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University of Auckland, University of Auckland, VSSUT Burla, IIT Bhubaneswar

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Souryabrata Mohapatra[1# [0000-0002-3627-8739]], Basil Sharp[1], Auro Kumar Sahoo[2] and Dukhabandhu Sahoo[3]

[1] Department of Economics, The University of Auckland, New Zealand
[2] Department of Humanities, Veer Surendra Sai University of Technology Burla, India
[3] School of Humanities Social Sciences and Management, Indian Institute of Technology Bhubaneswar, India
[#] smoh876@aucklanduni.ac.nz

Abstract. The paper examines the effect of seasonal weather variability and extremes on the mean and variance of rice yield in south India for 1990-2017. The Just and Pope stochastic production function is adopted to assess the extensive district-level data with linear and non-linear specifications. Estimation results based on feasible generalized least square method indicate that average yield and yield variability are climate-sensitive and seasonal weather variation and shock significantly influence rice production. Mean yield is observed to be primarily affected by changes in evapotranspiration and minimum temperature across seasons. Further, the minimum temperature parameter above normal is marked as a risk-increasing weather input for rice during the winter season. Countering adversities of climate change through coping strategies, region-specific policies, federal programmes and support are therefore recommended, thus pivotal for state-wide rice production and food security by extension.

Keywords: Climate Impact, Rice Production, Stochastic Production Function, South India.

1 Introduction

There is widespread concern about climate variability on crop production around the world, including crops that are well adjusted to their surroundings as environmental effects on crop yield stand significant [1]. Crop yield and food security are two core issues, as innate climate change and rising demand are anticipated to impair the global economy [2]. To serve the burgeoning population, food demand is projected to grow by 60% by 2050 [3]. In 2017, approximately 10% of the world's population was threatened by food insecurity through many socio-environmental conflicts [4]. About 350 million people in India were found malnourished, with nearly 47 million children suffering from chronic malnutrition [5, 6]. Consequently, the National Food Security Act was passed by the Indian government with an aim of distributing subsidized foodgrain to roughly two-thirds of the inhabitants. This required 33.6 million metric tonnes of rice annually for the national food distribution system [7]. Rice, one of India's dominant crops, is planted on about 43% of the farmland, with rainfed rice accounting for 52% of the overall planting area [8, 9]. Apparently, this rainfed cereal grain is often considered climate-vulnerable in southeast Asia because of limited water and land resources. Further, climate forecasts for India up until 2100 show a 2-4 degree climb in temperature and rise in rainfall intensity, particularly during the monsoon period [10]. Several studies have concluded that variations in seasonal precipitation and surface warming are predicted to induce dry spells and lower food availability in emerging economies, eliciting a significant risk to sustainable development. However, the climate effect on Indian agribusiness is more predominant, not only since a large chunk of the population is reliant on farming but also because there are extant pressures on resources and inadequate coping skills [11].

Numerous researchers have assessed the effect of meteorological factors on the production of rice in India. Generally, the studies have evaluated the impact using either agro-economic or econometric models. Using the fixed-effect model, Birthal et al [12] reported that rice harvest is highly susceptible to a rise in mean temperature, whereas Pattanayak and Kumar [13] documented that day and nighttime temperatures both exhibit detrimental impacts on rice output during various growing seasons. Based on panel-correlation standard error estimation, Gupta et al [14] confirmed that paddy yield is susceptible to weather factors, while Krishnamurthy [15] showed that rice output declined up to 3% due to climate stress. Given resource availability, the effect of seasonal climate varies across regions, as does crop productivity. The southern part of India identified as a climatic hotspot is projected to witness a climb in summer and winter temperature, an upsurge in rainfall events and a rise in the number of rainy days over 2.5 millimeters per day. The adverse climate in southern India, comprising states such as Tamil Nadu, Andhra Pradesh, Kerala, Karnataka and Telangana, is expected to affect the primary sectors most, multiplying the socio-economic inequities [16].

Given regional disparities and alarming changes in climate parameters, many researchers have also conducted state-specific studies. According to Geethalakshmi et al [17], rice yield is expected to fall by 41% in the Kaveri river basin, also known as Tamil Nadu's rice bowl, with temperatures reaching 4 degrees Celsius. Based on panel-corrected standard error estimation, Saravanakumar [18] reported that climate factors and rice yield exhibited a quadratic relationship in Tamil Nadu from 1971 to 2009. Further, with climate change, the enormity of the decrease in rice production across various districts of Tamil Nadu from 2050-2080 is expected to be greater than the decreases from 2000-2020 and 2020-

2050 [19]. Samiappan et al [20] investigated the effect of winter monsoon on the production of rabi rice in Tamil Nadu and foreseen that with an incline in monsoon rain and heat, the crop output is predicted to rise by 10-12% in 2050 and 5-33% in 2081-2100 climate scenarios. In the erstwhile Andhra Pradesh state, Padakandla [21] assessed climate effect on the principal crops and indicated that the yield of rice alongside groundnut and tobacco crops is more affected because of climate fluctuations than is sorghum and cotton yield. Using quantile regression from 1971-2004, Barnwal and Kotani [22] reported that kharif rice is more susceptible to variations in temperature and rainfall in Andhra Pradesh, whereas the rabi rice is more resilient.

Based on field experiments, Varghese et al [23] examined the predicted value of rice yield under future climate scenarios with constant carbon dioxide levels and varied meteorological factors in Kerala. They discovered that yield declines for planting dates and further decreases with a rising temperature affecting the crop duration. Using advanced simulation frameworks, Saseendran et al [24] predicted temperature and rainfall during the monsoon season in Kerala are likely to rise by 1.5 degrees Celsius and 2 millimeters per day, respectively, shortening the rice maturity period by 8%. Kumar et al [25] found a non-significant increase in rainfall in coastal Karnataka from 1980-2013; correlation analysis revealed a frail relationship between rice harvest and rainfall, with rain accounting for around 23% of fluctuations in rice production. Using taluk-level data from Karnataka, Murari et al [26] discovered an inverse linear association between rice yield and extreme degree days, indicating that extreme temperature results in a larger effect than rainfall and growing degree days. Using feasible generalized least squares estimation, Guntukula and Goyari [27] found that maximum temperature has a considerable negative impact on rice productivity, whereas minimum temperature is seen as a risk-increasing element for rice output in Telangana between 1956-2015. Given the climate sensitivity of the primary sector, frequent droughts and crop failures, Telangana state saw an upsurge in farmer suicide [28, 29]. Soora et al [30] indicated weather variation is likely to favour rice production by 10-15% in Karnataka, Tamil Nadu and Andhra Pradesh, whilst Debnath et al [31] predicted a major yield gap of above 1.5 tonnes per hectare in rice-growing southern states under future climate scenarios.

Past research on the climate effect on the production of rice in India has primarily focused on state-wise implications. Limited research has been conducted into a macro-level regional analysis considering south India as a tropical dry and wet climate zone. Implementing extensive district-level weather and non-weather data will improve accuracy in estimating the climate effect on regional rice yield. Several researches have exploited annual panel data and conventionally glanced at the effect of temperature and precipitation on aggregate yield. But there has been limited robust studies investigating the seasonal impact of other climate parameters and weather shocks on a single crop yield and on yield variability. Analysis of seasonal climate effect on the rice yield and associated variability at spatially disaggregated locations will explain the variation in rice harvest and will help in formulating policies to adapt Indian agriculture to changing climate. Thus, the present research, using stochastic frontier analysis, exploits district-level disaggregated data and assesses the effect of seasonal weather variability of five climate parameters and respective extremes on rice yield and variability, filling the research gap and contributing to existing literature.

The rest of the paper is structured as follows: the second section describes the data and methodology, the subsequent section reports the results and the last section concludes.

2 Material and Method

The study analyzes the district-level data for the five southern states of India, Tamil Nadu, Andhra Pradesh, Kerala, Karnataka and Telangana, based on the 2015 district boundary (a total of 99 districts). The district-level data was collected from the International Crops Research Institute for the Semi-Arid Tropics database for the period 1990 to 2017. The non-weather variables included in the study are rice production, gross irrigated area, gross cropped area, total agricultural labour employed and total fertilizer consumption. The dependent variable rice yield is the proportion of rice production to rice cropped area, expressed in tonne per hectare. Given that agricultural input variables are detailed in composite form, relevant rice-particular non-weather inputs are computed through prorating [14, 21, 32].

The data on weather variables are sourced from the Terra Climate database, which holds monthly temporal high-resolution meteorological data for the global terrestrial surface for the period 1958-2019. The data is transmitted in batch operation to develop annual tables at the state level for each variable. Weather variables are considered through four Indian Meteorological Department defined seasons: Summer (March-May), Rainy (June-September) and Autumn (October-December) and Winter (January-February). The independent seasonal weather variables included are minimum and maximum temperatures, evapotranspiration, rainfall and windspeed. Labels and summary statistics of both weather and non-weather variables of interest are presented in Table 1 and 2.

Given the possibility of a non-linear relationship between rice yield and climate, quadratic terms of seasonal weather variables are included. Further, seasonal weather anomalies are considered since seasonal weather variables deviating from climate normal are expected to affect agricultural performance. As per World Meteorological Organisation, climate normals are averages of climatology variables over at least two decades. Deviation of observed weather from such long period average (or weather anomaly) is considered normal if:

$$x_{it} \in \bar{x}_i \pm \tau \bar{x}_i \tag{1}$$

Where, x_{it} is the observed weather in district *i* at time *t,* $\bar{x}_i$ is the climate normal and τ is the climate threshold. Weather anomalies ω beyond $\pm\tau$ of $\bar{x}_i$ capturing weather shocks takes the asymmetric response of rice yield to extreme climate events into account [32]. To compute τ, normality of variables are assumed, which is often adopted to find outliers (climate extremes). Considering 99 percent confidence interval, climate threshold is expressed in a percentage as:

$$\tau = \frac{Z_{0.99}.\sigma}{\bar{x}_i} \times 100 \tag{2}$$

Where, $Z_{0.99}$ is the z-score of 99 percent confidence level and σ is the standard deviation of the sample statistics. Hence, post computing τ, forty weather anomalies of five climate parameters across four seasons is constructed and written as:

$$High\ \omega = \begin{cases} 1\ if\ x_{it} \geq (1+\tau)\bar{x}_i \\ 0\ otherwise \end{cases} \tag{3.1}$$

$$Low\ \omega = \begin{cases} 1\ if\ x_{it} \leq (1-\tau)\bar{x}_i \\ 0\ otherwise \end{cases} \tag{3.2}$$

To quantify the effect of weather variables and extremes on yield and associated variability, controlling non-weather factors, the production frontier developed by Just and Pope [33, 34] is used as follows:

$$y = f(X, \beta) + \mu = f(X, \beta) + h(X, \theta)\varepsilon \tag{4}$$

Where, y is the output, X is the vector of inputs, ε is random shock, β and θ are unknown parameters. Expected crop yield $E(y) = f(.)$ and crop variability $Var(\mu) = h\,(.)$; hence $f(.)$ and $h(.)$ respectively represent the mean yield and yield risk function. Based on these, regression equations estimating climate sensitivity of rice crop are written as:

$$E(y)_{it} = X_{it}\beta + Z_{it}\gamma + \alpha_i + \delta t + \epsilon_{it} \tag{5.1}$$

$$Var(\mu)_{it} = W_{it}\theta + \alpha_i + \delta t + \varepsilon_{it} \tag{5.2}$$

Where, X_{it} represents the vector of seasonal weather variables in district *i* in time *t* including minimum temperature, maximum temperature, rainfall, evapotranspiration and windspeed; Z_{it} represents the vector of non-weather variables in district *i* in time *t* including agricultural labour, fertilizer used and irrigated area; W_{it} represents the vector of seasonal weather anomalies in district *i* in time *t*; β, γ and θ are unknown parameters to be estimated; α_i are the district fixed-effects; δt is the time fixed-effects; ϵ_{it} and ε_{it} are error terms.

3 Results

Prior to estimation, weather and non-weather variables were examined for unit-root using the augmented Dickey-Fuller test and were found stationary. Since panel data is estimated utilizing either a random or fixed-effect model, the Hausman test is performed. This rejected the null hypothesis of non-correlation between district-specific effect and explanatory variables, prompting the adoption of a fixed-effect estimation. Also, the Breusch-Pagan test is used to screen for heteroscedasticity, which rejected the null hypothesis of homoscedastic variance. To account for heteroskedasticity as well as autocorrelation and cross-sectional dependence, a three-stage feasible generalized least square estimation is adopted for the Just Pope model. In the first stage, y_{it} is regressed on $f(.)$ and residuals are computed. In the second stage, the natural logarithm of the square of the estimated residual is regressed on $h\,(.)$. In the third stage, the first stage regression is reestimated applying deemed weights (predicted value of residuals) procured from the second stage. The second and third stages, respectively, provided consistent estimates of $h\,(.)$ and $f(.)$. Diagnostic tests and regression results are reported in Table 3 and 4.

The Akaike criterion, an estimator of prediction error, showed the quality of the statistical model and the probability value of F statistics and indicated that the model is statistically significant. Durbin-Watson statistics specified the presence of trivial positive autocorrelation among residuals. The mean yield of rice is considered as a measure of weather and non-weather factors in the estimated specifications, whereas climate extremes, as reflected by weather anomalies, are considered to determine rice yield variability. The coefficient of district-fixed effect and time trend are omitted. Even so, the latter was found positive and significant, demonstrating that technological advancement had increased mean yields and associated variability. In the second and third stages of regression, the coefficients obtained portray the marginal impacts of inputs on the mean and variance of yield. The elasticity, inflection point and semi-elasticity of non-weather, weather and anomaly inputs, respectively, are further computed to discern the range to which seasonal climate parameters influence rice production.

Increases in maximum temperature during the summer and autumn seasons decrease rice yield at an increasing rate, affecting planting and harvesting periods, with turning points at 33.15 and 33.67 degrees Celsius. Likewise, during the summer and rainy season, a rise in minimum temperature reduces yield at an increasing rate, obstructing the planting and growing period, with shifting points at 27.20 and 26.93 degrees Celsius, respectively. But as the minimum temperature increases beyond 22.78 degrees in the autumn season, the expected yield declines as the harvesting is affected. Warmer climate protects plants from pest attacks, but temperature above optimal level with increased moisture loss is harmful for rice production, damaging root growth.

Turning now to essential water elements for a crop cycle, an increase in rainfall during the rainy and winter seasons decreases yield at an increasing rate, affecting the growing period, with turning points of 812.03 and -46.80 millimeters, respectively. But during winter seasons, heavy rain raises rice yield at a rising rate with a shifting point at -46.80 millimeters. Though rice flourishes in flooded soil, intense rain causes oxygen deficiency that damages temperate crops during the growing period. As evapotranspiration, quantifying the water use in the rice production process, increases beyond 105.05 and 30.92 millimeters in summer and winter, the expected yield drops as the planting period is mainly impeded. Similarly, a rise in evapotranspiration during the rainy season reduces rice yield at an increasing rate, affecting the growing period, with a turning point at 83.77 millimeters. Higher evapotranspiration coupled with solar radiation dries out the soil, physically impairs plants and affects germination. Moving on to consider the velocity of wind, as windspeed rises above 1.52 meters per second in the winter season, yields decline. Moderate wind favours plants by increasing carbon dioxide supply, but strong wind knocks plants over, abrading the plant tissues.

Variability in rice yield is mainly found to be sensitive to the minimum nighttime temperature. A minimum temperature of 1 degree Celsius below climate normal in the winter season increases yield variability by 251.01 percent. Likewise, as the minimum temperature in the winter season exceeds the climate normal by a unit, yield variability increases by 317.67 percent. Because of the higher minimum temperatures, increased seasonal heat-flux during nighttime poses a greater effect on rice yield risk than on vegetative growth, because of the increased rate of senescence. Considering the non-weather factors, with a yield elasticity of 0.04, rice production increased by 848.0 kilos per hectare when an added tonne of fertilizer was practiced per unit of gross cultivated area. Similarly, a unit increase in the irrigated area raises mean yield by 1300.8 kilos per hectare with a yield elasticity of 0.18. Given rice farming is input-intensive, adequate nitrogen fertilizer use and irrigation expansion provide the required nutrients, allowing for a consistent food supply.

4 Conclusion

Using the Just and Pope production function, this paper examined the impact of non-climate and climate factors on rice yield and variability in south India from 1990 to 2017. This study relied on district-level panel data, reflecting a larger magnitude of estimated changes in rice production to relative changes in the weather pattern, undertaking seasonal measures of the following climate parameters: minimum and maximum temperatures, rainfall, evapotranspiration and windspeed. It furthermore expands the research by incorporating seasonal weather anomalies to assess weather shocks, allowing for asymmetric climate effects by separately estimating positive and negative anomalies. Since non-weather variables could either increase or decrease production risk, the analysis controls these factors when evaluating the production frontier. The estimation results indicate that average yield and yield variability are climate-sensitive and seasonal weather variations and extremes significantly influence rice production.

Rice yield is found to be sensitive to changes in evapotranspiration, maximum and minimum temperature in the summer season, while in the rainy season, shifts in minimum temperature rainfall and evapotranspiration are observed to affect yield. In the autumn season, variation in rainfall, windspeed and evapotranspiration are found to influence mean yield, while rice yield is reported susceptible to changes in minimum and maximum temperature in the winter season. Analysis showed that expected yield across seasons is primarily influenced by two climate parameters: evapotranspiration and minimum temperature. Furthermore, the minimum temperature above normal is observed as a risk-increasing weather input for rice during the winter season. As it happens, all non-weather inputs are reported positively related to rice yield, as Pattanayak and Kumar [13] found. Also, present empirical outcomes converge towards that of Arshad et al [35], Arumugam et al [36] and Poudel et al [37]. As Barnwal and Kotani [22] noted, increased temperature is found to decrease the yield and increased rain is found to increase the yield. Seasonal differences in surface temperature and precipitation influence crop yields through their effect on plant development, whereas weather anomalies sway farmer crop management decisions.

The current study underscores the importance of implementing appropriate policy measures, making south Indian agriculture more resilient to changing climate. Given the dominance of the primary sector and economic relevance of this principal staple crop to south India as well as the national economy, weather fluctuations are expected to exacerbate the annual rice availability with elevated price volatility [38], worsening the production and the state of the poor. Changes in cropping patterns, the installation of climate-smart systems, changes in land use, crop diversification, the selection of short-duration varieties, the introduction of high-yielding temperature-tolerant varieties using genetic approaches, insurance provision and improved irrigation are examples of coping mechanisms that ought to be implemented [39, 40]. Delaying profound adaptation efforts by even ten years might double the adaptation cost [16]. Countering adversities of changing climate through mitigation and adaptation strategies, region-specific policies, federal programmes and support are therefore recommended, thus pivotal for state-wide rice production and, by extension, food security.

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Appendix

Table 1 (Variable labels)

Variable	Label	Variable	Label
Yield	Yield in tonne per hectare	WSR2	Square of windspeed in rainy season
AgriLab	Number of agricultural labour per hectare	WSA2	Square of windspeed in autumn season
FertCons	Fertilizer consumption in tonne per hectare	MXT1	High maximum temperature anomaly in winter season
IrriArea	Irrigation area per hectare	MXT2	Low maximum temperature anomaly in winter season
MAXTW	Maximum temperature in winter season	MXT3	High maximum temperature anomaly in summer season
MAXTS	Maximum temperature in summer season	MXT4	Low maximum temperature anomaly in summer season
MAXTR	Maximum temperature in rainy season	MXT5	High maximum temperature anomaly in rainy season
MAXTA	Maximum temperature in autumn season	MXT6	Low maximum temperature anomaly in rainy season
MAXTW2	Square of maximum temperature in winter season	MXT7	High maximum temperature anomaly in autumn season
MAXTS2	Square of maximum temperature in summer season	MXT8	Low maximum temperature anomaly in autumn season
MAXTR2	Square of maximum temperature in rainy season	MNT1	High minimum temperature anomaly in winter season
MAXTA2	Square of maximum temperature in autumn season	MNT2	Low minimum temperature anomaly in winter season
MINTW	Minimum temperature in winter season	MNT3	High minimum temperature anomaly in summer season
MINTS	Minimum temperature in summer season	MNT4	Low minimum temperature anomaly in summer season
MINTR	Minimum temperature in rainy season	MNT5	High minimum temperature anomaly in rainy season
MINTA	Minimum temperature in autumn season	MNT6	Low minimum temperature anomaly in rainy season
MINTW2	Square of minimum temperature in winter season	MNT7	High minimum temperature anomaly in autumn season
MINTS2	Square of minimum temperature in summer season	MNT8	Low minimum temperature anomaly in autumn season
MINTR2	Square of minimum temperature in rainy season	RA1	High rainfall anomaly in winter season
MINTA2	Square of minimum temperature in autumn season	RA2	Low rainfall anomaly in winter season
RFW	Rainfall in winter season	RA3	High rainfall anomaly in summer season
RFS	Rainfall in summer season	RA4	Low rainfall anomaly in summer season
RFR	Rainfall in rainy season	RA5	High rainfall anomaly in rainy season
RFA	Rainfall in autumn season	RA6	Low rainfall anomaly in rainy season
RFW2	Square of rainfall in winter season	RA7	High rainfall anomaly in autumn season
RFS2	Square of rainfall in summer season	RA8	Low rainfall anomaly in autumn season

RFR2	Square of rainfall in rainy season	EV1	High evapotranspiration anomaly in winter season
RFA2	Square of rainfall in autumn season	EV2	Low evapotranspiration anomaly in winter season
EVW	Evapotranspiration in winter season	EV3	High evapotranspiration anomaly in summer season
EVS	Evapotranspiration in summer season	EV4	Low evapotranspiration anomaly in summer season
EVR	Evapotranspiration in rainy season	EV5	High evapotranspiration anomaly in rainy season
EVA	Evapotranspiration in autumn season	EV6	Low evapotranspiration anomaly in rainy season
EVW2	Square of evapotranspiration in winter season	EV7	High evapotranspiration anomaly in autumn season
EVS2	Square of evapotranspiration in summer season	EV8	Low evapotranspiration anomaly in autumn season
EVR2	Square of evapotranspiration in rainy season	WS1	High windspeed anomaly in winter season
EVA2	Square of evapotranspiration in autumn season	WS2	Low windspeed anomaly in winter season
WSW	Winspeed in winter season	WS3	High windspeed anomaly in summer season
WSS	Windspeed in summer season	WS4	Low windspeed anomaly in summer season
WSR	Windspeed in rainy season	WS5	High windspeed anomaly in rainy season
WSA	Windspeed in winter season	WS6	Low windspeed anomaly in rainy season
WSW2	Square of windspeed in winter season	WS7	High windspeed anomaly in autumn season
WSS2	Square of windspeed in summer season	WS8	Low windspeed anomaly in autumn season

Table 2 (Descriptive statistics and stationarity check)

Descriptive statistics						Augmented Dickey-Fuller test					
	mean	variance		mean	variance		chi2	Prob>chi2		chi2	Prob>chi2
Yield	2.7307	0.9502	RFW	9.5154	197.2757	Yield	684.1295	0.0000	RFW	2838.1215	0.0000
FertCons	0.1449	0.0102	RFS	51.6969	1711.9632	FertCons	427.6974	0.0000	RFS	2699.1603	0.0000
AgriLab	1.0066	0.3741	RFR	212.6664	51554.8649	AgriLab	336.8273	0.0000	RFR	2038.3811	0.0000
IrriArea	0.3827	0.0498	RFA	117.6774	5268.4851	IrriArea	415.9711	0.0000	RFA	1832.2948	0.0000
MAXTW	30.9221	1.9838	EVW	38.5843	832.7628	MAXTW	2121.9727	0.0000	EVW	2087.3839	0.0000
MAXTS	35.0469	5.8863	EVS	56.4092	870.2671	MAXTS	2950.5180	0.0000	EVS	2798.3686	0.0000
MAXTR	31.1270	10.0142	EVR	92.9336	664.5672	MAXTR	1501.6028	0.0000	EVR	1664.9216	0.0000
MAXTA	29.4219	2.1994	EVA	85.0084	505.6674	MAXTA	802.7165	0.0000	EVA	1908.6518	0.0000
MINTW	19.1186	4.6758	WSW	1.7453	0.2217	MINTW	1263.0186	0.0000	WSW	597.3533	0.0000
MINTS	23.4742	4.1764	WSS	2.0244	0.1332	MINTS	1707.2087	0.0000	WSS	543.4573	0.0000

MINTR	23.0011	5.9739	WSR	2.5976	0.2876	MINTR	1123.7963	0.0000	WSR	365.1888	0.0000
MINTA	20.1486	4.9038	WSA	1.5720	0.1912	MINTA	1210.0548	0.0000	WSA	356.2514	0.0000

Numerically formatted to four decimal places

Table 3 (Diagnostics tests)

Pre estimation			Post estimation		
				Mean equation	Variance equation
	chi2	Prob>chi2	F-stats	577.4731	3.6333
Hausman	262.0670	0.0000	P-value(F)	0.0000	0.0000
Breusch-Pagan	3099.7300	0.0000	Log-likelihood	-5237.3660	-4628.5410
			Akaike criterion	10564.7300	9529.0830
			Schwarz criterion	10818.5200	10296.0700
			Hannan-Quinn	10657.7300	9810.1540
			Rho		0.0108
			Durbin-Watson		1.9076

Numerically formatted to four decimal places

Table 4 (Panel regression estimation)

	Mean equation							Variance equation						
	coefficient		std. error		coefficient		std. error		coefficient		std. error		coefficient	std. error
const	35.6986	***	3.2774	RFS	0.0008		0.0014	const	-7.1506	**	3.6324	RA6	0.2278	0.8409
AgriLab	0.0471		0.0392	RFS2	0.0000		0.0000	MXT1	-0.2061		0.9840	RA7	0.1060	0.5182
FertCons	0.8480	***	0.1512	RFR	-0.0016	***	0.0002	MXT2	-0.9975		0.9843	RA8	0.1580	0.5660
IrriArea	1.3008	***	0.0746	RFR2	0.0000	***	0.0000	MXT3	0.0716		0.3087	EV1	-0.2939	0.7269
MAXTW	-0.3333		0.2800	RFA	0.0005		0.0009	MXT4	0.3336		0.3116	EV2	-0.3926	0.7290
MAXTW2	0.0090	**	0.0044	RFA2	0.0000	*	0.0000	MXT5	-0.5646		0.4820	EV3	0.3328	0.4692
MAXTS	-0.4574	**	0.2053	EVW	0.0159	***	0.0027	MXT6	-0.5224		0.4673	EV4	-0.0104	0.4751
MAXTS2	0.0069	**	0.0030	EVW2	-0.0003	***	0.0000	MXT7	-0.2656		0.3947	EV5	0.1317	0.4724
MAXTR	0.0211		0.1439	EVS	0.0048	*	0.0026	MXT8	-0.1636		0.4079	EV6	0.3044	0.4617
MAXTR2	0.0009		0.0024	EVS2	0.0000		0.0000	MNT1	3.1767	**	1.4177	EV7	-0.9065	0.6487
MAXTA	-1.2548	***	0.3461	EVR	-0.0075	*	0.0039	MNT2	2.5101	**	1.2046	EV8	-1.0072	0.6744

MAXTA2	0.0186	***	0.0058	EVR2	0.0000	**	0.0000	MNT3	0.1118		0.4156	WS1	0.7532	0.5067
MINTW	0.1289		0.1742	EVA	0.0047		0.0050	MNT4	0.5490		0.4361	WS2	0.7500	0.5174
MINTW2	-0.0008		0.0045	EVA2	0.0000		0.0000	MNT5	0.2789		0.7139	WS3	0.4750	0.4081
MINTS	-1.0132	***	0.2703	WSW	0.6654	**	0.2633	MNT6	0.5097		0.6945	WS4	0.2764	0.4138
MINTS2	0.0186	***	0.0057	WSW2	-0.2196	***	0.0656	MNT7	0.1073		2.3668	WS5	0.0775	0.5651
MINTR	-0.4778	**	0.2297	WSS	-0.1681		0.3473	MNT8	0.0000		0.0000	WS6	-0.0465	0.6035
MINTR2	0.0089	*	0.0049	WSS2	0.0770		0.0793	RA1	-0.2109		0.3979	WS7	0.0089	0.9587
MINTA	1.0213	***	0.1981	WSR	-0.0501		0.2057	RA2	-0.1901		0.4018	WS8	0.3497	0.9888
MINTA2	-0.0224	***	0.0050	WSR2	0.0398		0.0398	RA3	-0.0290		0.2860			
RFW	0.0086	***	0.0026	WSA	-0.0689		0.2653	RA4	0.0805		0.2822			
RFW2	0.0001	***	0.0000	WSA2	0.0304		0.0739	RA5	-0.0321		0.8648			

Numerically formatted to four decimal places
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$