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Assessing Climate Vulnerability of Agricultural Systems Using High-order moments: A Case Study in the U.S. Pacific Northwest

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Abstract

This paper evaluates the effects of climate variables on the winter wheat yield distribution by using a moment-based approach. Farm-level data from the Agricultural Census were used to estimate the effects of climate variables on the mean and high-order moments of the winter wheat yield distribution and to assess the impact of climate change on climate vulnerability of winter wheat systems in the U.S. Pacific Northwest. Growing degree-days and freezing degree-days were shown to have a negative effect on winter wheat productivity, and precipitation and irrigation were found to improve winter wheat productivity. Growing degree-days, freezing degree-days, and precipitation were found to have a positive effect on the risk premium in the winter wheat yield model. Drought conditions were shown to have a large negative impact on the distribution of winter wheat yield. In the long run scenario (2066-2095), winter wheat farms in the U.S. Pacific Northwest on average are projected to experience a rise in expected losses from the winter wheat production due to climate change. Climate impacts on the farm-level winter wheat distribution are not uniformly distributed across farms; there are large uncertainties in the impacts of climate vulnerability on winter wheat systems in the U.S. Pacific Northwest due to substantial uncertainty in future climate projections.

Key Words: Climate Change, Wheat, Vulnerability, Moment, Drought

JEL Classification: C5, D8, Q1

1. Introduction

Increased temperature and precipitation variability and frequent extreme weather events are likely to occur due to climate change and potentially threaten farming operations and agricultural communities. A growing body of research using statistical approaches to estimate the mean economic impacts of climate change on U.S. agriculture found inconclusive results on county-level economic outcomes, e.g., crop yield, farmland value, and net return (Adams 1989; Mendelson et al. 1994; Deschenes and Greenstone 2007; Lobell et al. 2007; Schlenker and Roberts 2009; Burke and Emerick 2013; Ortiz-Bobea and Just 2013).

An understudied aspect of climate change impact assessment on agriculture is production risk associated with future climate scenarios. The mean indicators of economic impacts are important because policy makers and farmers could use this information to predict the aggregate effect of climate change on domestic agricultural market supply. However, these indicators neither represent the distributional impacts of climate change across individuals nor capture the climate vulnerabilities of individual farmers. To better model climate vulnerabilities on individual farmers, it is important for scientists to consider a research lens that focuses on less understood high-order impacts of climate change.

This paper assesses the climate vulnerability of agricultural systems by modeling not only mean but high-order moments of climate impacts. The traditional stochastic production models with an additive, multiplicative-heteroscedastic error, e.g., the Just-Pope model, impose arbitrary restrictions among the high-order moments of the output distribution. Antle (1983) developed a flexible moment-based approach by estimating a system of central moment functions to allow for flexible representations of output distributions and extended the approach by estimating partial moment functions (Antle 2010). Moment-based approaches have been widely used in a variety of applications in modelling decision-making under uncertainty, e.g., the mean-variance framework (Cooper 2010; Schoengold et al. 2015), the mean-variance-skewness framework (Di Falco and Chavas. 2006; Huang et al. 2015), the mean-variance-skewness-kurtosis framework (Koundouri et al. 2006), and the risk-value model (Jia et al. 2001; Delquie and Cillo 2006). Tack et al. (2012) used raw moments (moments about zero) to study the impact of climate change on cotton yield distributions. Although raw moments and central moments are theoretically equivalent, however, central moments have direct economic interpretation compared with raw moments, and partial moments are better at measuring the asymmetry of distributions. More

importantly, the mean function is still needed to evaluate the overall effects of variables of interest, e.g., climate variables, on the output distribution. Accordingly, we follow the model proposed by Antle (2010) to use both central and partial moments to estimate the high-order impacts of climate variables on farm-level outcome distributions and evaluate the impacts of climate change on farm-level climate vulnerability in the future.

This study contributes to the literature threefold. First, to the best of our knowledge, we provide the first empirical analysis on the effects of climate variables on the distribution of crop yields. Tack et al. (2012) and Huang et al. (2015) estimated the high-order effects of weather variables on crop yields but not the impacts of climate variables. We emphasize that the ex-ante distributions of economic outcomes are dependent on climate variables rather than ex-post weather variables in agricultural production.

Second, we model farm-level distributions of crop productivity rather than at an aggregate level such as county. The estimates of climate variables based on aggregate data are likely to suffer from aggregation biases due to interactions between climate variables (Fezzi and Bateman 2015) or non-linear effects of weather or climate variables on crop growth (Schlenker and Roberts 2009; Burke and Emerick 2013). Farm-level analysis can overcome aggregation biases and assess climate vulnerabilities of agricultural systems at the farm, local, or regional level.

Third, we study the effects of climate variables on winter wheat systems. Most climate change impact assessment on the U.S. agricultural sector focuses on corn and soybeans. Winter wheat in temperate regions differs from corn and soybeans in that a typical timeline for winter wheat crops is stand seeding and emergence in the fall, dormancy in the winter, and maturity by the end of spring or early summer. Compared with corn and soybeans, the winter wheat production avoids extreme summer high temperatures but is exposed to extreme winter low temperatures. This implies that climate change may have different impacts on winter wheat systems than corn and soybeans systems.

The remainder of this paper is organized as follows. The first section presents a conceptual framework to show how the mean and high-order moments can be used to assess the impact of climate change on the vulnerability of agricultural systems. The second section presents an economic model to study the effects of climate variables on winter wheat yield distribution. The third section provides an econometric strategy for estimating the effects of

climate variables on winter wheat yield distribution. The fourth section introduces the data sources and presents summary statistics. The fifth section presents and discusses the estimation results. The sixth section projects the impact of climate change on the vulnerability of agricultural systems in the future based on current biophysical and socio-economic conditions. The last section concludes.

2. Conceptual Framework

In this section, we present a conceptual framework to evaluate the impacts of climate change on the vulnerability of agricultural systems by using the moments of weather and outcome distributions following the model developed by Antle (2010). We then define the climate vulnerability of agricultural systems and show how the moments can be used to construct a threshold indicator of the climate vulnerability.

Mean and High-order Impacts of Climate Change

In this subsection, we explore the process that generates the output distribution and its relation to a micro-climate. The goal here is to show how the moments can be used to capture the impact of climate change on the output distribution and provide a foundation to build an economic model to analyze the impact on agricultural systems. We define a micro-climate as a stochastic process that generates a weather distribution at a specified place in a given period. Weather represents a vector of variables, e.g., temperature, precipitation, and their interactions, and is a realization of the micro-climate.

Figure 1 illustrates the impact of climate change on the output distribution and the effects of adaptations to climate change. In this example, we assume farmers have access to a production technology, $y = f(x, w)$, where y is output, w is weather, and x represents other inputs (weather and other inputs are treated as scalars for simplicity). The right horizontal axis represents the weather from a micro-climate at a farm, denoted by $\chi(w|\theta)$, where θ is micro-climate variables. The positive vertical axis measures output per unit, e.g. yield, revenue or net return with the upper bound \bar{y} defined as the maximum output per unit, which represents the production frontier. The left horizontal axis measures the probability density of the output distribution conditional on other inputs x , denoted by $\phi(y|x)$.

A micro-climate can be represented by the moments of the weather distribution. Assume a micro-climate at a farm is represented by a distribution $\chi(w|\theta)$ before climate change. Climate

change at the farm then generates a new micro-climate represented by a distribution, $\chi(w|\theta')$, with a different location and shape characteristics. The output distribution under the climate change shifts from a distribution $\phi(y|x, \theta)$ to $\phi(y|x, \theta')$ without any adaptation by fixing other input use at x . Climate change presented here pushes the output distribution toward the upper bound, resulting in an increase in the variance and the negative skewness.

It is important to recognize that farmers can increase benefits or mitigate losses from climate change through adaptations: they can adjust input use and management practices in the short term, e.g., planting date, irrigation water application rate, seed varieties, and coverage of crop insurance; they can, additionally, adapt to climate change through long-term investments, e.g., changing farmland use or irrigation technologies. These adaptation strategies could shift the production function upward from $y = f(x, w)$ to $y = f(x', w)$ and shift the output distribution to the right from $\phi(y|x, \theta')$ to $\phi(y|x', \theta')$, and result in a higher certainty equivalent that would be expected to have a higher mean and different risk properties.

To demonstrate the empirical evidence of the hypothetical distributions in figure 1, figure 2 presents output distributions derived from the winter wheat yield data discussed in detail below. The data were stratified into groups by the levels of irrigation and climate variables: percentage of irrigated winter wheat acreage, growing season precipitation, or growing degree-days. Figure 2 shows the kernel densities of winter wheat yield from each group by one of the three variables. The output distribution with the lower level of the variable is skewed to the right, with the mass of the distribution concentrated at the negative tail. An increase in the level of the variable pushes the distribution toward the production frontier and leads to a higher variance, a lower skewness, and a higher kurtosis.

Climate Vulnerability of Agricultural Systems

In this subsection, we define the climate vulnerability of agricultural systems at an individual farm and show how the mean and high-order moments of the output distribution can be used to construct a threshold indicator of climate vulnerability at different spatial scales, according to the conceptual framework above.

The impacts of climate change on agricultural systems are multi-dimensional, comprising of economic, social and environmental consequences. For example, reducing precipitation on non-irrigated farms can reduce crop yields and household nutrition consumption and thus increase poverty rates in the developing world, while economic losses and environment

degradations are main concerns for the farm household in the developed counties, e.g., wheat farms in the U.S. Pacific Northwest. We need indicators to represent these economic, social and environmental outcomes, and use them to evaluate the impacts of climate change and potential adaptation strategies from new technologies and policies.

The focus of this paper is on measuring the economic vulnerability of agricultural systems from climate change. There are several ways that indicators of climate vulnerability can be defined at an individual farm level, i.e., in terms of absolute or relative impacts on the farm household's well-being (Reardon and Vosti 1995; Moser 1998; Maxell et al. 1998; Alwang et al. 2001; Ligon and Schechter 2003; Antle et al. 2004; Bourguignon et al. 2004; Chaudhuri et al. 2004; Christiaensen and Subbarao 2004; Kamanou and Morduch 2004). Following the Foster-Greer-Thorbecke (1978) poverty indicator concept, we define a threshold indicator of climate vulnerability as the absolute deviation below some reference level, i.e., the first-order lower partial moment of an outcome distribution, $I = \int_{-\infty}^r |q - r| \phi(q|x, \theta) dq$, where I is a threshold indicator of the climate vulnerability at an individual farm, q is an economic outcome from the output production, and r is the reference level. Note that q and r can be defined in absolute or relative terms.

One advantage of this threshold indicator is, compared with the mean indicators, that it captures not only the mean impact of climate change on farm-level average yield but also the high-order impacts on yield variability and crop failure. More importantly, this threshold indicator measures the impact of climate change on the survival rather than the average welfare. This is particularly important for poor farmers in the developing world who struggle with meeting the basic living standard. In higher income settings, such as the PNW region studied here, this type of indicator can be related to the household's current income. With suitable data on debt and assets, the income-based indicators used here could be related to financial vulnerability.

The quadrant in the upper left of figure 1 shows the impact of climate change on the farm-level climate vulnerability. The shaded areas measure the climate vulnerability of an individual farm under two micro-climates before and after climate change without adaptation. In the case presented in figure 1, the climate change reduces the vulnerability on agricultural production. Note that this vulnerability indicator measures both the probability and the severity of expected losses below some reference level; both of which depend on the location and shape

characteristics of the output distribution. We can use the mean and high-order moments of the output distribution to construct the climate vulnerability indicator and assess the overall impacts of climate change on the output distribution.

Moreover, we can generate a distribution of individual climate vulnerability across farms, and use this distribution to evaluate the climate vulnerability on agricultural systems at an aggregate level such as county. This farm-level vulnerability indicator provides a flexible way to compare the impacts of climate change on agricultural systems across regions, and to examine the distributional effects of climate change within a region. Policy makers can use this vulnerability indicator to target the most vulnerable farms under climate change and design policies to help them adapt to climate change.

This section provides a conceptual framework to assess the impacts of climate change and adaptations on the output distribution. We demonstrate how the mean and high-order moments of the output distribution can be used to measure the climate vulnerability of an individual farm through a threshold indicator. Before we quantify and examine the climate change impacts, we provide an economic model in the next section to guide the impact assessment on the behavior of a decision maker under uncertainty.

3. Economic Model

In this section, we develop an economic model where a risk-averse farmer makes decisions about variable input use and capital service in the long run to maximize the expected utility. The goal of this section is to model the long-run impact of climate change on agricultural systems. Farmers in the long run can optimally adjust both variable input use and capital service to adapt to climate change, whereas in the short run capital service is fixed. We begin with the analysis by using the expected utility model and then discuss extending the model to the risk-value model

Model Setup

We consider a farm that has a production technology where production is a single-period process for a single output. In the timeline, variable input and capital service are chosen, a weather shock occurs, and output is realized. Thus, production is determined by realized weather variables rather than expected climate variables. More specifically, the production function is defined as

$$(1) \quad q \equiv f(x, w, \mathbf{e}),$$

where q is output per unit, x is input use including variable input use and capital service, \mathbf{e} is a vector of site characteristics such as soil quality and managerial skills, w is weather variables (input use and weather variables are treated as scalars for simplicity).

We assume that: i) the production function is strictly concave and twice differentiable in input use and weather variables; ii) weather, w , follows a distribution, $w \sim \chi(w|\theta)$, where θ is micro-climate parameters of an individual farm, and output follows a distribution, $q \sim \phi(q|x, \theta, \mathbf{e})$; iii) the price of input use, v , is predetermined and nominalized by the output price; iv) farmers are risk-averse to production risk and downside risk.

Define the net return function, $\pi \equiv q - vx$, and then the goal of a risk-averse farmer is to maximize her expected utility by choosing q and x ,

$$(2) \quad \max_{q,x} E[U(\pi)] \\ \equiv \max_{q,x} \int U[f(x, w, \mathbf{e}) - vx] \chi(w|\theta) dw$$

where E is the expectation operator, U is the von Neumann-Morgenstern utility function.

Expected Utility Model

To simplify the presentation, we define μ_1 as the expected output, and μ_j as the j th central moment of the output distribution, $j \geq 2$. As shown by Antle (1987), the expected utility function $E[U(\pi)]$ can be specified as a function of all the moments of the net return distribution, so we let $E[U(\pi)] = U(\mu_1 - vx, \mu_2, \mu_3, \dots)$ and define $U_j \equiv \frac{\partial^j U(\mu_1 - vx)}{\partial \pi^j}$, $j \in \mathbb{N}$. Then, using a 3rd order approximation to the expected utility function, the first-order condition of (2) is,

$$(3) \quad \frac{\partial \mu_1}{\partial x} - v = - \sum_{j=2}^3 \frac{U_j}{U_1} \frac{\partial \mu_j}{\partial x},$$

We can write equation (3) in the elasticity form,

$$(3') \quad \mu_1^* - vx/\mu_1 = R_2 s_2 \mu_2^* - R_3 s_3 \mu_3^*,$$

where $\mu_j^* \equiv \frac{\partial \ln \mu_j}{\partial \ln x}$, $s_j \equiv \frac{\mu_j}{\mu_1 (\mu_1 - vx)^{j-1}}$, $R_j \equiv (-1)^{j-1} \frac{U_j}{U_1} (\mu_1 - vx)^j$, $j = 2, 3$. R_2 is approximately equal to one-half of the Arrow-Pratt relative risk aversion coefficient; R_3 is approximately equal to one-six of the relative downside risk aversion coefficient (Antle 1987). They represent the risk attitude and measure a decision-maker's willingness to substitute a change in the expected net return for a change in production risk and downside risk.

Note that the expected utility function can be rewritten in terms of the certainty equivalent (CE), i.e., $E[U(\pi)] = U(CE) = U(\mu_1 - vx - R)$, where R is the risk premium. Since the utility function is positively increasing in the net return, the decision-making in (2) is equivalent to maximize the certainty equivalent, and the resultant first-order condition is, $\partial\mu_1/\partial x - v = \partial R/\partial x$. In combination with equation (3), we have the marginal risk premium with respect to input use, x ,

$$(4) \quad \frac{\partial R}{\partial x} = \frac{R_2}{\mu_1 - vx} \frac{\partial \mu_2}{\partial x} - \frac{R_3}{(\mu_1 - vx)^2} \frac{\partial \mu_3}{\partial x}.$$

Now we can combine the effects of input choice on production risk and downside risk and measure its total effect on the risk premium according to equation (4). Following Chavas (2004), a risk-increasing input has a positive marginal risk premium; a risk-decreasing input has a negative marginal risk premium. The right-hand side of equation (4) can be interpreted as the marginal risk effect of input use that is equal to its marginal mean net return in equation (3). Farmers choose the input use to the point where the marginal net return of input use is equal to its marginal risk effect.

The solution of equation (3) takes the form,

$$(5a) \quad x^* = x(v, \mathbf{e}, \theta),$$

$$(5b) \quad q^* = q(v, \mathbf{e}, \theta).$$

Substituting (5a) and (5b) into the objective function (2), we can obtain the certainty equivalent, CE^* ,

$$(6) \quad CE^* = CE(v, \mathbf{e}, \theta) \\ \equiv \mu_1(x^*) - vx^* - R(x^*).$$

Note that (6) defines the *reduced-form* certainty equivalent which assumes that input use (including variable input use and capital service) is adjusted optimally according to equation (3) conditional on climates. We emphasize here that input choice, expected output, and certainty equivalent as shown in equations (5a), (5b) and (6) are dependent on micro-climate parameters, θ , rather than weather variables.

Since the certainty equivalent and the risk premium have clear welfare implications, so we use them in analyzing the impacts of climate variables. We assume the decision maker's risk preference is fixed, i.e., the Arrow-Pratt relative risk aversion coefficient and the relative downside risk aversion coefficient are constant. Consider the decision maker's certainty equivalent responds to a change in the climate,

$$\begin{aligned}
(7) \quad \frac{\partial CE^*}{\partial \theta} &= \frac{\partial [\mu_1(x^*) - vx^*]}{\partial \theta} - \frac{\partial R(x^*)}{\partial \theta} \\
&= \frac{\partial [\mu_1(x^*) - vx^*]}{\partial \theta} - \left[\frac{R_2}{\mu_1(x^*) - vx^*} \frac{\partial \mu_2(x^*)}{\partial \theta} - \frac{R_3}{[\mu_1(x^*) - vx^*]^2} \frac{\partial \mu_3(x^*)}{\partial \theta} \right].
\end{aligned}$$

Equation (7) shows that climate change affects the certainty equivalent of the decision-maker through the impacts on the mean and high-order moments of the output distribution. Without taking into account the high-order impacts, estimates of the impacts of climate change on the certainty equivalent are likely to be biased. Note that if input use is held constant at some specified level, then we obtain the impacts of climate change on the certainty equivalent without adjustment (or adaptation) of input use, i.e.,

$$\begin{aligned}
(7') \quad \frac{\partial CE^x}{\partial \theta} &= \frac{\partial [\mu_1(x) - vx]}{\partial \theta} - \frac{\partial R(x)}{\partial \theta} \\
&= \frac{\partial [\mu_1(x) - vx]}{\partial \theta} - \left[\frac{R_2}{\mu_1(x) - vx} \frac{\partial \mu_2(x)}{\partial \theta} - \frac{R_3}{[\mu_1(x) - vx]^2} \frac{\partial \mu_3(x)}{\partial \theta} \right].
\end{aligned}$$

Since input use in equation (7) is optimally adjusted, the marginal effects of climate variables on the certainty equivalent in equation (7) are smaller than in equation (7'). This implies that farmers can adapt to climate change by adjusting input use and technology. These changes will depend on how they affect the farmer's mean returns as well as the high-order moments of net returns.

Risk-Value Model

Our analysis of the economic impacts of climate change on the output distribution so far assumes that the decision maker has the same risk aversion on economic gains and losses deviated from the expectation in the expected utility model. The expected utility model is known to impose a number of strong restrictions on risk behavior, and has found to be systematically violated in experimental studies (Kahneman and Tversky 1979; Machina 1989; Conlisk 1996; Starmer 2000).

An alternative decision model that can be interpreted as a generalization of the expected utility model is the risk-value model (Jia et al. 2001; Antle 2010). In the risk-value model, the decision-maker's objective function depends on an "expected" or "anticipated" outcome, as in the certainty equivalent formulation of the expected utility model, but also depends on negative and positive deviations from this expected outcome, and attaches a negative value to deviations below and a positive value to deviations above this expected outcome. The risk-value model

provides a natural way to relate decisions to partial moments of outcome distributions, and also provides an intuitive link from the vulnerability concepts introduced in section 2 to the farmer's decision making.

To simplify the discussion and estimation below, we define the partial moments of the output distribution in absolute moments: the lower j th partial moment,

$$\eta_j = \int_{-\infty}^r |q - r|^j \phi(q|x, \theta, \mathbf{e}) \Phi(x, \theta, \mathbf{e}, r)^{-1} dq,$$

and the upper j th partial moment,

$$\varphi_j = \int_r^{+\infty} |q - r|^j \phi(q|x, \theta, \mathbf{e}) [1 - \Phi(x, \theta, \mathbf{e}, r)]^{-1} dq, j \geq 2,$$

where r is a reference level, $\Phi(x, \theta, \mathbf{e}, r)$ is the probability of the output below the reference level, $\Phi(x, \theta, \mathbf{e}, r) = \int_{-\infty}^r \phi(q|x, \theta, \mathbf{e}) dq$. In this study, the expected output is used as the reference level, and thus the central moments can be expressed as functions of partial moments,

$$\mu_j = (-1)^j \eta_j \Phi(x, \theta, \mathbf{e}, r) + \varphi_j [1 - \Phi(x, \theta, \mathbf{e}, r)].$$

Let the objective function be $U(\mu_1 - vx, \eta_2, \varphi_2, \eta_3, \varphi_3)$, and define $U_{j\eta} = \frac{\partial U}{\partial \eta_j}$, $U_{j\varphi} = \frac{\partial U}{\partial \varphi_j}$. Then, the objective of a risk-averse farmer is to maximize,

$$(8) \quad \max_{q, x} U(\mu_1 - vx, \eta_2, \varphi_2, \eta_3, \varphi_3).$$

The first-order condition of (8) in the elasticity form is given by,

$$(9) \quad \mu_1^* - vx/\mu_1 = s_2 (R_{2\eta} \eta_2^* - R_{2\varphi} \varphi_2^*) + s_3 (R_{3\eta} \eta_3^* - R_{3\varphi} \varphi_3^*),$$

where $\eta_j^* \equiv \frac{\partial \ln \eta_j}{\partial \ln x}$, $\varphi_j^* \equiv \frac{\partial \ln \varphi_j}{\partial \ln x}$, $R_{j\eta} \equiv -\frac{U_{j\eta} \eta_j}{U_1 \mu_j} (\mu_1 - vx)^{j-1}$, $R_{j\varphi} \equiv \frac{U_{j\varphi} \varphi_j}{U_1 \mu_j} (\mu_1 - vx)^{j-1}$, $j = 2, 3$.

$R_{j\eta}$ and $R_{j\varphi}$ represents the risk attitude to the negative and positive deviations from the expectation, and are interpreted as disappointment and elation in the risk value model. If input use has symmetric effects on the full moments of the output distribution, i.e., $\mu_2^* = \eta_2^* = \varphi_2^*$, $\mu_3^* = 0$, $\eta_3^* = \varphi_3^*$, then let $R_2 = R_{2\eta} - R_{2\varphi}$, and $R_{3\eta} = R_{3\varphi}$, so input use from equation (9) has the same risk implication as from equation (3') and is then equivalent to the expected utility model (Antle 2010). If input use has asymmetric effects on the full moments, then the expected utility model and the risk-value model can provide different risk implications for input use, and also indicate different welfare effects of exogenous changes in the output distribution due to climate change.

The solution of equation (9) takes the form, $x^{**} = x(v, \mathbf{e}, \theta)$, $q^{**} = q(v, \mathbf{e}, \theta)$, and the optimized certainty equivalent is given by $CE^{**} = CE(v, \mathbf{e}, \theta)$. Then, we can quantify the impacts of climate change on the certainty equivalent using the risk value model,

$$(10) \quad \frac{\partial CE^{**}}{\partial \theta} = \frac{\partial[\mu_1(x^*) - vx^*]}{\partial \theta} - \frac{\partial R(x^*)}{\partial \theta} \\ = \frac{\partial[\mu_1(x^*) - vx^*]}{\partial \theta} - \sum_{j=2}^3 \left[\frac{R_{j\eta}}{[\mu_1(x) - vx]^{j-1}} \frac{\partial \eta_j(x^{**})}{\partial \theta} \frac{\mu_j}{\eta_j} - \frac{R_{j\varphi}}{[\mu_1(x) - vx]^{j-1}} \frac{\partial \varphi_j(x^{**})}{\partial \theta} \frac{\mu_j}{\varphi_j} \right].$$

Compared with the expected utility model, the risk-value model can be used to estimate the asymmetric impacts of climate change and adaptations on the negative and positive tails of the output distribution through equations (9) and (10).

4. Econometric Strategy

In this section, we present an econometric strategy for estimating the mean and high-order impacts of climate variables on agricultural systems by using a heteroscedastic-consistent seemingly unrelated regression (SUR) model. The goal of this model is to specify the high-order moments of the output distribution without any arbitrary restrictions. The mean output function is specified as,

$$(11) \quad q_{it} = \mu_1(\mathbf{m}_{it}, \beta_{it}) + \varepsilon_{it}$$

where q_{it} is the output at farm i in year t , \mathbf{m}_{it} is a vector of site and farm characteristics, β_{it} is a vector of climate variables, ε_{it} is an idiosyncratic term.

Note that input and output prices are fixed across farms in all regression equations. There are two reasons: i) in the cross-sectional analysis there is a lack of variations in input and output prices; ii) agricultural output prices are set at the global level for the major field crops. Thus, input and output prices are dropped out of the regression equations.

Then, the high-order central moments of the output distribution are specified as,

$$(12) \quad \varepsilon_{it}^j = \mu_j(\mathbf{m}_{it}, \beta_{it}) + v_{it}, \quad j = 2, 3$$

The partial moment functions of the output distribution are specified as,

$$(13a) \quad |\varepsilon_{it}|^j = \eta_j(\mathbf{m}_{it}, \beta_{it}) + v_{nit} \text{ if } \varepsilon_{it} < 0$$

$$(13b) \quad |\varepsilon_{it}|^j = \varphi_j(\mathbf{m}_{it}, \beta_{it}) + v_{pit} \text{ if } \varepsilon_{it} > 0.$$

The specification of the mean output function is important for estimating the high-order moments functions. Equation (11) uses a flexible moment-based approach that relaxes the embedded restrictions of the high-order moments in the multiplicative error model and the

additive error model (for further critical discussion, see the study by Antle 1983). The consistent estimates of the mean function in equation (11) with a quadratic function form generate the residuals that are used to consistently estimate the high-order central moments functions in equations (12)-(13b). The error terms in (12), (13a) and (13b) are heteroscedastic and correlated across moments, and thus the simple equation-by-equation OLS estimators are not efficient. Antle (1983) showed that a joint feasible GLS can improve the estimation efficiency. To overcome the heteroscedasticity and the cross-equation correlations, we use the heteroscedastic-consistent SUR model. Also, a combination of equations (13a) and (13b) can be used to test for the symmetry of the partial moment parameters by a Chow test.

5. Data Sources and Summary Statistics

In this section we describe the sources of the data used in this analysis and report some summary statistics.

Economic and Social Variables

We compile farm-level agricultural data from the Agricultural Census in 2002, 2007 and 2012 to construct economic and social variables. A farm in the Agricultural Census is defined as any operation with \$1,000 or more of agriculture products produced or sold during each census year. The economic variables include winter wheat yield, farm size, percent of irrigated winter wheat acreage, and shares of farmland under CRP and WRP programs. The social variables include experience, land ownership, and off-farm employment. Because the primary goal of this analysis is to assess the impact of climate change on the vulnerability of winter wheat systems, we confine the study region to the U.S. Pacific Northwest (PNW) in our analysis. Zip codes are the finest geographical information available to locate farms and are used to link agricultural data to biophysical data.

Panel A in table 1 reports summary statistics of economic and social variables from the Agricultural Census in 2002, 2007 and 2012. We exclude small farms with less than 50 acres of cropland because they could be hobby farms or exist only for tax purposes rather than maximizing farm profit. There are 4518 to 5487 winter wheat farms in the sample depending on the census year. Several features are noteworthy. First, winter wheat yield increased over time. This implies that there may be year fixed-effects common to all winter wheat farms due to technology innovations. Second, winter wheat yield is higher on irrigated farms than non-

irrigated farms. This is intuitive because irrigation relaxes the water constraint and improves crop water use efficiency. Third, the proportion of large farms increased over time as the number of farming operations decreased. This may reflect a consolidation of the farming industry.

Soil Variables

We rely on the Gridded Soil Survey Geographic (gSSURGO) database to construct soil variables. The data in the gSSURGO database are derived from the Soil Survey Geographic database, which has the most detailed level of soil geographic data developed by the National Cooperative Soil Survey. Zip-code level soil variables are generated by overlaying a map of zip codes on the gSSURGO dataset for each polygon and taking the acreage-weighted average across all polygons within each zip-code area. Panel B in table 1 reports summary statistics of soil variables for winter wheat farms in the PNW.

Weather and Climate Variables

We obtain the downscaled historical weather data using the Multiplicative Adaptive Constructed Analogs (MACA) method (Abatzoglou and Brown, 2012). The MACA dataset downscales a large set of daily weather variables, e.g., precipitation, maximum temperature, minimum temperature and wind speed. The MACA dataset provides the historical daily weather data with a spatial resolution of 4-km for the entire coterminous U.S. The MACA model and data are used to develop daily measures of precipitation and temperature for agricultural land in each zip-code area from 1979-2013. This was accomplished by overlaying a land use map on the MACA dataset for each grid cell and then by taking the acreage-weighted average across all agricultural land grid cells within each zip-code area.

We use daily-level weather data on precipitation and temperature to calculate total precipitation, growing degree-days, and freezing degree-days during the growing season from October 1 of the previous year to July 30 of the reported census year. We construct the daily growing and freezing degree-days variables as a step function of daily mean temperature following Deschenes and Greenstone (2007). A daily mean temperature below 0°C generates 0 daily growing degree-days; a daily mean temperature between 0°C and 23°C generates the number of daily growing degree-days above 0°C; a daily mean temperature above 23°C generates 23 daily growing degree-days. The growing degree-days variable is then calculated by summing the daily measures over the entire growing season. Similarly, a daily mean temperature above

0°C generates 0 daily freezing degree-days; a daily mean temperature below 0°C generates the number of daily freezing degree-days below 0°C (in absolute values). The freezing degree-days variable is then calculated by summing the daily measures over the entire growing season.

We construct climate variables of precipitation and temperature before the growing season by taking the means of total precipitation and growing degree-days for 22 years (our historical weather data started in 1978). Panel C in table 1 reports summary statistics of climate variables for all winter wheat farms in the PNW. Note that extreme high temperature events are not constructed or modeled in this study for two reasons: i) there is a lack of enough spatial variations in the PNW for extreme high temperatures; ii) for extreme high temperatures, the damaging threshold for winter wheat is 35°C, which rarely occurs within the winter wheat growing season in this region.

6. Results

This section is divided into two subsections. The first subsection presents estimates of the effects of climate variables on the mean winter wheat yield. The second subsection presents estimates of the effects of climate variables on the high-order moments of the winter wheat yield distribution.

Climate Responses on the Mean Winter Wheat Yield

We estimate climate responses on the mean winter wheat yield in equation (11). We report the estimates of the mean winter wheat yield function in table 2. The A, B, C, and D columns in table 2 correspond to four sets of control variables. In the A column, we include growing degree-days, precipitation, irrigation, and an interaction term of irrigation with precipitation as well as other non-climate covariates. The specification in the B column adds an interaction term of growing degree-days with irrigation to the specification in the A column. The specification in the C column adds an interaction term of growing degree-days with precipitation to the specification in the B column. The entries in the D column are adjusted for quadratic terms of climate and irrigation variables from the specification in the C column. We weight the regression equations by the square root of cropland acres, and use robust standard errors to control heteroscedasticity.

We find that two temperature variables have a negative effect on winter wheat yield in this region. All four elasticities of growing degree-days and freezing degree-days are negative

and statistically significant in table 2. This implies that a warming climate will reduce freezing degree-days and benefit winter wheat production, but this beneficial effect will be offset by a negative effect due to an increase in the growing degree-days, resulting in a negative net impact on winter wheat yield. We also find that growing degree-days and freezing degree-days have a non-linear effect on winter wheat yield in the D column, which is consistent with the study by Shelenker and Robert (2009). Note that, contrary to the finding by Fezzi and Bateman (2005), an interaction between precipitation and growing degree-days negatively affects winter wheat yield in the D column.

Three of four precipitation elasticities of the mean winter wheat yield are statistically positive and stable across all four specifications, varying between 0.120 and 0.122. The coefficients of the interaction term of precipitation and irrigation are negative and statistically significant in each specification. This provides evidence that irrigation has a substitution effect on precipitation in winter wheat production. The coefficient of the quadratic term of precipitation in the D column is negative and statistically significant. This reflects the fact precipitation has a positive effect in the dry area but a negative effect in the wet area.

All irrigation elasticities of the mean winter wheat yield are statistically positive and stable across four specifications in table 2. Doubling irrigated winter wheat acreage increases winter wheat yield by 11-17 bushels per acre, depending on the function form. This first reflects that irrigation increases crop productivities by improving crop water use efficiency. Also, in interpreting the irrigation effect, keep in mind that we estimated a reduced-form function for winter wheat production, so other input use are optimally adjusted by equation (5) when irrigated winter wheat acreage increases. This implies that a rise in irrigated winter wheat acreage shifts the production function outward by increasing input use like fertilizer as illustrated in figure 1.

The farm characteristics—experience, ownership and off-farm employment—have no effects on the mean winter wheat yield. There are interesting findings about two of the economic and social variables. First, farm size has a positive effect on winter wheat yield. This is intuitive because large farms have more financial capital to improve crop productivity by adopting new technologies. Second, the share of cropland in CRP and WRP programs shows a negative effect on winter wheat yield in all four specifications. This simply reflects that farmers with a larger percent of farmland under CRP and WRP programs are more likely to have poor biophysical conditions for winter wheat growth and low winter wheat yields.

The elasticities of mean winter wheat yield with respect to soil variables have expected signs: total sand has a negative effect on winter wheat yield; soil organic matter has a positive effect on winter wheat yield; and less erodible soils benefit crop growth. These findings are consistent with agronomic experiments.

Overall, this subsection has produced a few important findings: i) precipitation and irrigation both positively affect winter wheat yield, and irrigation has a substitution effect on precipitation in winter wheat production; ii) temperature variables on average negatively affects winter wheat yield in this region but the effects are non-linear.

Climate Responses on High-order Moments of Winter Wheat Yield Distributions

We now examine the effects of climate variables on the high-order moments of winter wheat yield distributions. We obtain consistent residuals from the mean winter wheat yield function with a quadratic function form and estimate equations (12) – (13b) by using the heteroscedastic-consistent SUR model. Table 3 presents elasticities of the high-order moment function estimates. The six columns in table 3 correspond to six regressions of the high-order moments of the winter wheat yield distribution on the same set of control variables, including growing degree-days, precipitation, irrigation and their interactions as well as other non-climate covariates. Note that the lower third partial moment is estimated as an absolute moment, so the elasticities show opposite effects on the third central moment. We weight the regression equations by the square root of cropland acres, and include state-by-year dummies to control state-level unobservable determinants of dependent variables.

The F-statistics of a Chow test were calculated for the symmetry test for the equality of the partial moment parameters. Table 3 shows that the symmetry restrictions are rejected for the second moment. This implies that input choice and climate variables have asymmetric effects on the lower and upper semi-variances. Furthermore, the R^2 statistics show that the partial moment functions fit the data better than the full moment functions. More importantly, the full third moment function is almost not statistically significant and has a poor fit, whereas the third partial moments are statistically significant and have better fit, consistent with the finding in the study by Antle (2010).

The effects of precipitation and growing degree-days on the output distribution are likely to depend on the location of a farm. In the PNW, the majority of winter wheat farms are non-irrigated and located in the east Cascade where the climate variation is low and soil moisture

deficit is a constraint for winter wheat production. Under these conditions, an increase in precipitation is expected to shift the winter wheat yield distribution toward the production frontier and increase the negative skewness, but its effect on the variance is unclear, as shown in figure 2. An increase in growing degree-days may shift the distribution to the right or the left in the long run depending on adaptation abilities, e.g., heat-resistant seed variety, and its effects on the variance and skewness are not clear. An increase in freezing degree-days damages winter wheat production and is expected to shift the distribution to the left and increase the positive skewness. Irrigation is expected to be risk-decreasing because irrigated farms can mitigate the risk of precipitation reduction by applying more irrigation water.

With respect to the full moment functions, precipitation, growing degree-days, freezing degree-days, and irrigation positively affect the variance function. The third central moment function is statistically insignificant for climate variables, and none of the elasticities is statistically significant. These results suggest that irrigation is risk-increasing, contrary to expectations. The partial moment functions present different risk implications of precipitation, growing-degree days, freezing degree-days, and irrigation. On one hand, precipitation and growing degree-days have large and significant effects on both the positive and negative tails of the winter wheat yield distribution, resulting in a small reduction of the skewness. On the other hand, freezing degree-days has a large and significant effect on the lower third partial moment, resulting in a reduction in the positive skewness or a rise in the negative skewness. These effects are similar from those implied by the full moment functions except for precipitation. This provides more evidence that partial moments can better fit the data than full moments to capture asymmetric effects of input use on output distributions (Antle 2010).

We find irrigation positively affects the variance of winter wheat yield distribution, implying that irrigation is risk-increasing. The partial third moments, however, show that irrigation strongly increases the negative skewness as shown in figure 2. This reflects that, on the one hand, irrigation relaxes the constraint of soil moisture deficit and reduces the mass of the negative tail of the distribution, resulting in a reduction in the positive skewness. On the other hand, irrigation increases crop productivity through other input use like a higher application rate of fertilizer, shifts the production frontier rightward and extends the positive tail of the distribution, resulting in an increase in the positive skewness. The total effect of irrigation on the skewness of the distribution depends on whether the former or the latter is a dominant effect.

Given the fact that a majority of winter wheat farms in this region are non-irrigated and constrained by soil moisture, an increase in irrigated winter wheat acreage shifts the output distribution rightward and reduces the positive skewness.

There are several interesting findings about other non-climate variables. First, farm size negatively affects the variance function for winter wheat production by reducing the mass of the negative tail. Second, slope and total sand positively affect the variance function for winter wheat production, and soil organic matter negatively affects the variance. This can be interpreted by the fact that production risk is lower on high quality soils.

To further investigate the risk implications of precipitation, growing degree-days, freezing degree-days, and irrigation for the winter wheat production, panel A in table 4 presents the marginal risk premiums of climate and irrigation variables as a percent of the net return from the winter wheat yield model. We set the Arrow-Pratt relative risk aversion coefficient to 1 and the downside risk aversion coefficient to 2 in the expected utility model as in Antle (2010), and $R_{2\eta} = 1$, $R_{2\varphi} = 0.5$, $R_{3\eta} = 1/3$, $R_{3\varphi} = 1/3$ in the risk-value model. If climate and irrigation variables have symmetric effects on the partial moments, then these two models provide the same risk implications. Both the expected utility model and the risk-value model shows that precipitation, growing degree-days, freezing degree-days, and irrigation have positive effects on the risk premium in this region from the winter wheat yield model. Note that even though precipitation and irrigation variables are risk-increasing, their effects on the certainty equivalent are still positive due to increased mean winter wheat yields. The left panel in figure 3 shows that a rise in precipitation has a substantially large effect on the mean winter wheat yield and dominates its effect on the risk premium, resulting in a large positive effect on the certainty equivalent.

7. Climate Vulnerability

In this section, we examine and project the impacts of climate change on farm-level winter wheat yield distribution and climate vulnerability by choosing 2012 as the base period. The goal of this analysis is to evaluate the long-run impact of climate change on the vulnerability of *current* agricultural systems, conditional on biophysical, socio-economic, technological conditions and policies, over the 2066-2095 period.

Impacts of Climate Change on the Distribution of Winter Wheat Yield

In this subsection, we examine the impacts of extreme climate events on the winter wheat yield distribution under two hypothetical extreme conditions. One condition is a combination of a reduction in growing season precipitation by 30% and an increase in growing degree-days by 300 degree-days (an increase in daily mean temperature by about 1°C), referred to as “drought”; the other condition is a combination of an increase in growing season precipitation by 30% and a reduction in growing degree-days by 300 degree-days, referred to as “wet”.

To simulate the ex-ante distribution of winter wheat yield, we first predict the full moments and partial moments of the distributions by using the estimates from the above section under two hypothetical conditions. We then use the Pearson system to simulate the distributions (Johnson et al. 1994). The Pearson system includes a variety of distributions in the exponential family and requires the first four moments—mean, standard deviation, skewness, and kurtosis—to simulate a distribution. Compared with the entropy-based approach (Tack et al. 2012), we find the Pearson system is more robust and efficient to generate an outcome distribution.

Figure 4 shows the effects of two extreme climate conditions on the winter wheat yield distribution at the sample means of non-irrigated and irrigated winter wheat farms. It is apparent that the drought condition has a substantial negative effect on non-irrigated farms in both the expected utility model and the risk value model. The drought condition adversely affects the winter wheat production on non-irrigated farms by pushing the winter wheat yield distribution leftward and substantially increasing the positive skewness, resulting in the large mass concentrated on the negative tail. However, the wet condition is beneficial for the winter wheat production on non-irrigated farms by shifting the winter wheat yield distribution rightward. These two extreme conditions imply that non-irrigated farms are sensitive to the drought condition and become significantly vulnerable under a warmer and drier climate.

In interpreting the effects of two extreme climate conditions on irrigated farms, keep in mind that the percent of irrigated winter wheat acreage is fixed at the sample mean, so we implicitly assume that irrigation water is not limited under climate change. Thus, the effects of these two extreme climate conditions on irrigated farms are mainly due to the effect of temperature. On the one hand, the winter extreme low temperature is reduced under the drought condition and increased under the wet condition for the winter wheat production; and, on the other hand, the extreme heating days over the daily temperature threshold of 35°C are still rare within the winter wheat growing season. This explains why the drought condition has a positive

effect on the winter wheat yield distribution by shifting the distribution rightward, while the wet condition shows a negative effect.

Impacts of Climate Change on the Vulnerability of Agricultural Systems

In this subsection, we predict the impacts of climate change on the vulnerability of winter wheat farms in the PNW over the 2066-2095 period. Our prediction relies on the Met Office Hadley Centre's Second Hadley Global Environment Model with a carbon cycle process, which we refer to as HadGEM2-CC. The MACA method was used to statistically downscale daily weather variables from the HadGEM2-CC under two emission scenarios developed by the Representative Concentration Pathways (RCP), i.e., RCP 4.5 and 8.5 (RCP 8.5 represents a higher level of greenhouse gas concentration).

Climate variables of growing degree-days, freezing degree-days, and precipitation are constructed over the 2065-2099 period under two emission scenarios by using the MACA data set. The Pearson system was used to simulate the winter wheat yield distribution for each individual farm at the base and future periods. As explained in section 2, We define a threshold indicator of climate vulnerability as the absolute deviation below some reference level, i.e., the first-order lower partial moment of an outcome distribution, $I = \int_{-\infty}^r |q - r| \phi(w|\beta) dw$, $q = y, \pi$, where I is a threshold indicator of the climate vulnerability at an individual farm, r is the reference. q is an economic outcome from the output production including crop yield, y , and net return, π . $\phi(w|\beta)$ is a weather distribution of w determined by a micro-climate β . In this study, the expected winter wheat yield in 2012 were chosen as the reference levels to calculate farm-level climate vulnerability to expected winter wheat yield losses under the current and future climates.

Figure 5 presents the distributions of the changes in farm-level vulnerability indicators under the climate change. Climate change will be likely to damage the winter wheat production on average by increasing expected winter wheat yield losses in the PNW over the 2066-2095 period under two greenhouse gas emission scenarios. In the expected utility model, 64% of winter wheat farms will experience an increase in expected yield losses under the low greenhouse gas emission scenario; in the risk-value model, 86% of winter wheat farms will experience an increase in expected yield losses under the low greenhouse gas emission scenario.

This implies that winter wheat farms in the PNW on average become more vulnerable under the future climate by the end of this century.

The climate change impacts on the vulnerability to expected yield losses are not uniformly distributed among winter wheat farms in the PNW. Due to this heterogeneity, while a majority of winter wheat farms would tend to be more vulnerable to expected yield losses, some farms that would be less vulnerable to climate change. 36% of winter wheat farms in the expected utility model will experience a reduction in expected yield losses over the 2066-2095 period under the low greenhouse gas emission scenario, and 14% projected in the risk-value model.

There is substantial uncertainty in projections of future climates, including modelling uncertainty from more than 20 global climate models and input uncertainty from greenhouse gas emissions, and thus there are large uncertainties in the impacts on the vulnerabilities of winter wheat productivity. For example, as the greenhouse gas emission level goes up from RCP 4.5 to 8.5, 7% of winter wheat farms become less vulnerable to expected yield losses according to the expected utility model with an increase in the magnitude of expected yield losses.

8. Conclusions

Climate change is believed to have large impact on agricultural systems since temperature and precipitation are two direct inputs in the crops production. A large volume of research has been devoted to assess the impacts of climate change on agricultural production and agribusiness by using a variety of impact assessment approaches. The impacts of climate change on agricultural systems by the end of this century will be likely to vary substantially by region and crop. Research is needed to quantify the impacts of climate change on individual crop systems at a local or regional level.

Previous research has extensively examined the mean impacts of climate change on the U.S. agricultural sector with a focus on corn, soybean and cotton systems in the eastern U.S. This paper implemented a flexible moment-based approach to evaluate the high-order impacts of climate variables on farm-level winter wheat yield distribution in the U.S. Pacific Northwest. Farm-level economic data were compiled from the Agricultural Census in 2002, 2007 and 2012 to estimate the effects of climate variables on the means and high-order moments of farm-level yield distribution.

We find that growing degree-days and freezing degree-days negatively affect winter wheat productivity, and precipitation and irrigation improve winter wheat productivity in the U.S. Pacific Northwest. We also find that growing degree-days, freezing degree-days, and irrigation increase the risk premium from the winter wheat yield model, and the net effect of irrigation on the certainty equivalent is positive. The partial moments are demonstrated to better capture the asymmetric effects of climate variables on farm-level yield distribution than the full moments, although they provide similar risk implications of climate and irrigation variables for the winter wheat production in the study region.

We show that the drought condition has a large adverse effect on the winter wheat yield on non-irrigated winter wheat farms. The projections from the HadGEM2-CC model under two greenhouse gas emission scenarios show that winter wheat farms will be likely to become more vulnerable to expected yield losses, especially under the high greenhouse gas emission scenarios. However, the climate impacts on farm-level vulnerability are not uniformly distributed across farms, and due to this heterogeneity, there could be some winter wheat farms in the study region would still benefit from climate change.

In interpreting these findings it is important to keep in mind that important factors such as CO₂ fertilization effects are not accounted for in statistical approaches. Also, it is important to recognize that the projections presented here do not incorporate changes in biophysical, socioeconomic conditions, technologies, and policies in the future world accompanied with climate change. Future research need to combine statistical approaches with process-based approaches to examine the effects of rising CO₂ levels on the winter wheat production , and to design scenarios with consistent climate, biophysical, socioeconomic conditions, technologies, and policies for projecting the impacts of climate change in the future. Moreover, the irrigation in the historical period was subsidized by the government in the western U.S., and irrigation water rights are regulated by the law, so the percent of irrigated winter wheat acreage is fixed in the projections. Future research need to address this issue and explicitly model the decision making on irrigation.

References

- Abatzoglou, J.T., and T.J. Brown. 2012. "A Comparison of Statistical Downscaling Methods Suited for Wildfire Applications." *International Journal of Climatology*, 32: 772-780.
- Adams, R.M. 1989. "Global Climate Change and Agriculture: An Economic Perspective." *American Journal of Agricultural Economics*, 71(5): 1272-1279.
- Alwang, Jeffrey, Paul Siegel, and Steen Jorgensen. 2001. "Vulnerability: A View from Different Disciplines." Social Protection Discussion Paper No. 0115, Social Protection Unit, Human Development Network, World Bank, Washington, DC.
- Antle, J.M. 1983. "Testing the Stochastic Structure of Production: A Flexible Moment-based Approach." *Journal of Business & Economic Statistics*, 1(3): 192-201.
- Antle, J.M. 1987. "Econometric Estimation of Producers' Risk Attitudes." *American Journal of Agricultural Economics*, 69(3): 509-522.
- Antle, J.M., S.M. Capalbo, E.T. Elliott, and K.H. Paustian. 2004. "Adaptation, Spatial Heterogeneity, and the Vulnerability of Agricultural Systems to Climate Change and CO₂ Fertilization: An Integrated Assessment Approach." *Climatic Change* 64(3):289-315.
- Antle, J.M. 2010. "Asymmetry, Partial Moments and Production Risk." *American Journal of Agricultural Economics*, 92:1294-1309.
- Burke, M., and K. Emerick. 2012. "Adaptation to Climate Change: Evidence from US Agriculture." Working Paper.
- Bourguignon, F., C. Goh, and D. Kim. 2004. "Estimating Individual Vulnerability Using Pseudo-Panel Data". World Bank Policy Research Working Paper 3375.
- Chaudhuri, S., J. Jalan, and A. Suryahadi. 2002. "Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia". Columbia University, Discussion Paper 0102-52.
- Christiaensen, L. and K. Subbarao. 2004. "Toward an Understanding of Household Vulnerability in Rural Kenya". World Bank Policy Research Working Paper 3326.
- Cooper, J.C. 2010. "Average Crop Revenue Election: A Revenue-Based Alternative to Price-Based Commodity Payment Programs." *American Journal of Agricultural Economics*, 92(4): 1214-1228.
- Conlisk, J. 1996. "Why Bounded Rationality?" *Journal of Economic Literature*, 34(2): 669-700.

- Deschenes, O., and M. Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97(1): 354-385.
- Deschenes, 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): 3761-3773.
- Delquié, P., and A. Cillo. 2006. "Disappointment without Prior Expectation: A Unifying Perspective on Decision under Risk." *Journal of Risk and Uncertainty*, 33: 197-215.
- Di Falco, S., and J.-P. Chavas. 2006. "Crop Genetic Diversity, Risk Exposure, and Food Security in the Highlands of Ethiopia." *American Journal of Agricultural Economics*, 91(3):599-611.
- Fezzi, C., and I.J. Bateman. 2015. "The Impact of Climate Change on Agriculture: Nonlinear Effects and Aggregation Bias in Ricardian Models of Farmland Value." *Journal of the Association of Environmental and Resource Economists*, 2:57-92.
- Foster, J., J. Greer, and E. Thornbecke. 1984. "A Class of Decomposable Poverty Measures". *Econometrica*, 52(3): 761-766.
- Ghannoum, O., S.Von Caemmerer, L.H. Ziska, and J.P. Conroy. 2000. "The Growth Response of C4 Plants to Rising Atmospheric CO2 Partial Pressure: A Reassessment." *Plant, Cell and Environment*, 23:931-942.
- Huang, J., Y. Wang, and J. Wang. 2015. "Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China." *American Journal of Agricultural Economics*, 97(2): 602-617.
- Jia, J., J. S. Dyer, and J. C. Butler. 2001. "Generalized Disappointment Models." *Journal of Risk and Uncertainty* 22(1): 59-78.
- Johnson, N.L., S. Kotz, and N. Balakrishnan. 1994. *Continuous Univariate Distributions*, Volume 1, Wiley-Interscience, Pg 15.
- Just, R.E., and R.D., Pope. 1999. "Implications of Heterogeneity for Theory and Practice in Production Economics." *American Journal of Agricultural Economics*, 81: 711-718.
- Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk". *Econometrica*, 47(2): 263-291.

- Kamanou, G., and J. Morduch. 2004. "Measuring Vulnerability to Poverty", chapter in Dercon, S. (ed.), *Insurance against Poverty*, Oxford University Press.
- Koundouri, P., C. Nauges, and V. Tzouvelekas. 2006. "Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology". *American Journal of Agricultural Economics*, 88(3): 657-670.
- Ligon, E., and L. Schechter. 2003. "Measuring Vulnerability". *The Economic Journal*, 113(486): 95-102.
- Lobell, D.B., K.N. Cahill, and C.B. Field. 2007. "Historical Effects of Temperature and Precipitation on California Crop Yields." *Climatic Change*, 81:187-203.
- Lobell, D.B., Roberts, M.J., Schlenker, W., Braun, N., Little, B.B., Rejesus, R.M., and Hammer, G.L. 2014. "Greater Sensitivity to Drought Accompanies Maize Yield Increase in the U.S. Midwest." *Science*, 344(6183): 516-519
- Machina, M. 1989. "Dynamic Consistency and Non-Expected Utility Models of Choice Under Uncertainty", *Journal of Economic Literature*, 27(4): 1622-1668.
- Maxwell, D., C. Ahaideke, C. Levin, M. Armar-Klemesu, S. Zakariah, and G.M. Lamphey. 1999. "Alternative Food-Security Indicators: Revisiting the Frequency and Severity of Coping Strategies." *Food Policy*, 24: 411-429.
- Mendelsohn, R., and N. Rosenberg. 1994. "Measuring the Impact of Global Warming on Agriculture." *American Economic Review*, 84: 753-771.
- Moser, C. 1998. "The Asset Vulnerability Framework: Reassessing Urban Poverty Reduction Strategies." *World Development*, 26(1): 1-19.
- 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.
- Roberts, M.J., W. Schlenker, and J. Eyer. 2013. "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics*, 95(2):236-243.
- Reardon, T. and S. Vosti. 1995. "Links Between Rural Poverty and the Environment in Developing Countries: Asset Categories and Investment Poverty." *World Development* 23(9): 1495- 1506.

- Schlenker, W., and M.J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damage to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Science*, 106(37): 15594-98.
- Schoengold, K., Y. Ding, and R. Headlee. 2015. "The Impact of AD HOC Disaster and Crop Insurance Programs on the Use of Risk-reducing Conservation Tillage Practices." *American Journal of Agricultural Economics*, 97(3): 897-919.
- Starmer, C. 2000. "Developments in Non-expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk". *Journal of Economic Literature*, 38(2): 332-382.
- Tack, J., A. Harri, and K. Coble. 2012. "More Than Mean Effects: Modeling the Effect of Climate on the Higher Order Moments of Crop Yields." *American Journal of Agricultural Economics*, 94(5): 1037-54.

Figure 1. A Conceptual Framework of the Impacts of Climate Change on the Output Distribution

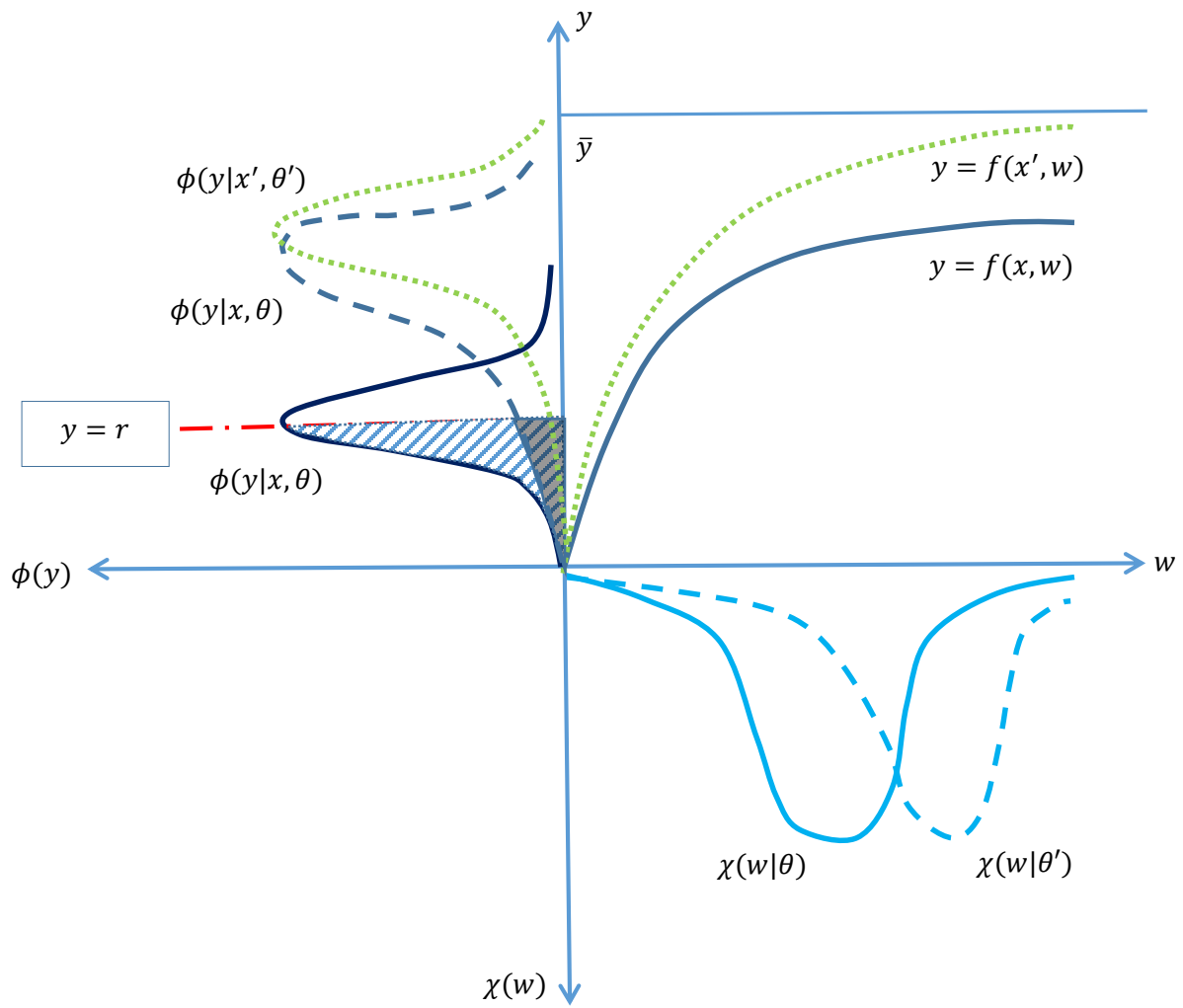


Figure 2. The Kernel Density of Winter Wheat Yields by Irrigation, Precipitation, and Growing Degree-days in the U.S. Pacific Northwest (Unit: bushels/acre)

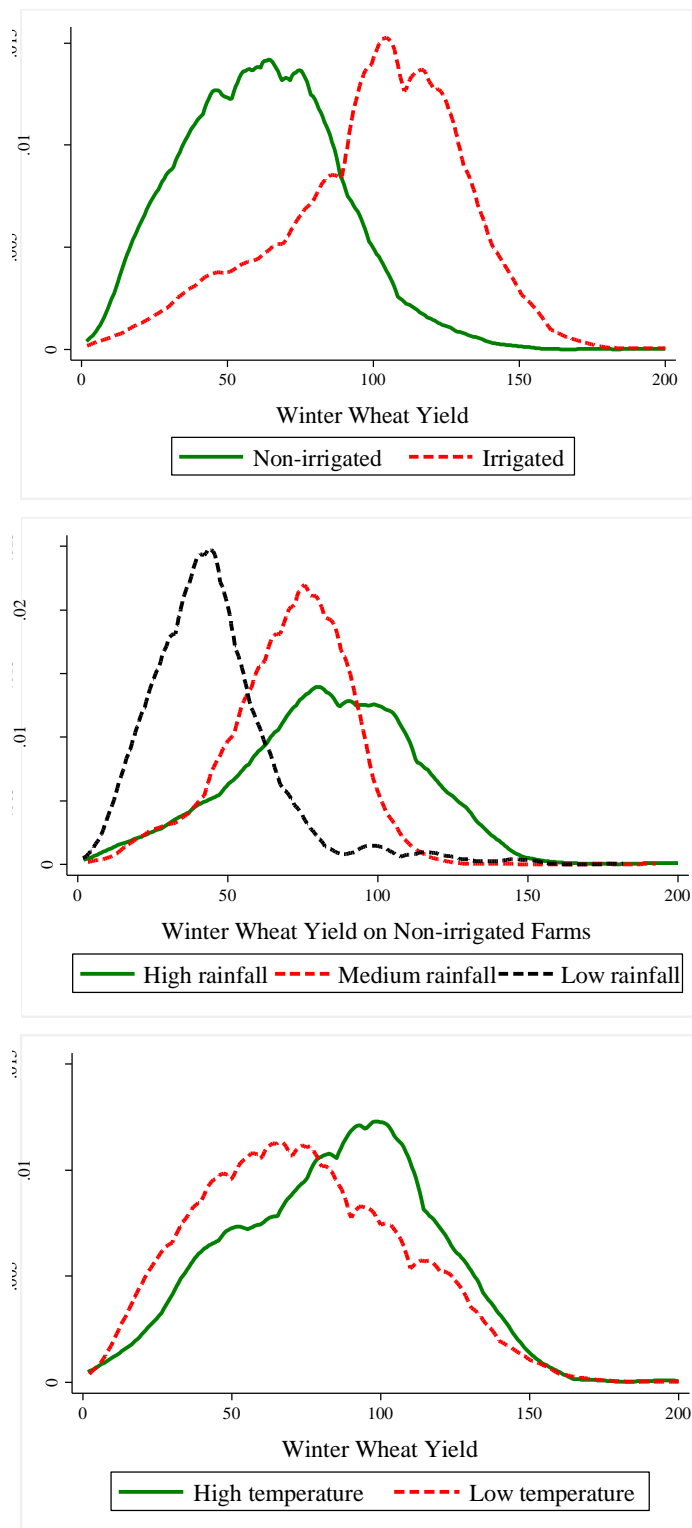


Figure 3. Marginal Effects of Growing Degree-days and Precipitation on the Mean Net Return, Risk Premium and Certainty Equivalent from the Yield Model based on the Expected Utility Model (Units: 2012\$)

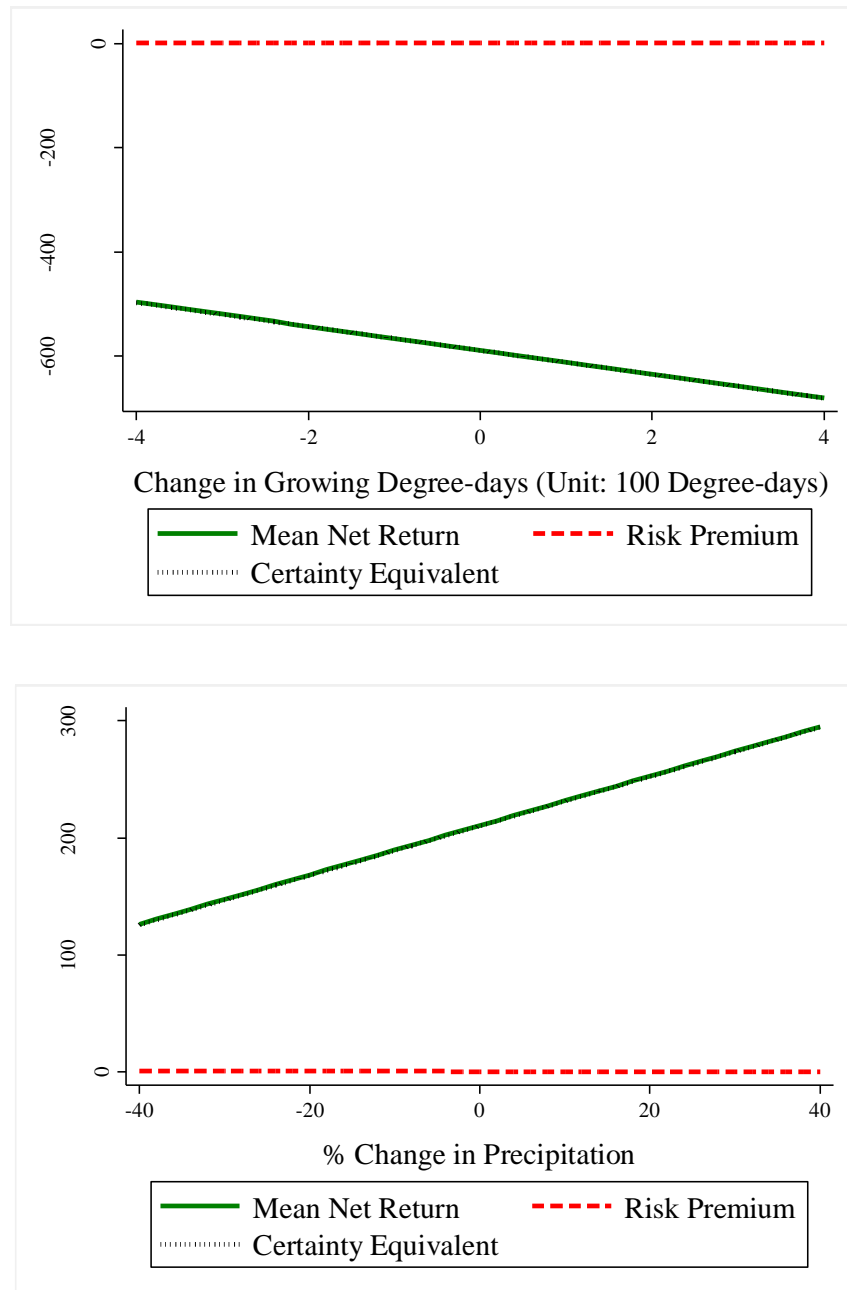
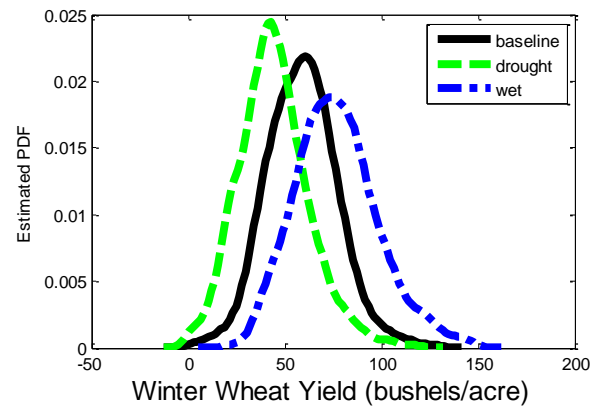
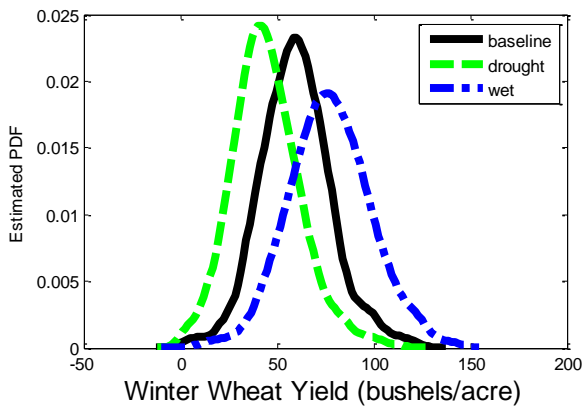


Figure 4. Effects of Climate Variables on the Distribution of Winter Wheat Yield from the Expected Utility Model (left panel) and the Risk Value Model (right panel)

(a) Non-irrigated Farms



(b) Irrigated Farms

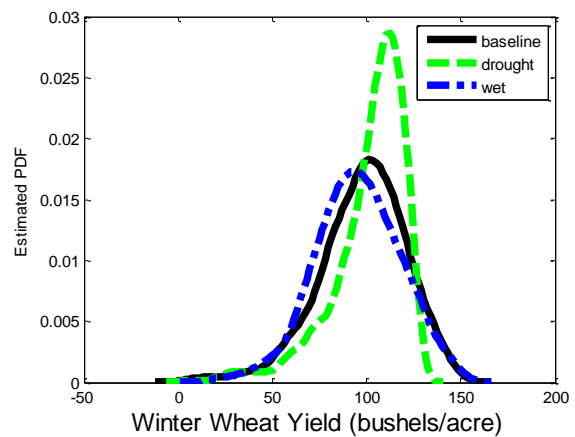
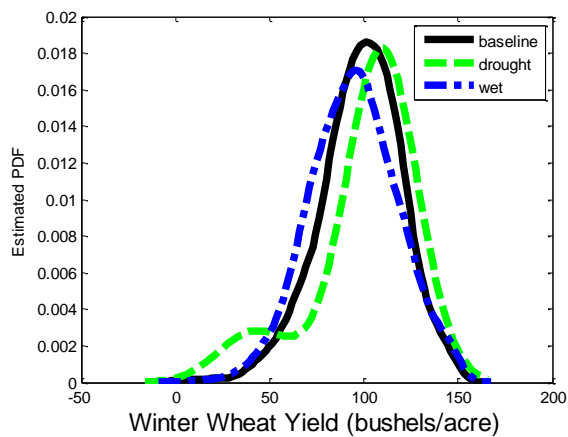


Figure 5. Impacts of Climate Change on the Vulnerability of Winter Wheat Systems in the U.S. Pacific Northwest based on the Expected Utility Model (top panel) and the Risk Value Model (bottom panel) from the Projections of the HadGEM2-CC over 2066-2095

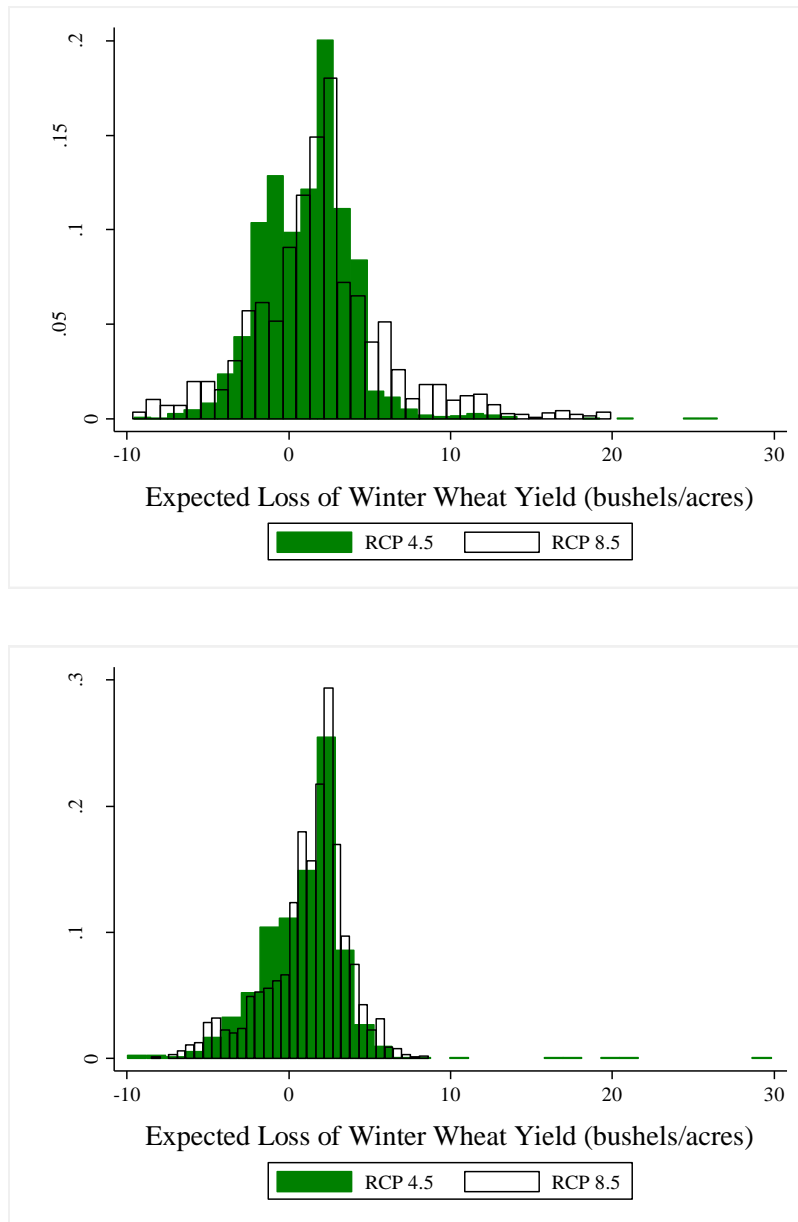


Table 1. Summary Statistics of Winter Wheat Farms in the U.S. Pacific Northwest

Variables	2002		2007		2012		Definition
	Mean	Std.	Mean	Std.	Mean	Std.	
<i>A. Economic and Social Variables</i>							
Winter wheat yield	70.8	33.0	73.2	33.4	81.1	33.6	Winter wheat yield (bushel/acre)
Farm sales	388.3	505.1	483.4	545.6	626.8	628.1	Farm sales over farmland acreage (\$/acre)
Farm expenditure	201.3	415.5	362.8	464.4	506.3	586.3	Farm expenditure over farmland acreage (\$/acre)
Farm net return	187.0	294.2	120.6	255.3	120.5	298.8	Farming net return over farmland acreage (\$/acre)
Large farm	0.4	0.5	0.6	0.5	0.7	0.5	Total farm revenue of over \$250,000 (1 = yes, 0 = no)
CRP and WRP programs	0.1	0.2	0.1	0.2	0.1	0.1	Share of cropland under CRP and WRP programs
Experience	24.3	13.3	26.3	13.6	27.1	14.0	Farming experience (years)
Ownership	0.8	0.4	0.8	0.4	0.8	0.4	Farm fully or partially owned by operator
Farming occupation	0.9	0.3	0.9	0.3	0.9	0.3	Operator occupation (1 = farming, 0 = others)
Irrigation	30.7	45.3	32.1	45.8	31.0	45.2	Percentage of irrigated winter wheat cropland
<i>B. Soil variables</i>							
Slope	14.7	8.7	14.6	8.6	14.4	8.7	Percentage of slope in field
Total sand	26.3	12.0	26.8	12.1	26.1	11.6	Percentage of soil less than 2 mm fraction
SOC	8.2	4.5	7.9	4.3	8.3	4.6	Soil organic matter in 1 meter depth, (kg C/m ²)
Potential wetland	3.0	6.4	2.7	6.5	3.6	7.5	Percentage of wet soils
T factor	3.7	0.7	3.7	0.7	3.7	0.7	Soil loss tolerance factor
<i>C. Climate variables</i>							
Precipitation	16.9	9.5	15.1	8.1	17.3	10.8	Mean precipitation over years (inch)
Growing degree-days	25.5	3.4	25.7	3.5	25.8	3.8	Mean growing degree-days over years (100 degree-days)
Freezing degree-days	2.2	1.2	2.2	1.3	1.8	1.3	Mean freezing degree-days over years (100 degree-days)
Observations	5487		4619		4518		

Note: Farm sales and expenditure are both in 2012 dollars.

Table 2. Estimates of the Mean Winter Wheat Yield Function

VARIABLES	A	B	C	D
Precipitation (<i>Pre.</i>)	1.108*** (0.072)	1.090*** (0.073)	0.992** (0.398)	4.741*** (0.644)
Growing degree-days (<i>GDD</i>)	-0.417*** (0.155)	-0.837*** (0.160)	-1.281*** (0.383)	-2.768*** (0.592)
Freezing degree-days (<i>FDD</i>)	-3.629*** (0.398)	-4.844*** (0.469)	-2.389** (0.996)	5.198*** (1.895)
Irrigation (<i>Irr.</i>)	0.939*** (0.024)	0.080 (0.131)	0.066 (0.138)	0.000 (0.156)
<i>Pre.*Irr.</i>	-0.027*** (0.002)	-0.026*** (0.002)	-0.026*** (0.002)	-0.025*** (0.002)
<i>GDD*Irr.</i>		0.027*** (0.004)	0.028*** (0.005)	0.022*** (0.005)
<i>FDD*Irr.</i>		0.058*** (0.009)	0.052*** (0.009)	0.027*** (0.010)
<i>Pre.*GDD</i>			0.007 (0.013)	-0.053*** (0.017)
<i>Pre.*FDD</i>			-0.216*** (0.054)	-0.662*** (0.091)
<i>Pre.*Pre.</i>				-0.031*** (0.006)
<i>GDD*GDD</i>				0.048*** (0.012)
<i>FDD*FDD</i>				-0.142 (0.139)
<i>Irr.*Irr.</i>				0.003*** (0.001)
Large farm	8.498*** (0.503)	8.433*** (0.498)	8.351*** (0.500)	8.509*** (0.498)
CRP and WRP programs	-16.122*** (1.922)	-15.316*** (1.908)	-15.545*** (1.920)	-14.805*** (1.935)
Experience	-0.025 (0.021)	-0.025 (0.021)	-0.023 (0.021)	-0.021 (0.020)
Ownership	-0.188 (0.661)	-0.098 (0.655)	-0.109 (0.652)	-0.174 (0.650)
Off-farm employment	0.767 (1.045)	0.800 (1.046)	0.702 (1.048)	0.847 (1.053)
Slope	-0.007 (0.043)	0.004 (0.043)	0.114*** (0.044)	0.052 (0.048)
Total sand	-0.125*** (0.032)	-0.119*** (0.032)	-0.117*** (0.032)	-0.100*** (0.032)
SOC	1.180*** (0.137)	1.126*** (0.136)	1.147*** (0.137)	0.826*** (0.130)

(continued)

Table 2. Continued

VARIABLES	A	B	C	D
Potential wetland	-0.101 (0.071)	-0.081 (0.071)	-0.090 (0.070)	-0.148** (0.069)
T factor	1.745*** (0.552)	1.785*** (0.560)	2.917*** (0.611)	3.097*** (0.597)
Constant	32.485*** (5.186)	45.327*** (5.222)	52.034*** (11.208)	32.906*** (12.352)
<i>Elasticities</i>				
Precipitation	0.120*** (0.017)	0.122*** (0.017)	0.036 (0.022)	0.122*** (0.028)
Growing degree-days	-0.160*** (0.059)	-0.105*** (0.058)	-0.231*** (0.076)	-0.247*** (0.084)
Freezing degree-days	-0.116*** (0.013)	-0.116*** (0.014)	-0.143*** (0.016)	-0.146*** (0.026)
Irrigation	0.170*** (0.004)	0.162*** (0.004)	0.160*** (0.004)	0.116*** (0.015)
Observations	14,624	14,624	14,624	14,624
R-squared	0.619	0.622	0.623	0.629
State by Year FE	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Estimates of the High-order Moment Functions for Winter Wheat Yield

VARIABLES	A Full 2 nd	B Full 3 rd	C Lower 2 nd	D Upper 2 nd	E Lower 3 rd	F Upper 3 rd
<i>Elasticities</i>						
Precipitation	1.028*** (0.182)	2.667 (5.160)	0.959*** (0.201)	0.780*** (0.290)	1.541*** (0.351)	1.241* (0.668)
Growing degree-days	2.743*** (0.552)	-1.904 (11.589)	2.789*** (0.621)	2.743*** (0.852)	4.913*** (1.200)	3.402** (1.581)
Freezing degree-days	0.472*** (0.117)	-1.694 (2.379)	0.443*** (0.123)	0.457** (0.200)	0.822*** (0.219)	0.501 (0.351)
Irrigation	0.281*** (0.040)	-1.000 (1.328)	0.417*** (0.056)	0.116** (0.055)	0.707*** (0.115)	0.203 (0.156)
Large farm	-0.084** (0.037)	2.656** (1.346)	-0.183*** (0.054)	0.018 (0.052)	-0.297*** (0.095)	0.136 (0.093)
CRP and WRP programs	0.009 (0.020)	0.005 (0.449)	0.026 (0.018)	0.006 (0.028)	0.041 (0.030)	0.021 (0.057)
Experience	-0.072 (0.055)	-0.856 (1.117)	-0.072 (0.062)	-0.078 (0.088)	-0.077 (0.097)	-0.223 (0.161)
Ownership	0.093* (0.048)	1.808* (0.987)	-0.008 (0.060)	0.177*** (0.066)	-0.035 (0.100)	0.348*** (0.103)
Off-farm employment	-0.195* (0.116)	-2.493 (3.000)	-0.041 (0.121)	-0.267 (0.194)	0.014 (0.175)	-0.514 (0.461)
Slope	0.154** (0.078)	-3.139 (2.698)	0.265*** (0.097)	0.021 (0.123)	0.445** (0.193)	-0.074 (0.280)
Total sand	0.161* (0.087)	1.956 (1.725)	0.055 (0.096)	0.224 (0.140)	0.119 (0.172)	0.283 (0.235)
SOC	-0.224** (0.096)	-3.424* (2.071)	-0.051 (0.114)	-0.426*** (0.158)	-0.063 (0.188)	-0.872*** (0.313)
Potential wetland	0.032* (0.019)	-0.416 (0.468)	0.032 (0.027)	0.040* (0.024)	0.055 (0.047)	0.033 (0.042)
T factor	0.002 (0.231)	-0.500 (4.678)	0.155 (0.294)	0.121 (0.361)	0.232 (0.566)	0.267 (0.642)
Observations	14,624	14,624	6,838	7,786	6,838	7,786
R-squared	0.062	0.022	0.130	0.059	0.110	0.052
Symmetry (F-statistic)			5.758		0.152	
State by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Elasticities of the Risk Premium with Respect to Climate and Irrigation Variables
(Unit: Percent)

VARIABLES	Expected Utility Model	Risk Value Model
<i>Winter Wheat Yield Model</i>		
Precipitation	10.2	10.9
Growing degree-days	26.8	27.4
Freezing degree-days	5.2	4.2
Irrigation	3.1	7.0