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EFFECTS OF CLIMATIC VARIATION ON RICE YIELD: AN ECONOMIC ANALYSIS OF LOWLAND RICE PRODUCTION IN SRI LANKA

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ABSTRACT

Agricultural production is vulnerable to variation in climate which affects almost all the regions in the world. Using a pooled cross-sectional data from major rice producing regions in Sri Lanka, the responsiveness of rice production to average temperature and rainfall variation was analysed. Output per farm is modelled as a quadratic function of temperature and rainfall (with other standard controls) using fixed effects equations. Monte Carlo simulations are used to model effect on rice yield under various climate change scenarios. Both average temperature and rainfall have concave, non-monotonic effects upon production, which implies that variations in growing climate are likely to have negative effects on rice production. It was found that modest increases in average temperature and variation in rainfall had only a small effect of ambiguous sign, but, increases in average temperature beyond 2 ^{0}C were likely to have strong negative effects on rice production. For example, 4°C increase in average temperature individually or in combination with changing rainfall can lead to approximately 30% yield drop in rice production. As rice production is a key component in economic performance of Sri Lanka and other developing countries, climate change is likely to have serious economic implications and food security issues in the future

Key words: Climatic variation, Cross-section data, Monte Carlo simulation, Rice

INTRODUCTION

In many parts of the world, species and ecosystems may experience climatic conditions at the limits of their optimal ranges or beyond. When optimal conditions prevail, there is no doubt that species or ecosystems thrive well, however when climatic conditions are beyond the optimal levels the impacts can be very complex and difficult to predict. Climate change, the gradual and long-term continuous change in average weather conditions over many decades has often been discussed in relation to its' many adverse outcomes in daily lives of people (Easterling *et al*., 2000; Tompkins, 2002; De Costa, 2010). Predominantly, extreme events such as floods, hurricanes, heat waves and droughts have been analysed in terms of the major impacts and costs for society. For example, the spill-over effects can destroy crops, wreck infrastructure and threaten lives and property.

These impacts and costs predominantly affect agricultural industries as the agricultural sector is extremely dependent on natural resources for production such as water, land (soil fertility), temperature and rainfall. Hence, agricultural production is vulnerable to variation in climate and which affects almost all the regions in the world. In particular, there are serious implications of climatic variation on livelihood in tropical Asia because many of the world's poor are housed in the region and they produce food for their subsistence under a prevailing tropical climate.

At the beginning of the 21st century, many countries in South Asia remained under-developed or developing despite varied socio-cultural and economic histories. Since then, the severity of the impact of climatic variation in these economies has been significant. Records show that extreme weather incidences cause one third of losses in agricultural and allied sectors in these economies (Lesk *et al.,* 2016). The Food and Agriculture Organization (2015) has estimated that, in developing countries, agriculture industries absorbed 22% of the damages from all natural disasters including drought and flood during 2003-2013. Of the total damage to agriculture, 42% has been in the crops sub-sector. In developing countries, the total economic losses in the crops sub-sector were shown to be US$ 13 billion during 2003-2013. Approximately 75% of the total damage was due to floods and drought (Food and Agriculture Organization, 2015).

Climate change and allied crop sector studies have mainly focused on the impact of climate change on crop productivity in a global as well as regional context. Many of them are experimental in nature, having used crop growth models to assess the impact of climate variation on crops. In these models, agronomic aspects and localized impacts of weather changes are often explored (Lansigan *et al*., 2000; Pirttioja *et al*., 2015; Chmielewski and Götz, 2016; Corbeels *et al*., 2016; Qian *et al*., 2016). However, these models are limited in exploring the impacts of climate variation over extended agro ecological and geographical regions as many of them require calibration for future projections (Challinor *et al*., 2015; Li *et al*., 2015).

The increased global temperature leads to rainfall deviations which can produce even more devastating results in crop growth (Ranatunge *et al*., 2003; Dore, 2005; Lobell *et al*., 2007; Auffhammer *et al.,* 2012). The water availability for crops essentially depends upon rainfall distribution and excessive rainfall can damage early crop growth until grain harvest. Moreover, intense rainfall can produce adverse effects, along with major flooding devastating vegetation (Rötter and Van de Geijn, 1999; Manawadu and Fernando, 2008). Rainfall is a highly variable climatic parameter and crop yield is also reduced under water shortage. It is clear from this literature that the impact of changing temperature as well as rainfall plays a pivotal role in food crop production (Rötter and Van de Geijn, 1999; Lansigan *et al*., 2000; Lobell *et al*., 2007; Auffhammer *et al*., 2012; Koubi *et al*., 2012).

Despite these studies that explore crop growth or bio-physical attributes, characterising the influence of climate within environmental time series framework is challenging for many reasons. Most importantly, many variables are embedded in climatic variation where the researchers are essentially forecasting climate under hypothetical conditions (Li *et al*., 2015). Lack of instrumental and observational data in climate science is also crucial. Empirical environmental economic studies that explore climatic impact on agriculture particularly in tropical developing countries are seldom reported. One possible reason could be limited access to primary farm level data as they are not publicly available (Mendelsohn, 2008). However, in this study, we use input and output data on rice production to characterise the influence of climate change within an environmental time series framework in a tropical food crop sub sector.

The agricultural sector in Sri Lanka occupies a prominent role in the economy, ensuring food supply and alleviating rural poverty, with its primal focus on food crop sector priorities (Central Bank of Sri Lanka, 2015; Amarasinghe *et al*., 2005; Gunasena, 2008; Davis *et al*., 2016). Sri Lanka claims self-sufficiency in rice production owing to conducive government policies and technological advancement in the rice industry. Rice serves as a staple food for people in the country and contributes to 11.3 % of the country's agricultural GDP where 28.2% of the population is employed in agriculture (Central Bank of Sri Lanka, 2015).

The distribution of rainfall in the country shows that rice is a seasonally produced food crop in Sri Lanka. The cultivated rice is considered to be semi-aquatic plant grown under controlled water supply. The source of water supply and degree of flooding are the primal environmental factors determining rice crop yield, among many other inputs. However, extreme weather incidences in Sri Lanka have been very frequent during the last five years and have created uncertainty in reaping a worthy harvest. The extreme weather conditions destroy not only the crop yield but also the entire infrastructural network in rice farming. As a result of the severe drought in 2014, for example, the total rice production reduced by 42% and the area harvested dropped by 37%. It is clear the rice production in Sri Lanka is highly sensitive to changing climatic conditions, where the production is often connected to risk and uncertainty. Therefore, this study was undertaken to assess the impact of short-run climatic variation on rice production in selected locations of a tropical agricultural country using Sri Lanka as a case study.

METHODOLOGY

Data

Data were sourced on farm inputs and weather parameters (for 2006-2013) respectively from the Socio Economics and Planning Centre of the Department of Agriculture (DOA) and the Department of Census and Statistics (DCS) of Sri Lanka. Rice production in eleven production regions (Ampara East, Ampara West, Anuradhapura, Gampaha, Hambanthota, Kalutara, Kandy, Kurunegala, Polonnaruwa, Mahaweli System C and System H) were considered for the analysis. The regions cover two major rice producing zones; Dry zone and Wet zone. Approximately, ranging between

30-50 farm households in each of the production regions in a single cropping season have created an unbalanced pseudo panel for 2008-2013. The panel (unit of analysis is an individual farmer) has 16 successive cropping seasons consisting two cropping seasons within a single year (*Maha*-major season and *Yala*-minor season). We treated our data set as a pooled cross-section (pseudo panel) which includes both the farm inputs and climatic variables in different regions for eight years. The definitions of the variables used in the study are given below (Table 1).

Table 1. Definition of variables.

Category	Variable	Description	Source
Dependent variable (y_{it})	Rice Production	Total rice production by i^{th} farmer in time t (kg/season)	DOA
Weather variables	Temperature (T_{jt})	Seasonal average air temperature (^{0}C)	DCS
	Rainfall (RF_{jt})	Seasonal total rainfall (mm)	DCS
	Relative Humidity (day)	Seasonal average relative humidity of the daytime (%)	DCS
	Relative Humidity (night)	Seasonal average relative humidity of the night time (%)	DCS
Control variables (farm inputs) (x_{it})	Extent	Area cultivated (ha/season)	DOA
	Seed	Quantity of seed paddy (kg/season)	DOA
	Fertilizer	Quantity of NPK fertilizer (kg/season)	DOA
	Labour	Quantity of total labour input (Man days/season)	DOA
	Tractor	Rental cost on tractors (LKR*/season)	DOA
	Weedicide	Cost of weedicides (LKR*/season)	DOA
Dummy variables	Year (P_t)	Reporting year (2008 is the base year)	
	Region (D_1)	Cultivated region (*Kalutara* is the base case)	
	Season (D_2)	Cultivated season of the year (*Yala* season is the base case)	

Note: *LKR- Sri Lankan Rupees.

The empirical estimation of this study is composed of two main sections; i) estimation of regression model and ii) Monte Carlo simulations based upon the temperature and rainfall variations. The specification of the regression model is presented in the section on regression analysis and the simulation is presented thereafter.

Regression analysis

Various facets of crop models have been tested in literature in estimating the climatic impact on crop yield (Kim *et al*., 2013). We developed a fixed-effects spatial model to estimate the effect of weather variables on rice yield. Firstly, the model controlled for region-specific fixed effects to adjust for time-invariant unobserved factors that are unique to each rice producing region (e.g. soil fertility and topography). Next, yearly fixed effects were also imposed to track any unobserved factors that are common to all rice producing regions within a given year/period. In addition to weather variables, we included farm inputs as control variables to increase the precision of estimates (Chen *et al*., 2014).

The method adopted by Auffhammer *et al*., (2012) was followed. The generic form of regression model for the area specific rice production in a given time at farmer level is given below (Equation 1). The model is in the log-log form.

$$y_{it} = \sum_{j=1}^{k} \alpha_j D_j + \sum_{t=1}^{m} \gamma_t P_{it} + \theta_1 T_{jit} + \theta_2 T_{jit}^2 + \phi_1 RF_{jit} + \phi_2 RF_{jit}^2 + \delta_1 RH_{jit} + \sum_{i=1}^{n} \beta_i x_{it} + \varepsilon_{it} \quad (1)$$

Where, y_{it} is the log of rice production of i^{th} farmer in year *t*. There are two fixed effects for the region and for the year/period. The alpha terms are region fixed effects and D_j is a collection of j=1…k dummies (region and season) while α_j represents region-specific fixed effects. Similarly P_t represents dummies for the year and γ_t is period-specific fixed effect on annual time trend of *t=1..m* years. T_{jit} is average seasonal temperature and RF_{jit} represents the seasonal rainfall in j^{th} region at period *t*. In addition, Relative Humidity was also included in the model (RH_{jit}) as weather variables. Associated regression coefficients for temperature, rainfall and relative humidity are respectively given by θ_i, ϕ_i and δ_1. The farm inputs x_{it} are given as control variables, while β_i is the input-specific regression coefficient. The main variables of interest (weather variables) are measured at the region level, *j=1…k* while the controls are farm specific, *i=1…n* are the subscripts; ε_{it} is the error term.

The dependent variable; $\ln(y_{it})$, rice production, was obtained from each farmer for different regions (respective district or area)[1] for each season of the year. Studies have replaced production with productivity/yield (i.e. production per unit area) which had minimal impact on the final results according to recent findings (Auffhammer *et al.,* 2012). Therefore, we used rice production as the dependent variable.

In Equation 1, farm inputs and weather variables were included as independent variables. Eleven predominant regions of rice production in the country were included; Ampara East, Ampara West, Anuradhapura, Gampaha, Hambanthota, Kalutara, Kandy, Kurunegala, Polonnaruwa, Mahaweli System C and System H. All the regions were represented using a region dummy. Based on the availability of data, 2008 was chosen as the base year and 2013 as the end. Two rice cropping seasons; *Yala* (dry season) and *Maha* (wet season), were also considered as the production environment is completely different in these two settings. The seasonal segregation is bi-annual. For example, rice production in 2006 is separately reported as 2006 *Yala* and 2006-07 *Maha* to complete the annual production. In order to represent the production season in a particular year, a season dummy was used. Hence there were three dummies in total for region, year, and producing season.

Weather variables considered were, total seasonal rainfall, daily average temperature, and both day and night relative humidity from the respective regional weather stations. Cumulative rainfall within a six month period was considered (i.e. rainfall from April to September in 2008 was

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[1] Regions include districts, divisions of districts and *Mahaweli* systems

aggregated to calculate total rainfall in 2008 *Yala* season while rainfall from October 2008 to March 2009 was aggregated to calculate total rainfall for 2008-09 *Maha*). The aggregation of rainfall in the respective months for the two seasons was based on the standard definition of the rice cropping calendar which coincides with bi-modal monsoonal rains. The average seasonal temperature was calculated for the same six month duration for each region/farm respectively. In addition to rainfall and temperature variables, squared terms of the same variables were also incorporated in the model to capture the quadratic effect of climatic variables for rice production. It is evident that (Iglesias *et al.*, 2000), optimal rice production is reduced when temperature and rainfall deviates from the expected levels. Therefore, the squared form together with the level form of rainfall and temperature variables were used to capture the non-linearity behaviour of weather variables which causes a drop in rice production in either direction. In addition, average relative humidity at day-time and night-time as two variables for respective seasons were used in the model.

Six farm inputs in rice production were identified and treated them as control variables. They were area cultivated, amount of seed, fertilizer quantity, labour quantity, tractor cost and cost of weedicide. The area cultivated in rice by each farm was included as an independent variable (extent) since we recorded production as our dependent variable. Quantity of seed paddy (seed), total NPK[2] fertilizer (fertilizer) and labour hours (labour) for a single season were calculated. We were unable to obtain data on other farm inputs such as tractor hours and amount of agrochemicals used to control pests in rice. Therefore, a total cost on tractors (tractor) and total cost on weedicides (weedicide) for a single season were used as proxy variables to represent power use and chemical use. We transformed all the farm inputs and the weather variables into natural logarithms as specified in Equation1.

Simulation analysis

The parameters θ_i, ϕ_i and δ_1 of Equation 1 analyses how rice production is affected by climatic variables when all the other farm inputs are

[2]NPK-Nitrogen, Phosphorous and Potassium fertilizer

present. We simulated rice production under various temperature and rainfall projections, because the directions as well as the magnitude of changes in weather variables imply different production levels. This is of use for planning future rice production under different climatic conditions with varying rainfall and temperature. Subsequently, we estimated a multi-variate normal to the variables of interest (temperature and rainfall).

The simulations were conducted as follows. A bivariate Gaussian density was estimated for the temperature and logged rainfall data as it varied spatially and over time. We then manipulated the parameters of this density, either shifting it rightward to reflect increases in temperature ($\hat{\mu}_T + 2^0$ and $\hat{\mu}_T + 4^0$) or rescaling the variation in rainfall (such that $\hat{\sigma}_{RF} \times 2$ and $\hat{\sigma}_{RF} \div 2$). 1000 Random draws were then taken from the transformed density and fed into the regression equation to obtain predictions of not just the mean, but also of the full distribution of expected values under different climate conditions. Thus we were able to obtain estimates of how average production levels are likely to fluctuate under both standard climatic variation and also those induced by climate change. The overall results suggest that the average rice production is higher in the absence of natural climatic variation.

For the simulation exercise, predicted values in the Equation 1 were used as the base case. We simulated future climatic conditions under four scenarios i) temperature increase by 2^0C, ii) temperature increase by 4^0C iii) rainfall increase by 50% and iv) rainfall decrease by 50%, in comparison to the base-case scenario (Table 3). In doing this we only considered the incremental temperature proposed by global warming phenomenon (Root *et al*., 2003). Alternative to temperature, change in rainfall in both directions (increase or decrease) were considered. The basis for each scenario was determined according previous studies (Easterling *et al*., 2000; Matthews *et al*., 1997; Peng *et al*., 2004). Thereafter, individual effects and the combined effects of temperature and rainfall were simulated accordingly. The combined effects were derived for all the possible pairs of temperature and rainfall scenarios. Afterwards, the simulated rice production was estimated for individual and combined effect scenarios. The expected level of rice production was then plotted against each weather scenario.

From the results of the simulation exercise, we calculated the projected yield change due to changing climatic scenario using the expected levels of yield. The yield changes were reported for all possible individual variations for temperature as well as for rainfall while the combined effects were reported only for significant yield changes (Table 3).

RESULTS AND DISCUSSION

Regression results

The model was fitted using Ordinary Least Square method (OLS) and robust standard errors were used to avoid possible misspecification in the model (White, 1980). Results of the regression are presented in Table 2. According to the results, all the weather variables indicated a significant effect on rice production and the coefficients were of the expected sign. The relationship between temperature or rainfall variables with production is quadratic.

In addition to weather variables, all the farm inputs were positive and indicative of a high level of statistical significance on rice production. Therefore, we can infer that area cultivated, amount of seed, fertilizer quantity, labour input as well as tractor and weedicide use can increase rice production significantly. Production in *Maha* season is favourable as this shows an additional production potential of 13% compared to *Yala* season. Therefore, we conclude that production in *Maha* is greater to that of *Yala*. With the time effects, compared to the rice production in 2008, a lower production was reported in 2009, 2010 and 2013, due to the drought in the respective years. Relatively to 2008, production years 2011 and 2012 recorded a bumper harvest perhaps due to favourable weather. Region dummies suggested that, relative to *Kalutara* region, all the other regions significantly produce high rice volume.

Table 2. Parameter estimates of variables in the regression model (dependent variable is log of rice production).

Variable	Estimate	Standard error	p value
Weather variables			
Temperature	342.999***	54.522	0.000
Temperature^2	-51.028***	8.175	0.000
Rainfall	0.661**	0.254	0.009
Rainfall^2	-0.053**	0.020	0.009
Relative Humidity-day	-0.706*	0.402	0.079
Relative Humidity-night	1.445***	0.413	0.000
Farm variables			
Seed	0.121***	0.025	0.000
Fertilizer	0.176***	0.025	0.000
Area	0.595***	0.038	0.000
Labour	0.044***	0.012	0.000
Tractor	0.037**	0.012	0.002
Weedicide	0.029**	0.012	0.020
Dummy variables			
Maha Season (wet)	0.125**	0.042	0.003
Year			
2009	-0.057**	0.023	0.015
2010	-0.023	0.027	0.388
2011	0.050**	0.023	0.027
2012	0.026	0.029	0.386
2013	-0.012	0.031	0.678
Region			
Ampara East	0.622***	0.045	0.000
Ampara West	0.421***	0.039	0.000
Anuradhapura	0.389***	0.057	0.000
Gampaha	0.074*	0.040	0.068
Hambanthota	0.605***	0.037	0.000
Kandy	0.699***	0.134	0.000
Kurunegala	0.406***	0.055	0.000
Polonnaruwa	0.522***	0.060	0.000
System C	0.438***	0.058	0.000
System H	0.358***	0.055	0.000
Constant	-576.205***	90.409	0.000
N	3,375		
Prob>F	0.000		
R^2	86.57%		
Root MSE	0.360		

Note:* indicates 10% level, ** indicates 5% level, *** indicates 1% level. All the variables in logarithmic forms, p values rounded to 3 decimal places and standard errors are the robust standard errors.

Simulation results

The theoretical base for the simulation exercise was adopted from Jensen's Inequality predictions which provide a powerful tool for predicting some direct effects of environmental variance in biological systems (Ruel and Ayres, 1999). Jensen's inequality implies that environmental variance (i.e. change in temperature or rainfall) can have important and predictable biological consequences that cannot be inferred from average environmental conditions. When the response function is nonlinear, environmental variance will consistently elevate or depress the response (Roitberg and Mangel, 2016). Thus, the projected response would follow a concave relationship against the variation in rainfall or temperature as shown in Figure 1.

A. Log of production with change in temperature

B. Log of production with change in rainfall

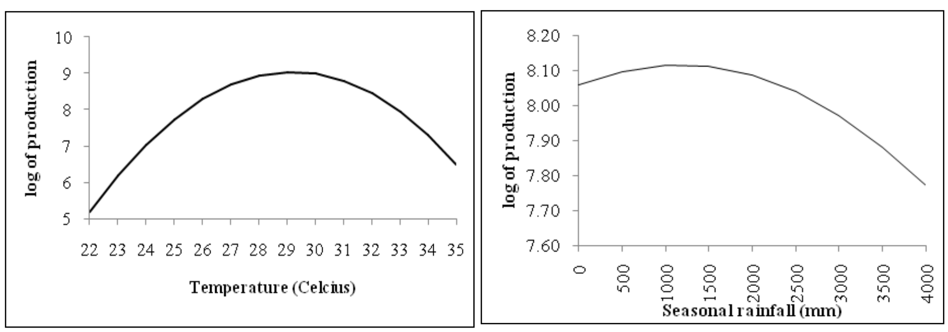
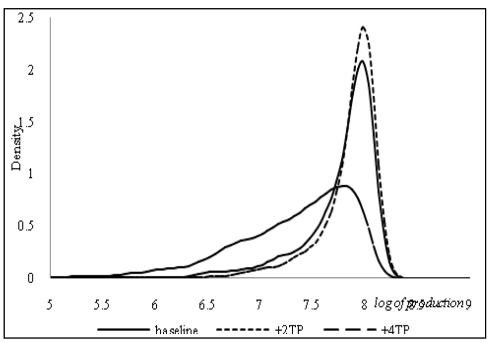


Figure 1. Performance profile with temperature and rainfall variations.

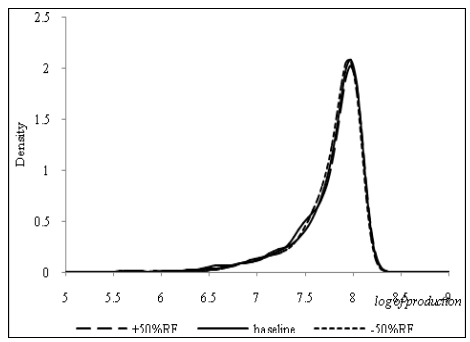
Figure 1 suggests the non-linear response behaviour of log of production to variation in average temperature or rainfall. When average temperature increases, log of production increases up to until the average temperature reaches 29^{0}C and it decreases thereafter. Similarly, log of production is maximum when rainfall is ranged from 1000-1500 mm/season. Based on the above discussion, we present the simulation results in two composite panels in Figure 2; i) individual effects in panel A, B and ii) combined effects in panel C,D. The panel A illustrates the individual effect of average temperature change on rice production whereas panel B suggests the yield response for rainfall change. The combined effect for both the average temperature and rainfall are given in panels C and D. In terms of average temperature changes, according to panel A, a severe production loss was observed at a 4^0C rise in average temperature while the 2^0C average temperature rise did not cause a substantial production loss. As shown in panel B, the rainfall change by 50% did not imply a notable drop in production from the baseline. However, the combined effect of a 4^0C average temperature rise with a 50% change in rainfall resulted in a significant drop in production (panel D).

Among these four simulated scenarios, a notable production loss[3] is reported when average temperature is increased by +4^0C and rainfall by 50%. Therefore, we can conclude that, the production is severely affected with the increase of average temperature by +4^0C. However, the scenarios with a rainfall change of 50% did not indicate a major impact on rice production.

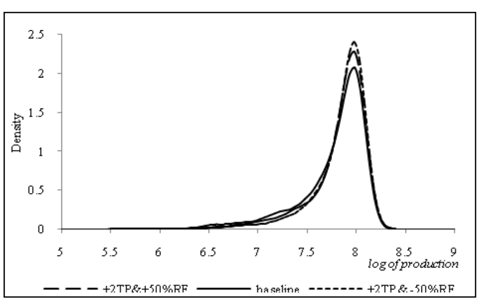
A. Temperature effect Temperature change by +2^0C and +4^0C



B. Rainfall effect
Rainfall change by ±50%



C. Combined effect (+2TP and RF change)
Temperature at +2^0C and Rainfall change by ±50%



D. Combined effect (+4TP and RF change)
Temperature at +4^0C and Rainfall change by ±50 %

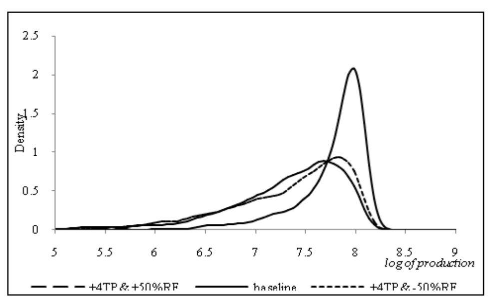


Figure 2. Expected levels of rice production under different change in climate scenario

[3] The yield was compared between predicted base case verses simulated production at each scenario

Yield projections

The above simulation analysis produces the expected yield levels and direction of yield change at different climate scenarios. Subsequently, we calculated the percentage yield change from the base case scenario to derive a quantitative measure to depict the effect of climatic variation. Table 3 summarizes the yield changes compared to the baseline yield level at different climatic scenarios, for individual average temperature and rainfall changes as well as for the combined weather scenarios. It is important to note that there are noted regional variations in the production loss while we only present a summary of the island-wide effect.

Firstly, individual weather effects were analysed. At the baseline condition, the predicted yield is 2,459.58 kg/ha. A significant reduction in this yield, which is approximately 30%, is seen when the average temperature is increased by 4 ^{0}C from the baseline in the simulation exercise. This is mainly because of bio-physical reasons such as rice plants inability to withstand adverse temperature regimes and a loss in fertility occurring as heat is generated through average temperature increases (Morita *et al*., 2004). However, the projected yield did not show a reduction when average temperature is increased by 2^{0}C. Studies have proven that the small change in average temperature can sometimes increase rice yield at a tropical climate (Satake and Yoshida, 1978; Morita *et al*., 2004; Peng *et al.,* 2004). The simulation exercise for rainfall variation did not result in a substantial impact on rice production as in the case of temperature. The yield drop due to 50% increase in rainfall is only 2.48% while the drop from to 50% decrease in rainfall is only 0.18%. Several reasons can account for this observation. Unlike average temperature, farmers can regulate water levels in rice fields depending on the rainfall distribution. Moreover, wide spread use of irrigation and drainage mechanisms currently in place can assure water availability in rice fields against rainfall variations. Therefore, rainfall variation appears to have less impact on production.

Table 3. Percentage yield change from the baseline in different climate scenario.

Scenario	Baseline Average Yield (kg/ha)	Yield Change* (%)
Baseline	2,459.58	
Individual effect –Average temperature		
2^0C increase	2,600.12	5.71
4^0C increase	1,727.75	-29.75
Individual effect - Rainfall		
50% decrease	2,455.15	-0.18
50% increase	2,398.56	-2.48
Combined effect		
Temperature increase by 4^0C & Rainfall increase by 50%	1,669.21	-32.13
Temperature increase by 4^0C & Rainfall decrease by 50%	1,781.57	-27.57

Note*:* * Yield change compared to the predicted value of base case

In addition to the individual effects given above, we simulated combined effects for temperature and rainfall conditions using the hypothetical scenarios (Table 3). The combined effect of a 4 ^{0}C average temperature rise with a 50% rainfall increase may cause 32.13% damage in rice yield. However, the combined effect of 4 ^{0}C average temperature increase and decrease in rainfall by 50% can reduce rice yield by 27.57%. Hence we conclude that the combined effect of different climatic conditions would produce more severe results than that of individual effects. In summary, climate smart cropping strategies will be of timely importance for sustained production against climate variation.

CONCLUSION

This paper analysed the effects of changing climatic conditions on rice production in Sri Lanka. Using a pooled-cross section data collected from 2008 to 2013, the study found significant concavities and non-monotonicities in the relationships between climatic variables and logged output, controlling for a number of other determinants. Simulation results were conducted for the expected value of production under different assumptions about future climatic conditions. It was found that modest increases in average temperature and variation in rainfall had only small effects of ambiguous sign, but increases in average temperature beyond 2^{o}C degrees were likely to have strong negative effects on rice production. For instance, 4^{o}C increases in average temperature individually or in combination with changing rainfall can lead to approximately 30% yield drop in production. The primary channel for this effect appears to be via increasing temperature. Perhaps due to the widespread use of irrigation/drainage infrastructure, variations in rainfall seem less important for output.

In terms of policy, our results highlight the ability of climate change to threaten the stability of rice production in sub-continental Asia. Finding ways to ensure food security appears to be an important priority. Further the fact that output seems more sensitive to rising average temperature can help to guide scientific research in the production of crops/varieties that are more robust to this particular phenomena.

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