	40071.6	-17343.9
	(19.73)	(15.66)	(743.6)	(473.0)	(31667.3)	(15386.3)
Total precipitation	-0.433	1.852***	11.33	52.31***	1086.6	1571.5***
	(0.909)	(0.645)	(32.56)	(18.53)	(1301.1)	(598.3)
Total precipitation^2	0.00259	-0.00891***	-0.0668	-0.241***	-6.332	-7.025***
	(0.00510)	(0.00273)	(0.183)	(0.0791)	(7.313)	(2.604)
Irrigation $\times$ Total precipitation	3.590***	-0.00743	104.4**	-5.773	3399.7*	-331.6
	(1.367)	(0.648)	(50.73)	(17.00)	(1984.0)	(498.3)
Irrigation $\times$ Mean temperature	-13.20*	2.674	-456.5*	80.81	-17534.3*	2670.8
	(7.427)	(6.863)	(244.3)	(203.6)	(9263.0)	(6642.4)
Growing season degree-days	-0.396*	0.123	-14.62**	4.819	-507.3**	170.5
	(0.225)	(0.275)	(6.498)	(7.876)	(209.3)	(241.1)
Moderate Drought	27.11*	17.27	549.0	446.6	11163.0	12231.5
	(16.25)	(15.57)	(551.7)	(473.1)	(20552.4)	(15761.9)
Severe Drought	69.98***	43.90**	1633.8***	1240.9**	38069.1*	34836.2*
	(19.79)	(20.27)	(601.4)	(593.5)	(19874.9)	(18346.9)
Irrigation rate	-131.0***	9.727	-3439.6**	314.4	-104857.3**	11513.0
	(40.67)	(31.20)	(1381.9)	(868.0)	(51326.9)	(26030.3)
Total population	-0.0395	-0.0882	-3.271	-2.909*	-170.5	-96.05*
	(0.104)	(0.0625)	(3.772)	(1.755)	(148.0)	(56.17)
Per capita income	3.629	2.430	156.7	46.19	6487.4	622.0
	(3.276)	(2.293)	(121.8)	(59.67)	(4825.7)	(1715.1)
Time trend	0.315	4.707	18.89	107.7	1402.0	2604.9
	(4.135)	(3.322)	(155.9)	(105.7)	(6450.9)	(3794.1)

Time trend^2	-0.0341	-0.168	-2.623	-3.624	-149.9	-76.04
	(0.136)	(0.105)	(5.126)	(3.248)	(210.8)	(113.7)
Constant	-213.9	229.1	-11088.4*	6218.6	-476496.2*	182415.9
	(172.0)	(155.7)	(6424.8)	(4808.9)	(265213.2)	(161566.7)
Soil variables	Y	Y	Y	Y	Y	Y
N	1052	1055	1052	1055	1052	1055
adj. R-sq	0.079	0.025	0.066	0.013	0.049	0.005
r2	0.0997	0.0473	0.0876	0.0358	0.0712	0.0278
F	2.958	3.135	2.222	2.336	1.699	1.796
p	0.0000	0.0000	0.0007	0.0003	0.0193	0.0108
Symmetry test	70.17		61.88		58.31	
	[0.0000]		[0.0000]		[0.0000]	

Note: [a] indicates the negative residual from the mean equation; [b] indicates positive residuals from the mean equation. * p<0.1, ** p<0.05 and *** p<0.01; Symmetry test with the Ho: the coefficients estimated from the positive partial moment function are equal to the coefficients estimated over the negative one; p-value of the symmetric test statistic is in square-parenthesis.

Table 6 Marginal Effects and Elasticity of Precipitation, Temperature and Irrigation on Winter Wheat Yield

		Total precipitation		Irrigation rate		Mean temperature	
		MFX[a]	ELS[b]	MFX	ELS	MFX	ELS
μ_1		0.0698***	0.1756***	31.2407***	0.3739***	0.4465	0.0327
		(0.0201)	(0.0505)	(2.6509)	(0.0317)	(0.2808)	(0.0206)
μ_2		0.6302***	0.3735***	43.2652	0.1219	3.7095	0.064
		(0.2502)	(0.1483)	(34.8937)	(0.0983)	(4.3745)	(0.0755)
μ_3		-7.3603	3.6256	-1546.204	3.6203	-78.3139	1.1236
		(9.1154)	(4.4901)	(1336.677)	(3.1297)	(150.0708)	(2.1532)
μ_4		691.0952**	0.8792**	37941.97	0.2294	2849.017	0.1056
		(308.9291)	(0.393)	(44889.39)	(0.2714)	(4881.207)	(0.1809)
μ_2	P[c]	0.6107**	0.3725**	14.628	0.0424	-2.2475	-0.0399
		(0.3092)	(0.1886)	(34.5768)	(0.1002)	(6.4085)	(0.1139)
μ_3	P	16.8207**	0.549**	76.528	0.0119	-151.8616	-0.1444
		(8.358)	(0.2728)	(943.5162)	(0.1464)	(188.4451)	(0.1792)
μ_4	P	484.5796*	0.702*	-6142.386	-0.0423	-6157.051	-0.2598
		(247.7805)	(0.3589)	(27708.64)	(0.1908)	(5958.744)	(0.2514)
μ_2	N[d]	1.1146**	0.6376**	91.9713	0.2501	4.691	0.0782
		(0.4504)	(0.2577)	(67.374)	(0.1832)	(5.9461)	(0.0991)
μ_3	N	36.5433**	1.0281**	2897.021	0.3874	217.6215	0.1783
		(16.4934)	(0.464)	(2510.118)	(0.3357)	(199.4464)	(0.1634)
μ_4	N	1329.691**	1.4665**	96085.62	0.5037	8240.246	0.2647
		(657.9002)	(0.7256)	(97419.61)	(0.5107)	(7478.226)	(0.2402)

Note: standard errors are in parentheses; * p<0.1, ** p<0.05 and *** p<0.01; [a] indicates marginal effects; [b] indicates elasticity; [c] indicates positive residuals from the mean equation; [d] indicates the negative residual from the mean equation.

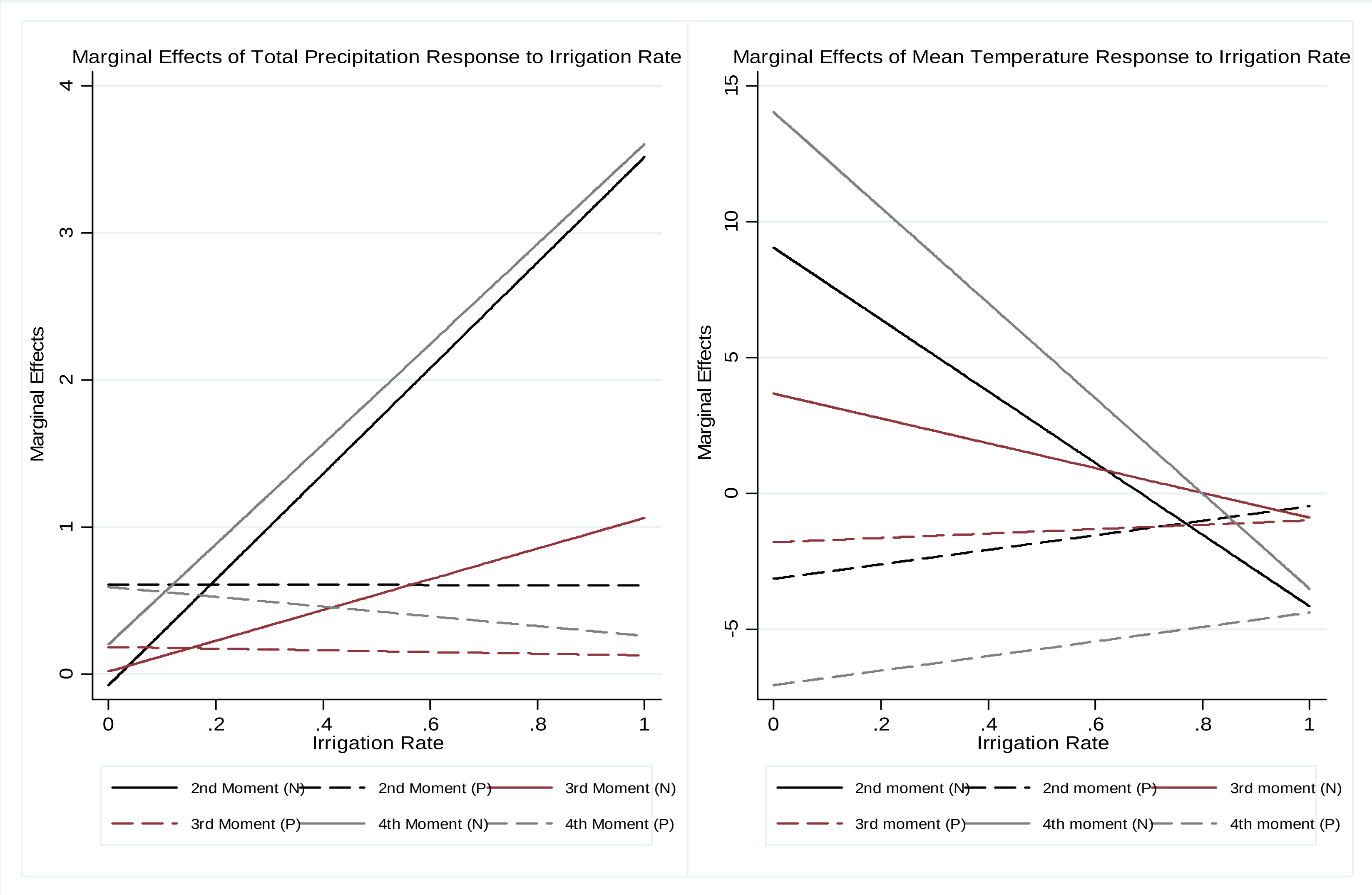

Figure 1 Marginal Effects of Mean Temperature and Total Precipitation Response to Irrigation Rate (Note: we control precipitation or temperature at their sample means when calculating the marginal effects in the graphs. Therefore, the marginal effects are only corresponding to changes of irrigation rate. In addition, marginal effects of the 3rd and 4th partial moments are rescaled by dividing 100 and 1000, respectively)

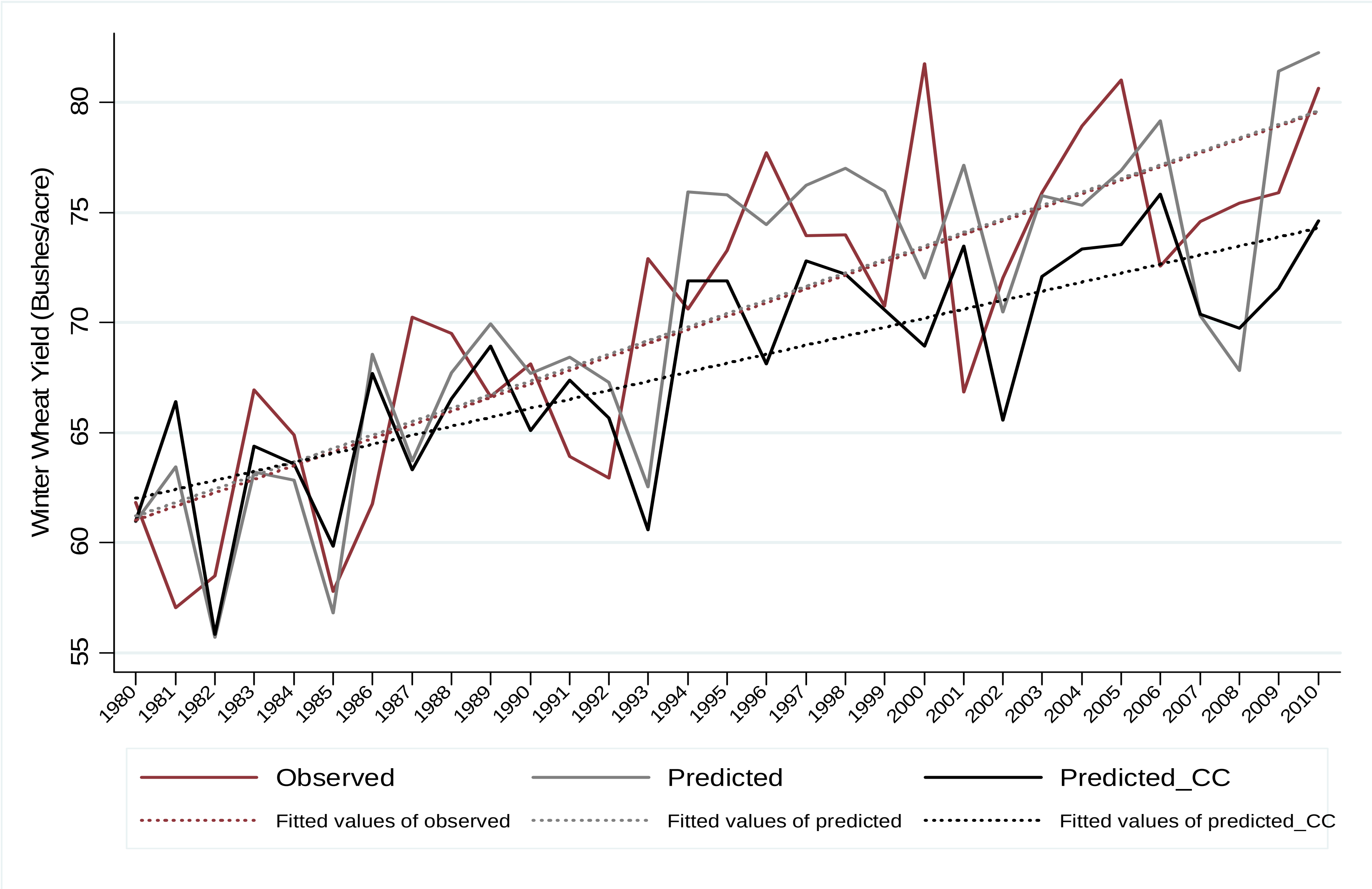

Figure 2 Predicted v.s. Observed Winter Wheat Yield (Note: the black line of “Predicted_CC” shows the predicted mean yield only varying climate variable and controlling all other variables at sample means; the gray line of “Predicted” shows the within sample prediction)

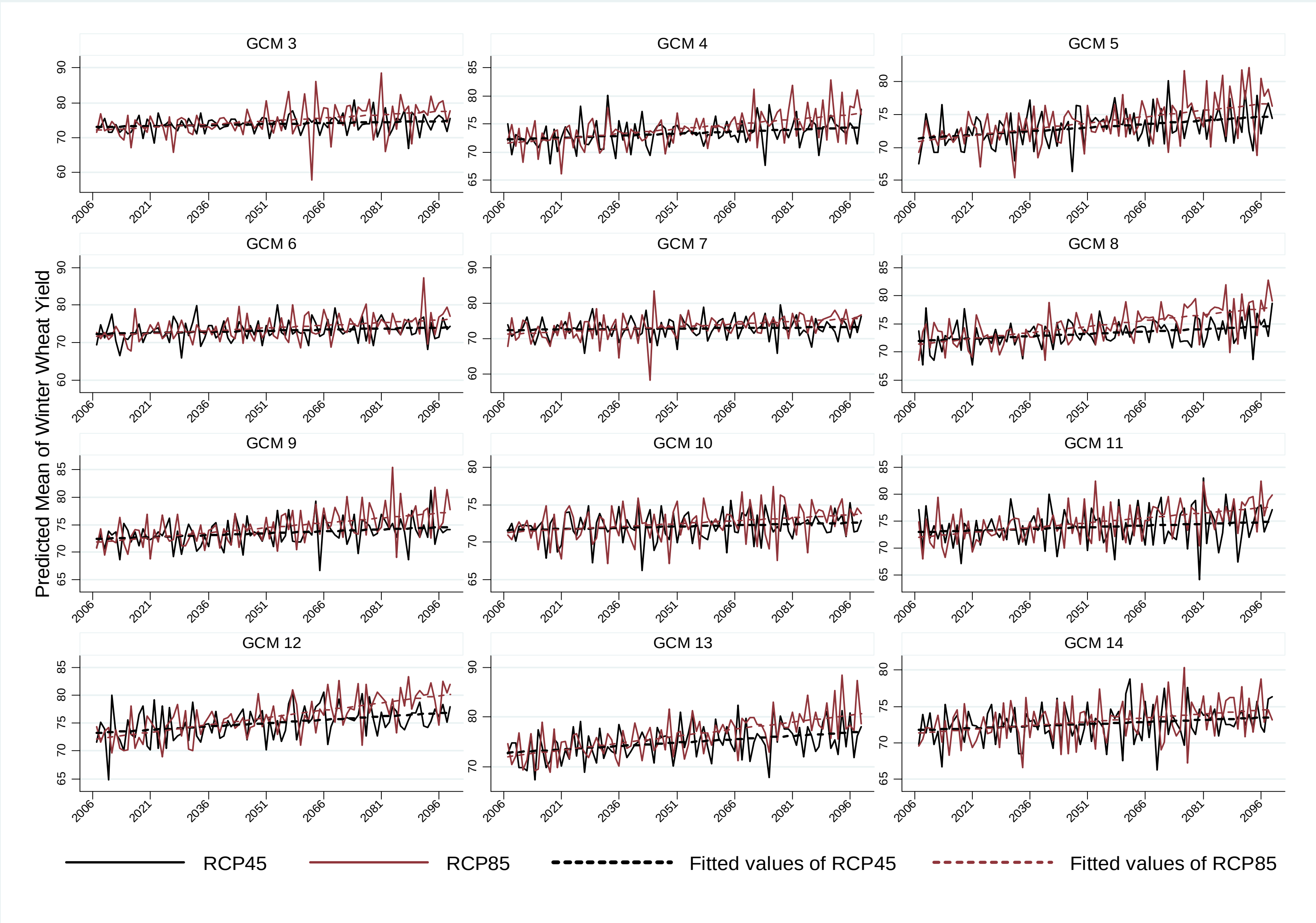

Figure 3 Predicted Mean of Winter Wheat Yield Distribution under Different GCM Climates

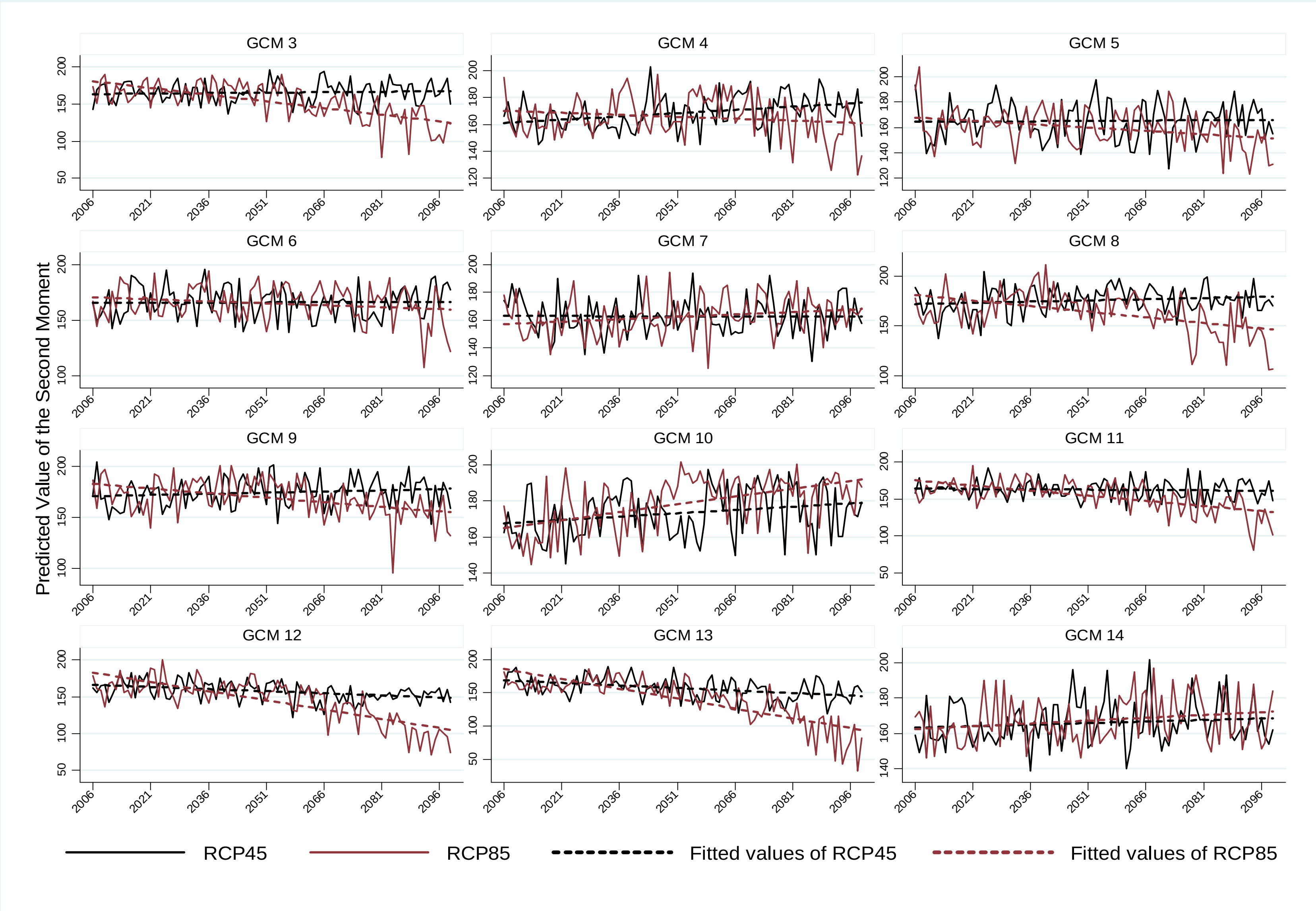

Figure 4 Predicted Value of the Second Moment under Different GCM Climates

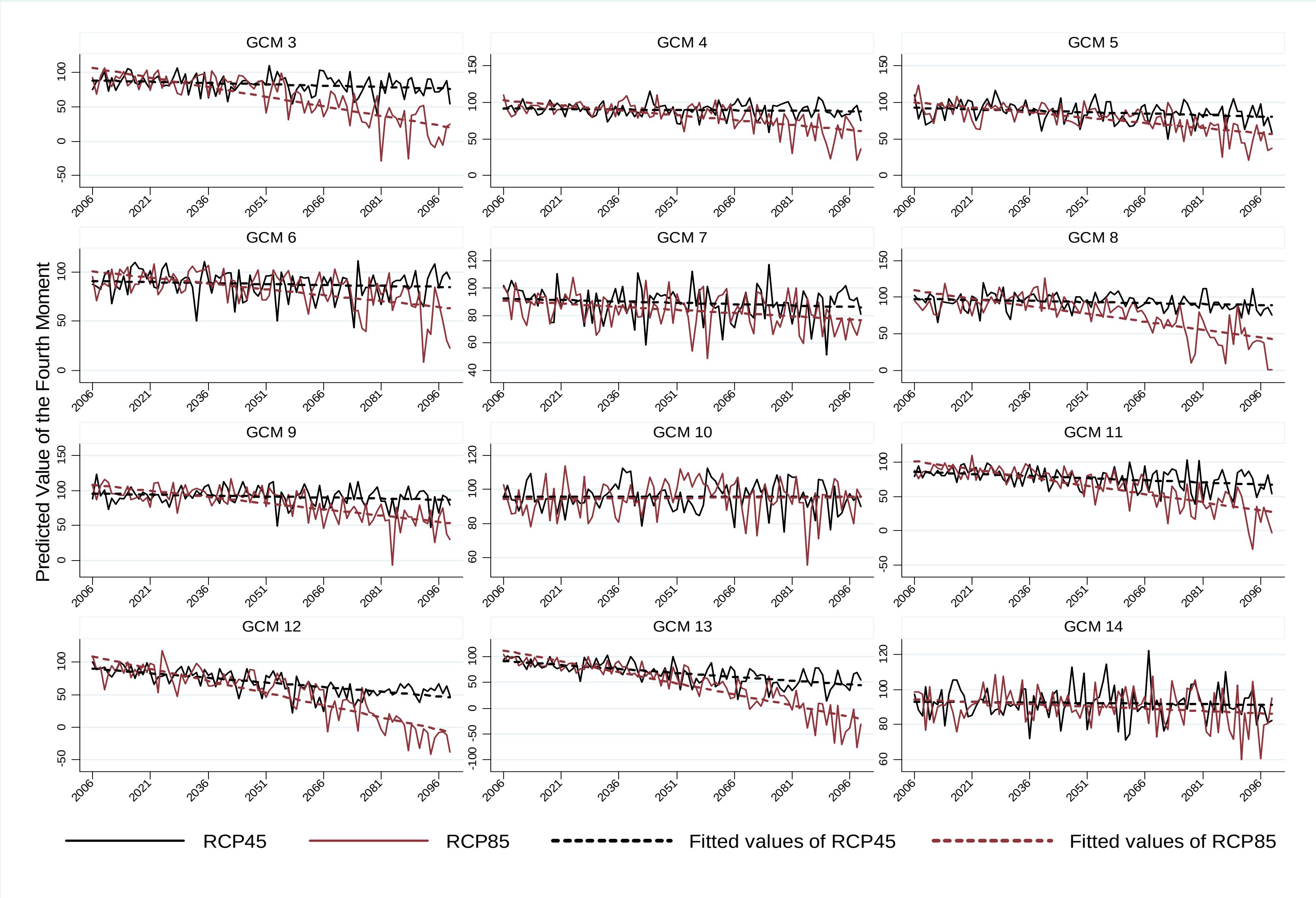

Figure 5 Predicted Value of the Fourth Moment under Different GCM Climates (Note: values of the fourth moment are rescaled by dividing 1000)