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Climate Change and Crop Yield Distribution:
Some New Evidence from Panel Data Models

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Abstract

This study examines the impact of climate on the yields of seven major crops in Taiwan based on pooled panel data for 15 prefectures over the 1977-1996 period. Unit-root tests and maximum likelihood methods involving a panel data model are explored to obtain reliable estimates. The results suggest that climate has different impacts on different crops and a gradual increase in crop yield variation is expected as global warming prevails. Policy measures to counteract yield variability should therefore be carefully evaluated to protect farmers from exposure to these long-lasting and increasingly climate-related risks.

Key words: Yield response, Climate change, Panel data, Unit-root test

JEL code: D24, C23

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I. Introduction

Climate change is an important global issue that has been much discussed in recent years. Even if the nature of changes in climatic conditions were known, there would remain considerable uncertainty as to the kinds of impacts that these changes would have. Agriculture is one of the most vulnerable sectors in the economy as changes in atmospheric conditions have implications for water supply and plant growth, as well as for pests and diseases. Thus, many climate simulation-based climate forecasting models and crop growth models have been developed to examine the vulnerability of agriculture to global warming (Hoogenboom, 2000).

In Asia, a number of modeling studies of the effect of climate change on rice production have emerged since the late 1980s.[1] However, wide range of predictions have been made, partly due to the assumptions made in both the climate forecasting and the crop simulation models, partly from the use of limited sites for which historical weather data is available, and partly from the complexity in the management practices to cope with these climate effects (Bachelet et al., 1993; Mattews et al., 1997). The

[1] See Matthews et al (1997) for a comprehensive review on the modeling studies of the likely impacts of climate change on rice production.

controlled experiments, which are the core of the crop simulation models, are expensive and time-consuming to validate and, as argued by Mendelsohn et al. (1996), "provide poor estimates of the actual magnitude of impacts because they fail to account for the many adjustments that farmers make to environmental conditions".

Little evidence is available for other tropical and semi-tropical crops grown in the Asian region as the use of simulation models is still an evolving science in this region. In this paper, we propose the use of econometric methods as an alternative to examine the changes of yield distributions in response to climate change. Panel unit-root tests and maximum likelihood estimates will be explored in order to obtain reliable estimates using a panel regression model. Seven field crops in Taiwan are under investigation for our empirical study. The results not only illustrate the sensitivity of crop yield distribution in response to climate change in this area, but also identify the atmospheric conditions which control the yield distributions. The information can assist us in understanding any possible adaptive behavior that may be available to cope with these changes.

In this study, the yield response to climate variability is also under investigation because most studies have concentrated on the effects of mean changes in climate variables. Climate variability influences farming's management practices, while short-term weather episodes affect crop yields by inducing changes in temperature, potential evapotranspiration, and moisture availability. Katz and Brown (1992) have shown that, for a given climate variable, a change in the variance has a larger effect on the cropping system than a change in the mean. Climate variability also influences other factors such as any incidences of pests and epidemic diseases that may hamper crop growth. However, the results are very sensitive to the cultivation systems and water supply (Luo et al, 1998). Thus, analyses of the associated effects on cop yields are highly speculative and, therefore, deserve additional attention.

Another motivation stems from the increasing popularity of using crop insurance programs as alternative income stabilizing schemes for the post-Uruguay Round agricultural policy reforms in many countries. Our study has implications for crop insurance, because the shape of yield distributions is one of the key parameters for designing crop insurance programs (Just and Weninger, 1999). If climate change shows great potential to alter the shape of these crop yield distributions, we have to identify or estimate the direction and magnitude of these influences. Ignoring these influences will lead to distributional misspecifications, which in turn will bias the calculation of insurance premiums and indemnity.

In the following section, we provide the model structure for constructing the relationship between climate variables and yields. Section III implements the panel unit root tests proposed by Im et al. (1997) based on a sample of 15 prefectures over the 1977~1996 period. In Section IV, the methodologies related to testing the panel model characteristics are illustrated and the estimation results presented. The final section provides policy implications for crop insurance design.

II. Crop Yield Response Models

The results of previous crop response models suggest that changes in crop yields must be interpreted as being conditional upon the specific changes in the spatial patterns of temperature and rainfall as well as specific changes taking place over time. Changes in climate conditions not only have an effect on the mean yields, but they can also affect the higher moments of crop yield distributions. In this paper, a stochastic production function of the Just-Pope type (Just and Pope, 1978) is assumed as follows:

$$Y = f(X) + h(X)\varepsilon , \tag{1}$$

where Y is the yield, and X is a set of explanatory variables, e.g., climate, location and technology. The function $h(X)\varepsilon$ for the error term is an explicit form for heteroscedastic errors that allows for the estimation of the variance effects. The estimation of the parameter $f(X)$ gives the average effect of the explanatory variables on yield, while $g(X)$ gives their effect on the variance of yield.

Temperature and precipitation are considered to be the major climate variables.

Their corresponding variations are also included to reflect the influence of departures from normal climatic conditions on crop yields. For example, Thompson (1986) reported that decreasing weather variability was favorable for U.S. corn yields before 1970. Using a mechanical crop model and farm-level yields, Park and Sinclair (1993) found that variations in temperature and precipitation affected the distribution of U.S. corn yields over time and space. Mendelsohn et al. (1994, 1996) also showed that omitting the variation terms biased the effect from global warming. In this paper, climate variability is approximated by the variations of monthly mean temperature and precipitation from their 20-year monthly averages, respectively.

A time-trend variable is also added to represent the effect of technological progress during the sample period, which can be attributed to increasing fertilizer application, new high-yielding crop varieties, improved cropping practices, etc. The main purpose behind adding this time-trend variable is to capture the contribution from technology and management improvements.

In this study, pooled time-series cross-sectional data for Taiwan's seven major field crops (rice, corn, soybeans, peanuts, adzuki beans, sweet potatoes, and potatoes) over the 1977~1996 period are used to measure the sensitivity of their yields in response to climate change. The data on crop yields are drawn from the Agricultural Yearbook.

Monthly weather data on temperature and precipitation are obtained from Taiwan's Central Weather Bureau. The summary statistics are presented in Table 1, which shows that higher means are correlated with higher standard deviations. As for the climate variables, the variations in precipitation are more dramatic than the variations in temperature.

The subtropical weather in Taiwan permits the growing of a great variety of crops. According to a recent study by Hsu and Chen (2002), over the past 100 years Taiwan has experienced an island-wide warming trend of up to 1.4℃. Both the annual and daily temperature ranges have also increased. The precipitation has exhibited a more complicated spatial variation with a tendency to increase in the northern part of the island and to decrease in the south. This phenomenon occurs mainly in either the dry or the rainy season and thus results in an enhanced seasonal cycle. Other tropical climatic phenomena such as typhoons are also critical to agricultural production in Taiwan. According to the Agricultural Yearbook of 1999, climate-related disasters have caused US$ 1.8 billion in crop losses[2] during 1990-1999, which amounted to about 4 percent of the total crop values produced during the 10-year period. Therefore, like most of her Asian neighbors, climate variability is a constant threat to Taiwan's crop production.

[2] This estimate excludes the losses due to soil erosion and damaged farm facilities, but includes the damages from diseases and pests.

By using a price-endogenous mathematical-programming model, Chang (2002) has simulated the potential effect of climate change on regional production and welfare distribution in Taiwan. Sixty crop yield response functions were regressed using panel data and simple least square methods to extrapolate the climate impact on yields. Some discrepancies were found between this study and previous ones from the crop simulation models. For example, in the case of rice, Chang's results showed that warmer temperatures were yield-decreasing. However, Matthews et al. (1997) found that while China, Thailand, Bangladesh and Japan would experience a decline in rice production, Taiwan as well as Indonesia, Malaysia, and parts of India and China were predicted to benefit from global warming. Therefore, the magnitudes and the directions of these extrapolated yield changes are highly speculative. In the analysis that follows, we will strengthen our estimation results by adopting up-to-date panel data testing techniques and maximum likelihood methods.

III. Testing for Unit Roots

This study utilizes pooled time-series and cross-sectional data for 15 regions over the 1977-1996 period. Pooled panel data possess several advantages over conventional single time-series or cross-sectional data, especially when the time series for the data may not be very long but may be available across different regions. However, in panel data, if the individual time series are non-stationary, the standard asymptotic properties of the regression model are, in general, no longer applicable. In particular, a non-stationary variable may result in an inflated standard t-statistic or an inefficient estimation. Therefore, it is necessary to conduct tests for stationarity before conducting the regression analysis. If the tests indicate nonstationarity, a solution has to be developed, e.g., estimation in first differences.

Panel unit root tests have been advanced by Quah (1994), Levin and Lin (1992, 1993) and Levin et al. (2002). Levin et al.'s tests are more general than those of Quah because their tests can accommodate heterogeneity across cross-sectional units and different types of serial correlations in the residuals, while independence across cross-sectional units is retained. Their tests have gained popularity in international finance and macroeconomic applications. However, their tests are written under the null hypothesis of non-stationarity against the alternative of non-stationarity but with homogeneous serial correlation across units. Im et al. (1997) propose a relaxation which permits the autoregressive parameters to differ across the cross-sectional units under the alternative hypothesis. They develop a group-mean Lagrange multiplier (LM-bar) statistic which is distributed as standard normal as long as the number of regions (N) is large relative to the number of time periods (*T*). Therefore, Im et al.'s approach also relaxes the requirement of a particular rate of divergence as *N* and *T* move to infinity in Levin et al.'s tests.

The general form used to test for stationarity is as follows:

$$x_t = \phi_0 + \phi_1 x_{t-1} + at + \varepsilon_t, \qquad t = 1,\ldots, T \ , \tag{2}$$

where x_t is the variable under consideration, ϕ_0, ϕ_1 and a are the coefficient parameters, and ε_t is the error term. If ϕ_1 is smaller than 1, then x_t is stationary; otherwise, one has to take the first-order difference in relation to x_t. Equation (3) is the general form after the differencing and x_t will be stationary if $\gamma \neq 0$.

$$\Delta x_t = a + b_t t + \gamma x_{t-1} + \sum_{j=1}^{p-1} \phi_j \Delta x_{t-j} + \varepsilon_t \tag{3}$$

Equation (3) is the basis for the conventional Dickey-Fuller (1981) test in a time-series model where Δ is the first-order difference operator and *p* is the lag length. Im et al. propose an LM-bar test, which is based on the mean of the individual unit root statistics in a dynamic heterogeneous panel. Now let us consider the following panel model of a sample of *N* regions observed over *T* time periods:

$$\Delta x_{it} = \alpha_i + \beta_i x_{i,t-1} + \varepsilon_{it} \qquad i = 1,\ldots, N, \qquad t = 1,\ldots,T \tag{4}$$

where x_{it} is the variable of interests generated by a first-order autoregressive process for region *i* and time period *t*, $\Delta x_{it} = x_{it} - x_{i,t-1}$, ε_{it} is independently and identically distributed both across *i* and *t*. The null hypothesis of a unit root in (4) is then a test of

$$H_0 : \beta_i = 0 \quad \forall\, i, \tag{5}$$

against the alternatives[3],

$$\begin{aligned} H_1 : \beta_i &< 0, \qquad i = 1,\ldots, N_1, \\ \beta_i &= 0, \qquad i = N_1 + 1,\ldots, N \end{aligned} \tag{6}$$

Under the assumption of serially autocorrelated errors with different serial correlation across regions, the standardized LM-bar ($\overline{LM}$) statistic used to test for the null hypothesis is derived from the following Augmented Dickey-Fuller (ADF) equation:

$$\Delta x_{it} = \alpha_i + \beta_i x_{i,t-1} + \sum_{j=1}^{p_i} \rho_{ij} x_{i,t-j} + \varepsilon_{it} \qquad i = 1,\ldots, N, \qquad t = 1,\ldots, T\,, \tag{7}$$

where p_i is the lag length of Δx_{it}, and ρ_i is the coefficients vector of the augmented lagged differences.

The standardized LM-bar statistic is expressed in equation (8):

$$\Gamma_{\overline{LM}} = \frac{\sqrt{N}\{\overline{LM}_{NT} - \frac{1}{N}\sum_{i=1}^{N} E[LM_{iT}(p_i, 0) \mid \beta_i = 0]\}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var[LM_{iT}(p_i, 0) \mid \beta_i = 0]}}\,, \tag{8}$$

where $\overline{LM}_{NT}$ is the simple average of *N* individual LM statistics for testing $\beta_i = 0$, namely, $\overline{LM}_{NT} = \frac{1}{N}\sum_{i=1}^{N} LM_{iT}(p_i, \rho_i)$. Under the null hypothesis (5) and $N/T \rightarrow k$, $\Gamma_{\overline{LM}}$ converges to a standard normal distribution. Under the alternative hypothesis (6),

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[3] This formulation allows for β_i to differ across regions, and is more general than the homogeneous alternative hypothesis, namely $\beta_i = \beta < 0 \quad \forall\, i$ which is implicit in both the Levin-Lin and Quah approaches. (Im et al., 1997)

$\Gamma_{\overline{LM}}$ will diverge to a positive infinity. (See Theorem 4.1 and Appendix A.4 in Im et al.)

In addition, if we consider the case where the disturbances are also correlated across the cross-sectional data, the LM-bar test can be extended to a de-meaned regression as shown in (4.10) on page 8 of Im et al.'s paper. The robust unit-root test requires that the data have to pass both tests.

The panels in relation to seven crop yields and four climate variables from 15 regions over the 1977~1996 period are tested for unit roots before their estimations are performed. The test results are shown in Table 2. Table 2 shows that the crop yields for rice, corn, peanuts, soybeans and sweet potatoes pass all three tests and are thus stationary. However, the null hypothesis of no unit root is not rejected for adzuki bean and potato yields. After a first-order difference in potato yield and a second-order difference in adzuki bean yield are taken, both of them are found to pass the test and become stationary. All climate data also pass the panel-based unit-root tests. Therefore, they are now ready for use in our panel model estimation.

IV. Estimation and Results

Before estimating the crop yield response function, it is important to establish the correct panel model form. While the Hausman test could be applied to test for fixed or random effects, the Hausman test is, however, not valid if there exists either heteroscedasticity or serial correlation in the disturbance term. Arellano (1993) has therefore derived an *h* statistic as an alternative when heteroscedasticity or serial correlation is present.

Let Y_{it} denote the crop yield for individual *i* at time *t* and X_{it} represent the explanatory variables such as technology, temperature, precipitation, etc. The yield response function in a panel model with two-way error components is then written as:

$$Y_{it} = \alpha + X'_{it}\beta + u_{it}, \tag{9}$$

where $u_{it} = \mu_i + \lambda_t + v_{it}$. The term μ_i denotes the unobserved specific region effects, while λ_t stands for the unobserved time effects and v_{it} is the disturbance term. Their variances are $\sigma_\mu^2, \sigma_\lambda^2$ and σ_v^2, respectively.

The test in the case of the fixed effects model assumes that there is no correlation between the disturbance term (u_{it}) and the independent variables (X_{it}) so that the null hypothesis is written as $H_0 : E(u_{it} \mid X_{it}) = 0$. The Hausman test can be obtained as a Wald statistic with the restriction $\gamma = 0$ from the OLS estimates of the model in (10):

$$\begin{bmatrix} y_i^* \\ \bar{y}_i \end{bmatrix} = \begin{bmatrix} X_i^* & 0 \\ \bar{x}_i' & \bar{x}_i' \end{bmatrix} \begin{bmatrix} \beta \\ \gamma \end{bmatrix} + \begin{bmatrix} v_i^* \\ \bar{u}_i \end{bmatrix} \tag{10}$$

where $y_i^* = Ay_i$, $X_i^* = AX_i$, $\bar{x}_i = X'_i \iota / T$, *A* is the *(T-1)*T* forward orthogonal deviations operator and ι is a $T*1$ vector of ones (Arellano, 1993). The estimator of $\hat{\gamma}$ is $\hat{b}_{BG} - \hat{\beta}_{WG}$, where $b_{BG} = (\overline{X}'\hat{\overline{X}})^{-1}\overline{X}'\overline{y}$, $\hat{\beta}_{WG} = (X^{*\prime}X^{*})^{-1}X^{*\prime}y^{*}$. This test will not be valid given the heteroscedasticity or serial correlation. Arellano pointed out, however, that the generalized h^* statistic test is robust in relation to both heteroscedasticity and serial correlation. The h^* statistic is

$$h^* = \hat{\gamma}'\hat{V}_{\gamma\gamma}^{-1}\hat{\gamma} \tag{11}$$

where $\hat{V}_{\delta\delta} = (W'W)^{-1}[\sum_{i=1}^{N} W_i' \hat{u}_i^{+} \hat{u}_i^{+\prime} W_i](W'W)^{-1} = \begin{bmatrix} \hat{V}_{\beta\beta} & \hat{V}_{\beta\gamma} \\ \hat{V}_{\gamma\beta} & \hat{V}_{\gamma\gamma} \end{bmatrix}$, $W = \begin{bmatrix} X_i^{*} & 0 \\ \overline{x}_i' & x_{i'} \end{bmatrix}$, and the $\hat{u}_i^{+}$ are OLS residuals from equation (10). The test results for the fixed versus the random effects models are listed in the second row of Table 3, which indicates that a random effects specification cannot be rejected for all crop models.

Next, in order to obtain efficient results, heteroscedasticity will be tested before estimating the crop yield response functions. Bartlett's test is adopted here as recommended by Baltagi (1995) and explained in Judge et al. (1985, p. 448). The test results are shown in the third row of Table 3. Heteroscedasticity is present in the cases of all crops except rice.

Our next step is to test for serial correlation under a random effects model. Baltagi and Li (1995) present a series of LM tests for serial correlation that are carried out jointly with various assumptions concerning individual effects. The test results are displayed in the last row of Table 3. Only the yield response function for sweet potato exhibits serial correlation.

Based on these test results, the heteroscedasticity problem is seen to prevail in the random effects panel model. Therefore, the generalized least squares (GLS) method can be used to obtain efficient estimates. Saha et al. (1997) show by means of Monte Carlo experiments that, for small samples, the maximum likelihood estimation (MLE) approach is more efficient than GLS. Therefore, the MLE approach is adopted here, and the likelihood function is as follows:

$$\begin{aligned} L(\alpha,\beta,\gamma,\delta) = {} & constant - NT/2*\log(h(X,\alpha)) \\ & + N/2*\log[h(X,\alpha)/(T*I(X,\gamma)+h(X,\alpha))] \\ & + T/2*\log[h(X,\alpha)/(N*T(X,\delta)+h(X,\alpha))] \\ & -1/2*\log[h(X,\alpha)/(T*I(X,\gamma)+h(X,\alpha))+h(X,\alpha)/(N*T(X,\delta)+h(X,\alpha)) \\ & \qquad -h(X,\alpha)/(N*T(X,\delta)+h(X,\alpha))*h(X,\alpha)/(N*T(X,\delta)+h(X,\alpha))] \\ & -1/2*f(X,\beta)^2/h(X,\alpha) \end{aligned}, \quad (12)$$

where $f(X,\beta)$ is the crop yield response function, and $h(X,\alpha)+I(X,\gamma)+T(X,\delta)$ is the yield variation function. The latter has three components: $h(X,\alpha)$ represents the variation from the disturbance term (v_{it}), while $I(X,\gamma), T(X,\delta)$ represent, respectively, the variations from both the individual and time effects.

The estimation results are presented in Tables 4 and 5. Because the log-linear form is adopted, the numbers listed in Tables 4 and 5 are the elasticities. First, Table 4 shows that the time trend coefficients are positive in most cases. Therefore, the crop production technology (except in the case of the adzuki bean) has been yield-improving over the last 20 years. Second, the climate variables are seen to have had diversified impacts on crop yields. The increases in temperature and precipitation have lowered the crop yields in relation to rice, corn, and peanuts. However, the warmer climate has also resulted in higher yields in relation to soybeans and potatoes while more rainfall has been detrimental. On the other hand, the increased variation in temperature has reduced the crop yields in relation to rice, soybeans and adzuki beans, but the opposite situation has occurred in the cases of corn, peanuts, sweet potatoes and potatoes. This indicates that crops harvested from under the ground (or the so-called root crops), such as peanuts or potatoes, are more able to withstand variations in temperature while other crops such as rice and adzuki beans are more susceptible to changes in temperature. Similarly, the increased variation in precipitation has reduced the crop yield in the case of the adzuki bean while it has increased the yields of other crops.

Finally, the results show that, as the climate has become warmer, higher yield variability has been observed in regard to these selected crops. In addition, more rainfall has increased the yield variability in relation to rice, corn, and potatoes. The increased variation in precipitation is also expected to increase crop yield variability in relation to soybeans, peanuts, adzuki beans, and sweet potatoes. Although it may be too early to draw conclusions, a gradual increase in crop yield variation can be expected as global warming prevails. Policy measures to counteract yield variability such as crop insurance should therefore be carefully evaluated to protect farmers from exposure to these long-lasting and increasingly climate-related risks.

V. Implications for Adaptation Strategies

The success of crop insurance as a risk-managing policy tool depends on its insurance design being fair to both farmers and the insurance agency, whether for an advanced or developing country (Ahsan et al., 1982). In most countries, the sum insured is based on the prospective values of the yield. If the expected values of yields vary over time depending on the risk profile of the climate conditions, additional safeguard against this climate-related risk by fixing the sum insured to a certain percentage of the yield or by adding a safety loading factor into the premium ratio may be necessary. Therefore, understanding how crop yield distributions is related to the climate change as shown in our Tables 4 and 5 have important implications for ensuring feasibility of a crop insurance scheme.

Our results may also have other policy implications besides insurance. For example, if the results show that climate conditions contribute significantly to crop yield risk, then weather insurance/derivatives—an emerging market to hedge against production risk instead of price risk—may have a significant role to play (Turvey, 2001). For developing countries, farmers could adjust their crop mix (e.g., by substituting high-risk crops for low-risk crops or vice versa) according to the crop yield distributions under different climatic conditions, simply because our results show that climate change tends to impact different crops differently. Such an adjustment is viewed as a self-insurance scheme, and could reduce the size or the probability of a loss caused by a change in climate.[4] The crop yield response functions can also be applied to other price stabilization tools such as storage or stock acquisition. Farmers could adjust their storage activities according to the crop yield distributions in response to the climate change.

Ehrlich and Becker (1972) have shown that, under certain conditions, market insurance and self-insurance can be complements in the sense that the availability of the former could increase the demand for the latter. Consequently, it is possible that a fair market insurance price could result in an increase in self-insurance activities. If so, then the moral hazard would not limit the development of market insurance. On the other

[4] Ehrlich and Becker (1972) distinguish between self-insurance (a reduction in the size of a loss) and self-protection (a reduction in the probability of a loss) as two different alternatives to market insurance. However, we think the distinction may be vague in our case and thus ignore it.

hand, self-insurance and market insurance could also be substitutes in which moral hazard might be an issue. Therefore, if these self-insurance alternatives do exist, then a farmer's demand for insurance should be viewed within the context of a more comprehensive insurance scheme.

Based on our results, global warming has the potential to increase yield variability and to impact different crops differently. In countries like Taiwan where crop insurance policies are not available, many self-insurance activities will be pursued as the chief means of redistributing income toward less-favorable climatic conditions. In the cases of many of the small-scale farmers in the East Asian economies, this can be seen from the tendency for them to diversify into a greater number of enterprises or to grow larger shares of their family food requirements. This tendency, however, will make their agricultural sector increasingly vulnerable as the economy becomes more open to large-scale, highly commercialized, and low-price imports. Thus, adopting crop insurance has become a popular option and has received special attention in recent years, as the government seeks to strengthen the competitiveness of its farmers while adhering to international trade agreements. Our results suggest that the insurance policies have to be carefully designed to recognize the existence of these agro-climatic relationships and the self-insured alternatives so that the moral hazard problem can be minimized.

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Table 1. Sample Statistics on Climate and Yields

	Unit	Mean	Standard Deviation	Minimum	Maximum
Rice	(kg/ha)	4510	976	2229	6656
Corn	(kg/ha)	3116	912	1117	5632
Soybean	(kg/ha)	1711	434	995	3375
Peanut	(kg/ha)	1677	293	1036	2750
Adzuki Bean	(kg/ha)	1527	433	700	2664
Sweet Potato	(kg/ha)	15748	4908	8941	31489
Potato	(kg/ha)	15591	5687	3889	29202
Temperature	(^{o}C)	22.79	1.87	16.18	25.48
Precipitation	(mm)	189.35	89.41	44	533

Table 2 Unit Root Test Results on Crop Yield and Climate Variables

	Serial Correlation	Correlation across Groups
Rice	110.46*	82.95*
Corn	48.65*	20.95*
Soybean	54.39*	11.86*
Peanut	65.71*	22.21*
Adzuki Bean[a]	10.87*	1.58 6.32*
Sweet Potato	73.58*	36.36*
Potato[a]	6.36*	-1.65 -1.85*
Average Temperature	43.02*	17.60*
Average Precipitation	52.02*	-3.83*
Variation in Temperature	232.96*	-8.91*
Variation in Precipitation	27.89*	7.76*

Notes: "Serial correlation" statistics are robust to error term serial correlation, while "correlation across groups" statistics are robust to serial correlation in the cross-section dimension.

[a] When there are two statistics in a cell, the top number represents the test results on the un-differenced data, and the bottom one is for the data after first-order differencing.

* The null hypothesis of non-stationarity is rejected with 99% confidence.

Table 3. Specification Test Results of the Panel Data Model

	Fixed vs. Random Effects	Heteroscedasticity	Serial Correlation
Rice	160425*	3.58	0.47
Corn	87897*	70.24*	1.38
Soybean	17345*	244.81*	0.70
Peanut	10436*	73.98*	0.94
Adzuki Bean	72055*	14.49*	0.84
Sweet Potato	36323*	167.32*	2.79*
Potato	729467*	422.84*	0.07

Note: The fixed vs. random effects test is implemented using an *h* statistic baaed on Arellano. The *h* statistic is a chi-square distribution with *k* degrees of freedom where *k* is the number of regressors.

* means rejecting the fixed effect null hypothesis with 99% confidence. The Bartlett test is based on a chi-square distribution with *N-1* degrees of freedom where *N* is the sample size. Serial correlation is a normal distribution with *N(0,1)*.

Table 4. Elasticity Estimates of Crop Yields with Respect to Climate Changes

	Time Trend	Average Temperature	Average Precipitation	Variation in Temperature	Variation in Precipitation
Rice	0.253*	-0.787*	-0.333*	-0.033*	0.084*
	(0.0006)	(0.0056)	(0.0019)	(0.0011)	(0.0008)
Corn	0.146*	-1.333*	-0.629*	0.077*	0.192*
	(0.0009)	(0.0116)	(0.0040)	(0.0024)	(0.0015)
Soybean	0.118*	1.328*	-0.125*	-0.028*	0.045*
	(0.0015)	(0.0521)	(0.0067)	(0.0052)	(0.0025)
Peanut	0.088*	-0.368*	-0.268*	0.003*	0.082*
	(0.0006)	(0.0076)	(0.0022)	(0.0016)	(0.0010)
Adzuki Bean	-0.370*	-27.946*	0.359	-2.025*	-0.813*
	(0.0415)	(1.316)	(0.219)	(0.136)	(0.0837)
Sweet Potato	0.068*	0.012	-0.485*	0.088*	0.153*
	(0.0008)	(0.0081)	(0.0031)	(0.0046)	(0.0015)
Potato	0.188*	-0.174	-0.735*	0.621*	-0.225*
	(0.0039)	(0.127)	(0.0163)	(0.0192)	(0.0068)

* significant at 95% confidence level.

Note: Numbers in parentheses are standard deviations.

Table 5. Elasticity Estimates of Crop Yield Variability with Respect to Climate Changes

	Time Trend	Average Temperature	Average Precipitation	Variation in Temperature	Variation in Precipitation
Rice	-0.015	0.236	0.152	0.042	-0.399
Corn	0.021	0.717	0.090	0.136	-0.529
Soybean	-0.002	0.045	-0.009	0.0001	0.037
Peanut	0.002	0.013	-0.016	0.012	0.075
Adzuki Bean	-0.011	-0.500	-0.103	0.017	0.623
Sweet Potato	0.001	0.023	-0.022	-0.012	0.003
Potato	0.007	-0.375	0.603	-0.010	-1.631

Note: The numbers in this table are calculated from the table in the Appendix and the elasticity formula is as follows:

$$[\hat{\alpha} * x / h(x, \hat{\alpha}) + \hat{\gamma} * x / I(x, \hat{\gamma}) + \hat{\delta} * x / T(x, \hat{\delta})] * x / [h(x, \hat{\alpha}) + I(x, \hat{\gamma}) + T(x, \hat{\delta})] \,.$$

Appendix. Maximum Likelihood Estimates of Crop Yield Response Functions

Variation in Disturbance	Time Trend	Average Temperature	Average Precipitation	Variation in Temperature	Variation in Precipitation
Rice	-0.753*	5.177*	1.264*	0.951*	-0.361*
	(0.0067)	(0.0893)	(0.0239)	(0.0169)	(0.0104)
Corn	0.220*	4.391*	0.313*	0.831*	0.081*
	(0.0071)	(0.0784)	(0.0246)	(0.0185)	(0.0107)
Soybean	0.676*	5.561*	0.416*	0.498*	-0.163*
	(0.0151)	(0.380)	(0.0546)	(0.0402)	(0.0215)
Peanut	0.126*	0.426*	-0.188*	0.406*	0.216*
	(0.0062)	(0.0852)	(0.0227)	(0.0016)	(0.0011)
Adzuki Bean	-0.217*	- 4.410*	-0.375*	0.219*	0.356*
	(0.0215)	(0.895)	(0.1198)	(0.1031)	(0.0492)
Sweet Potato	0.291*	1.690*	-0.651*	-0.898*	0.285*
	(0.0062)	(0.0703)	(0.0217)	(0.0238)	(0.0095)
Potato	0.042*	-0.972*	0.636*	-0.031	-0.404*
	(0.0146)	(0.446)	(0.0727)	(0.442)	(0.0331)
Variation in Individual Effects	**Time Trend**	**Average Temperature**	**Average Precipitation**	**Variation in Temperature**	**Variation in Precipitation**
Rice	-21.42*	-42.86*	133.98*	5.490*	-64.538*
	(0.211)	(0.830)	(0.836)	(0.824)	(0.417)
Corn	0.954*	9.187*	-21.907*	30.623*	-18.781*
	(0.410)	(0.928)	(0.889)	(0.919)	(0.497)
Soybean	14.245*	-54.706*	6.040*	-11.610*	9.831*
	(0.135)	(0.918)	(0.896)	(0.483)	(0.379)
Peanut	-92.559	74.510	-171.18	137.73	12.773
	(2876)	(9768)	(9496)	(8847)	(4800)
Adzuki Bean	0.172	-0.196	-0.883	0.001	-2.880*
	(0.985)	(0.966)	(0.915)	(0.976)	(0.558)
Sweet Potato	14.615*	-255.35*	-66.959*	186.33*	41.074*
	(0.571)	(0.989)	(0.917)	(0.962)	(0.536)
Potato	-17.658	-14.266	1.963	20.062	-5.644
	(329930)	(23170)	(31113)	(48610)	(79934)

Appendix (Continued).

Variation in Time Effects	Time Trend	Average Temperature	Average Precipitation	Variation in Temperature	Variation in Precipitation
Rice	0.326	1.591	-1.911*	1.101	-5.462*
	(0.985)	(0.968)	(0.911)	(0.971)	(0.569)
Corn	0.664	1.519	-1.052	1.160	-3.604*
	(0.986)	(0.969)	(0.911)	(0.971)	(0.570)
Soybean	-118.52*	-22.443*	-86.454*	-49.744*	56.339*
	(0.288)	(0.966)	(0.939)	(0.969)	(104.22)
Peanut	-2.053	13.838	39.687	-21.243	-14.656
	(3943)	(2589)	(4174)	(9834)	(3769)
Adzuki Bean	-0.252	-0.880	-1.954*	-0.573	-5.083*
	(0.985)	(0.966)	(0.915)	(0.976)	(0.557)
Sweet Potato	-2.345*	-2.209*	-7.926*	-2.524*	-17.409*
	(0.985)	(0.968)	(0.911)	(0.971)	(0.570)
Potato	-14.747	48.643	-1.443	-46.452	-8.672
	(263030)	(935030)	(31855)	(820700)	(162170)

Note: Numbers in parentheses are the standard-error deviations.

* significant at 95% confidence level.

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