Impact of Climate Change on Rice Production in Thailand

John Felkner
National Opinion Research Center

Kamilya Tazhibayeva
University of Chicago

and

Robert Townsend
MIT

December 2008

Contact e-mails: john3@uchicago.edu; kamilya@uchicago.edu; rtownsen@mit.edu.

I Introduction

Our goal is to evaluate variations in rice yields for likely climate changes for Southeast Asia. To do so we integrate economic modeling with soil science crop growth simulation model, weather simulation model and global climate change models. We estimate impacts of climate change under two different climate scenarios, one assuming high future global anthropogenic pollution emissions, and the other assuming low future emissions.

While other studies have used crop growth models to assess future climate change impacts, this study is somewhat unique in that we draw data and run the crop model initially across more than 1000 crop-plots in Thailand, obtaining predictions that are significantly correlated with actual yields, and then generate climate impact predictions for 100 crop-plots. The running of crop-growth models across such a large number of plots simultaneously is quite rare[1], and allows for assessment of larger trends and impacts across the plots.

The economic, crop, weather and climate change models used here are all individually highly complex models, all requiring multiple inputs. Thus the process of obtaining the necessary input data and linking their operations and interactions is inherently challenging. However, the interdisciplinary integration of these models provides promising potential for evaluation of future climate change effects.

Our findings are interesting in several ways. Comparison of the effects of two different future climate scenarios reveals existence of large variation in the effects of climate change on rice yields and correspondingly the types of adjustments farmers choose in response to different climate changes. Analysis of results from different stages of our integrated interdisciplinary model

[1] New codes were written to augment the DSSAT crop model for large-scale batch processing.

illustrates the advantages of such integration, as well as the importance of adjustment choices made by farmers in the evaluation of climate effects on rice yields.

This paper is organized into seven sections. Section 2 outlines the economic model. Section 3 describes the data. Section 4 discusses the modeling of climate change for Southeast Asia. Section 5 describes how we integrate economic, crop growth, weather and climate models. Section 6 presents our results. Section 7 concludes the paper.

II Modeling Rice Cultivation

Economic analysis of production traditionally assumes that production process occurs in one stage. All input choices are made at the start of production. Within the single production stage, all inputs are utilized simultaneously and timing of input usage does not affect realized output. Inputs are defined solely on the basis of their physical characteristics.

The single stage approach is ill-suited for analysis of agricultural crop production. Crop production is defined by the process of a crop's biological growth. This biological growth consists of distinct, chronologically sequential phases. A crop's need for and responsiveness to a given physical input varies across different growth phases. Depending on the progress of crop growth, the farmer may want to adjust the amounts and types of physical inputs used in response to realized production shocks and observed crop state. As a result, input decisions are sequential in nature, and are not all made at the start of production. This is a source of endogeneity, as input decisions at later stages are based on realizations of production shocks in previous stages, some of which the econometrician does not see. Realized production shocks also alter farmer's expectation of production shocks in future stages by updating his information set.

With crop cultivation, each sequential stage can be thought of as a separate production subprocess with its own production function. We map the growth phases of biological development of the rice plant into economic production stages by matching the timing of production operations to the timing of plant development. First is the juvenile growth phase, during which germination takes place. It corresponds in the production process to planting of seeds and growing and transplanting of seedlings. The second is the intermediate phase, during which panicle initiation and heading occur. It corresponds to crop maintenance stage, which includes such operations as weeding and fertilizing. Third is the final phase, during which grains fill and mature. It corresponds to harvest collection and storage.

Using this mapping, we construct a three-stage rice production function. Within each stage, several operations can be performed simultaneously. Output from the previous stage is an initial condition for next stage production subprocess. Input decisions are made at the start of each stage, after output from the previous stage is observed, before production shocks for the starting stage are realized, and with updated expectations based on history at that point in time. Let i index the three production stages and L_i and K_i denote, correspondingly, labor and capital inputs in stage i.[2] Let y_i be output of stage i, with y_0 describing initial conditions of production such as plot characteristics. Let e_i be production shock realized during stage i. Then output in stage i is $y_i = f_i(y_{i-1}, L_i, K_i)\exp(e_i)$, for $i = 1, 2, 3$, where f_i is stage i - specific Cobb-Douglas production function.[3] This three-stage production process is illustrated in figure 1. Substituting in recursively for intermediate outputs, we obtain a composite production function which describes final harvest as a function of initial plot conditions, inputs and realized production shocks: $y_3 =$

[2] To account for several operations performed simultaneously during stage i, L_i and K_i can be thought of as vectors of length J_i, where J_i is the number of operations performed in stage i.

[3] Values of inputs, outputs and production shocks are plot-specific. Plot indexing is omitted for simplicity of presentation.

$f\left(y_0, \{L_i, K_i, \exp(e_i)\}_{i=1}^{3}\right)$.

This approach incorporates the two separate manifestations of sequential nature of crop production. One is a forward effect, where production shocks and input decisions from earlier stages affect initial conditions and therefore input decisions at later stages. The other is a backward effect, where input decisions at earlier stages are influenced by their expected effect on inputs in subsequent stages.

At each stage, farmer chooses inputs to maximize expected profits. Let p denote the price of final output, w_i denote wage rate for labor used in stage i, and r_i denote price of non-labor input used in stage i. Assume the farmer knows all current and future input prices for a given growing season, as well as final output price. At the beginning of stage i, farmer solves:

$$\underset{L_i, K_i}{Max}\, E_3\left[\pi\right] = pE_i[y_3] - \sum_{j=i}^{3}\left(w_j L_j + r_j K_j\right).$$

Note that at this point in production process farmer does not yet know all information that determines actual amounts of inputs used in future stages - namely, he does not yet know the size of production shocks that will be realized during stage i. Therefore, farmer chooses optimal levels of stage i inputs based on expected values of input levels in future stages, where expectation is computed over the information set available to the farmer at the beginning of stage i.

Taking the first order conditions, we get:

$$\text{wrt } L_i\text{:}\;\; p\frac{\partial E_i[y_3]}{\partial L_i} = w_i + \sum_{j=i+1}^{3}\left(w_j \overbrace{\frac{\partial E_i[L_j]}{\partial y_i}\frac{\partial y_i}{\partial L_i}}^{\text{Backward sequential effect}} + r_j \frac{\partial E_i[K_j]}{\partial y_i}\frac{\partial y_i}{\partial L_i}\right),$$

$$\text{wrt } K_i: \ p\frac{\partial E_i[y_3]}{\partial K_i} = r_i + \sum_{j=1}^{3}\left(w_j \frac{\partial E_i[L_j]}{\partial y_i}\frac{\partial y_i}{\partial K_i} + r_i \frac{\partial E_i[K_j]}{\partial y_i}\frac{\partial y_i}{\partial K_i}\right).$$

Note that the marginal cost of each input in stage i has two components. One is increase in current expenses on the input, measured by its price. Another is change in future expenses on inputs in future stages $j > i$ that will be caused by adjustment of optimal levels of stage j inputs with respect to change in levels of stage i inputs actually used. Thus the marginal product of all intermediate inputs reflects sequential nature of multistage production process and captures both immediate direct and future indirect (through levels of future inputs) contributions of intermediate inputs to final output.

John Felkner, Kamilya Tazhibayeva and Robert M. Townsend (2008) provide a detailed description of this three-stage production function, solve the farmer's optimization problem, and estimate rice production function assuming the Cobb-Douglas specification. To account for endogeneity of input decisions, they estimate the composite production function and input decision rules as a system of simultaneous equations, making use of stage- and operation-specific input prices as well as farmer-specific rainfall expectations. At each stage, inputs are determined simultaneously and also depend on intermediate output, or crop state, of previous stage, farmer's expectation of production shocks, and input prices. A number of time and observation indicators are used, to account for province and village time trends as well as for village and household fixed effects[4]. Month indicators keep track of differences in stage timing across farmers and years.[5] The simultaneous system approach delivers estimates of both composite production function and decision rules for all production inputs. This paper uses the same approach as Felkner et al. (2008) and

[4] As described in the next section, we use panel data to estimate the economic model.

[5] To clarify, while we perform very detailed analysis to incorporate heterogeneous timing of stages, and thus inputs application, across farmers and different years, we do not endogenize timing decisions but treat them as predetermined.

builds up on their results. We next describe the data and our handling of unobservable production shocks and intermediate output levels.

III Data

Our data come from the Townsend Thai Project[6]. We focus on rice farmers in four villages in Sisaket province, located in predominantly rural and poor north-eastern part of the country. It is an unbalanced five-year panel with monthly interviews. Data are on household-plot level, with many households cultivating several plots in a given year. A total of 137 households were surveyed, resulting in 1,030 overall observation points.

The data both cover a wide range of variables and provide rich detail within each variable group. We have monthly measures of both physical amounts and cost of labor, equipment and other non-labor inputs such as seeds and fertilizer used in separate production operations. We also have sets of measures of plot soil quality, household socio-economic characteristics, including non-agricultural wages of household members, and environmental data such as daily rainfall and the chemical composition of water sources[7].

The fact that data were gathered monthly for each plot enables us to avoid imposing uniform bounds on stage timing and duration. Rather, we allow for plot-specific timing and duration of stages. The fact that timing and duration of stages and of the overall production cycle vary across households and plots has several important implications. Stage timing reflects variation in a number of plot-specific phenomena that determine it, such as plot characteristics, current state of the

[6]Detailed description of the project can be found at Thailand Database Research Archive (2008) web site, http://cier.uchicago.edu/intro.htm.

[7]Rainfall data were collected from five stations in each survey village. Each plot was linked to the closest station. For details, see John Felkner, Kamilya Tazhibayeva and Robert M. Townsend (2008).

crop, realized or expected production shocks and the farmer's approach to rice cultivation. By incorporating variation in stage timing we take advantage of these additional information contained in the data. Moreover, aggregate production shocks such as rainfall have different effect on different plots because they may hit these plots during different production stages. Thus using plot-specific stage timing enables us to estimate the effects of changes in rainfall on rice cultivation with increased accuracy. We do not endogenize the planting decision however.

Rainfall shocks are of high significance for rice cultivation. Rice is a very water-demanding plant. Most rice cultivation in Thailand is rainfed and makes little use of irrigation. Farmers have to take the possibility of adverse rainfall shocks into account when making input decisions. We use historic daily rainfall to construct a measure of expected future rainfall at the beginning of each production stage. Although rainfall is an aggregate shock, expected rainfall varies across plots due to variation in stage timing. Soil type and slope also impact soil moisture, the key latent variable.

We need a consistent estimate for levels of intermediate outputs. One such measure is provided by DSSAT. DSSAT is a powerful computer crop growth prediction model, the Decisions Support System for Agrotechnology Transfer (DSSAT)[8]. The DSSAT system (Jones et al., 2003) takes in measures of non-labor and non-equipment production factors including quantities of seeds planted and fertilizer used, as well as inherent soil and climatic conditions. These include multiple measures of soil quality, actual historical data on daily variation in weather (precipitation, maximum and minimum temperature, solar radiation), individual crop cultivar genetic growth coefficients and the physical modeling and simulation of soil-plant-atmosphere interactions. It then simulates, day by-day, the biological growth of the plant growing on a uniform area of land under prescribed

[8]DSSAT has been in use for more than 15 years, and has been used by researchers in more than 100 countries. The software is a coordinated system of multiple physical and biophysical models integrated by scientists to simulate the growth of crops, and has been maintained and supported by the International Consortium for Agricultural Systems Applications (ICASA). See: http://www.icasa.net/index.html

or simulated management regimes, as well as with changes in soil water, carbon and nitrogen that take place under the cropping system over time. DSSAT tracks plant's growth with a large variety of dynamic indicators such as number of leaves per stem, root density and weight, stem and canopy weight, etc. For this study, highly detailed data on soil quality was gathered in each crop-plot, as well as data on farmer management inputs (including planting date, amount and type of fertilizer and herbicide, and quantity of seed planted) collected through the Townsend Thai Project. Thai rice genetic profiles and soil-depth profiles specific to the study were used as inputs to DSSAT, along with daily weather data from the study area on precipitation, maximum and minimum temperature, and hours of solar radiation.

The great advantage of the DSSAT model is that it allows us to capture crop response due to purely climatic and soil conditions. Note, however, that DSSAT does not take into account labor inputs, farmer's decisions with regards to some production operations, or idiosyncratic shocks. In other words, DSSAT simulates plant growth due to exogenous climatic and soil conditions, but does not consider all factors and shocks under which rice cultivation occurs. DSSAT simulations are thus not exact measures of actual crop state. Rather, they are approximations of crop state that should occur under observed soil parameters, climatic conditions and crop inputs, as a result of quantified crop-specific growth responses measured precisely in laboratory conditions. However, despite the high precision and accuracy of DSSAT crop-growth simulations, the software typically is not able to model certain particular and idiosyncratic environmental stresses that reduce crop growth from the optimal predicted amounts. Thus, DSSAT typically overpredicts actual crop states, and must be rigorously calibrated to specific study areas (Jones et al., 2003).

The advantage of our economic model of rice production function over DSSAT is that our economic model takes into account farmer's decisions on timing and labor inputs. The advantage of DSSAT over our economic model is that DSSAT has information on the way plant develops biologically and therefore can trace the state of the crop throughout the whole production cycle. This allows us to use DSSAT simulations as imperfect estimates of intermediate outputs. We used measures of leaf weight and root weight as indicators of intermediate output from stage one, and measures of leaf weight, root weight and stem weight as indicators of intermediate output from stage two. Because DSSAT does not incorporate labor input, we use DSSAT indicators of intermediate output together with measures of labor inputs in previous stages to provide a more accurate proxy for intermediate output. The next section introduces our approach to modeling climate change, and after that we describe how we integrate economic model with DSSAT and climate change models.

IV Climate Change Impact Modeling

A Global Circulation Models

As an input into our process of climate change impact assessment, we make use of climate change predictions for Southeast Asia produced by the United Nation's Intergovernmental Panel on Climate Change (IPCC)[9] for their fourth Assessment Report, released in 2007[10]. These climate change predictions were produced from an "ensemble mean" simulation of multiple coupled Atmosphere-Oceanic General Circulation Models (AOGCMs) run by international climate research institutes under the oversight of the IPCC, to produce mean predictions for likely future climate changes for multiple regions of the world[11]. These computationally intensive numerical models are driven

[9] See http://www.ipcc.ch/.
[10] See http://www.ipcc.ch/ipccreports/assessments-reports.htm.
[11] See, for example, http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php.

by equations for atmospheric and oceanic processes, and integrate these forward in time, utilizing equations that are stepped forward sequentially (e.g. temperature, moisture, surface pressure) as well as equations that are evaluated from the simultaneous values of key variables. Representing the current pinnacle of complexity in climate change prediction models, coupled atmospheric-oceanic general circulation models (such as the HadCM3 (Collins, Tett, and Cooper 2001)) are typically evaluated for performance accuracy and error by running them to predict climate using historical data for historical time periods, and then obtaining error estimates through comparison of the actual versus predicted climate (Min et al., 2004). While the models are acknowledged to have flaws, and to be stronger in the prediction of certain variables than in others[12], in recent years, advances in measurement and modeling have resulted in improved global and regional climate predictions, and are capable of reproducing the general features of the observed global climate observed over the past century (McCarthy et al., 2001).

Climate projections must utilize both climate models that can assess and predict natural climate variability, independent of anthropogenic impacts, but must also develop creditable scenarios that account for changes in atmospheric chemistry and global land cover due to demographic development, socio-economic development, and technological change (Nakicenovic et al., 2000). In the scientific literature, atmospheric changes due to anthropogenic emissions are referred to as the forced climate signal, as distinguished from the natural climate variability.

[12]The models are acknowledged to have specific flaws, including albedo error and prediction of tropospheric conditions, as well as inadequate modeling of external factors that could change results, such as percent of cloud cover (Soden & Held, 2006).

B Climate Change Scenarios and IPCC SRES

For this study, we have chosen to use climate change predictions based on an "ensemble-mean" output of more than 20 internationally reputable coupled global climate models, simulated under the oversight of the IPCC using a range of carefully constructed anthropogenic emissions scenarios, each based on different assumptions about future economic and technological development, including projections for future GDP and levels of consumption. These future emissions scenarios were developed for the IPCC by a coordinated team of scientists and economists (Nakicenovic et al., 2000), and we use specific regional predictions made for Southeast Asia under the ensemble-mean of global climate models for the 2007 IPCC fourth Assessment Reports. Of course, the SRES scenarios, as with all economic scenarios of emissions and their reliability are a source of some controversy[13]. We accept them as given here, for this micro study.

The SRES scenarios are grouped into six "families", each making different projections regarding future greenhouse gas pollution and land use. The "highest emission trajectory", A1F1, assumes very rapid future global economic growth, the rapid introduction of new technologies, increasing global convergence and reduction in regional differences in per capita income. The "lowest emissions trajectory", B1, assumes a global economy that emphasizes services and information sectors, with reductions in material intensity and the introduction of resource-efficient technologies (Christensen et al., 2007).

To avoid potential bias or possible flaws inherent in any particular global climate model, the

[13]For example, the IPCC SRES economic emissions scenarios have been criticized, specifically for their use of Market Exchange Rates (MER) for international comparison, in lieu of theoretically favored PPP exchanges rates, which correct for differences in purchasing power. Castles and Henderson (2003) have argued that because of this, the SRES scenarios overestimated future economic growth in developing countries, leading to an overestimate of future emissions. In a PPP scenario, China and India have a much smaller share of global emissions. It would also affect vulnerability to climate change: in a PPP scenario, poor countries grow slower and would face greater impacts.

IPCC organized the controlled simultaneous running of multiple hand-picked coupled global climate models to produce "ensemble-mean" area-averaged predictions for the 2007 4th Assessment Report. Known as the Multi-Model Dataset (MMD)[14], and specifically used to simulate the SRES scenarios by six international climate modeling research groups (Christensen et al., 2007), the models outputs included predicted changes in monthly mean temperature and precipitation (with respect to the 1960 to 1990 baseline period) for the seven sub-regions of Asia, including Southeast Asia, for several future time periods[15].

C Predicted Climate Changes and Agricultural Impacts for Southeast Asia

Climate trends in the last half of the 20th century in Asia were characterized by increasing surface air temperatures, ranging between 1 and 3 degree C per century, with a 0.1 to 0.3 degree C increase per decade in Southeast Asia (Savelieva et al., 2000; Izrael et al., 2002; Gruza and Rankova, 2004). However, the IPCC ensemble-mean results for all scenarios for the 21st century predicts a significant acceleration of warming over the last century (Ruosteenoja et al., 2003; Christensen et al., 2007), with a net annual increase in temperature of between 1.96 °C (lowest emissions scenario B1) and 3.77 °C (highest emissions scenario A1F1) for the 2070-2099 period, relative to the baseline 1961-1990 period. For precipitation, the consensus of the IPCC ensemble-models for the 21st century is for an increase in annual precipitation, varying between a net annual increase of 8 % (highest emissions) and 3 % (lowest emissions) (Lal, 2003; Rupa Kumar et al., 2003; Japan Meteorological Agency, 2005).

[14] The models are listed at http://www-pcmdi.llnl.gov/ipcc/model_documentation/ipcc_model_documentation.php.

[15] Theoretically, the ensemble-mean approach results in a superior delineation of the forced climate change signal from the natural background variability of the system than does the running of one or two models (Giorgi and Mearns 2002).

Predicting the impact of these temperature and precipitation increases on future agricultural outputs and crop yields can be complex because, in general, increased precipitation tends to improve crop growth, resulting in higher yields, while temperature increases tend to add stress to plants and reduce plant growth. Of course, future crop yields under climate change will also be affected by economic factors, including possibly changes in agricultural technology or improvements in farmer inputs. Consequently, studies predicting the impact of these climate changes on future crop yields have produced mixed results, and it is further acknowledged that regional differences in the response of wheat, maize and rice yields could be significant (Parry et al., 1999; Rosenzweig et al., 2001). A number of studies predict that the net impact of these climate changes will be crop yield reductions in Asia, due primarily to temperature increases, resulting in thermal plant stress. In recent decades, production of rice, maize and wheat in Asia has been shown to decline due in part to increasing temperatures (Wijeratne, 1996; Aggarwal et al., 2000; Fischer et al., 2002), and rice production in Asia has been predicted to decline significantly by the end of the 21st century due in part to the thermal stress effect (Murdiyarso, 2000). For the warming projections under the highest emission trajectory A1FI scenario, decreases in crop yields by 2.5 to 10 percent have been projected in parts of Asia (Parry et al., 2004). Other crop simulation modeling studies based on future climate change scenarios indicate substantial losses in rain-fed crops in South and South-East Asia (Fischer et al., 2002). On the other hand, results of crop yield projection using the HadCM2 global climate model indicate that crop yields could likely increase up to 20% in East and South-East Asia while it could decrease up to 30% in Central and South Asia (Cruz et al., 2007).

Because future temperature increases due to climate change will tend to act as plant stressors and inhibit plant growth, while increased precipitation will in general have a beneficial impact, it is not clear that there will be a linear relationship between increased anthropogenic emissions, and either reductions or increases in crop yields, since the relationship between an individual crop's growth and temperature or precipitation changes is not linear.

V Climate Change Impact Modeling: Integration of Crop, Weather, Climate and Economic Models

The integrated approach began by running DSSAT to simulate rice growth for 1,030 individual crop-plots in northern Sisaket province using multiple soil and farmer inputs collected for each plot during 1998-2002 (as described above). Although DSSAT overpredicted yields, as expected, the DSSAT predictions were positively and significantly correlated with yield variation across the plots for those years: specifically, across the entire sample of more than 1000 plots for 5 years of data, a correlation coefficient of .09 was estimated that was significant with a probability-value of 0.005. This correlation provided confirmation of the predictive accuracy of DSSAT given soil, environmental and farmer crop inputs.

The next step was to estimate the economic model. It was done with the same data on 1,030 crop-plots. Actual rain data were used to construct farmer's rain expectations. DSSAT predictions from the first step were used to construct measures of intermediate output from stages one and two.

To simulate potential rice yields under likely future climate change scenarios, we simulated likely future "synthetic" weather from the widely-used WGEN weather simulation model (Richardson 1984), generating different future daily weather for each of the climate change scenarios, using IPCC predicted changes to temperature and precipitation. First, WGEN was used to simulate synthetic stochastic realizations of future weather under forced SRES climate change scenarios, based on the statistical characteristics of actual daily precipitation, maximum and minimum temperatures, and solar radiation amounts for the study area from 1972-2003, collected from official Thai government weather station data.

The WGEN weather generation model (specific details can be found in Richardson (1981), Richardson & Wright (1984), Semenov et al. (1998) and Mavromatis & Hansen (2001)) begins by first calculating an extensive set of statistical parameters describing the observed, historical 1972-2003 daily weather data, including mean monthly amounts for all key input variables, as well as including probabilities of wet days, probabilities of dry days, and within-year precipitation variation. WGEN then generates daily values for precipitation, maximum and minimum air temperature and solar radiation for a N-year period at a given location. The precipitation component of WGEN is a Markov-chain–gamma-distribution model. The occurrence of wet or dry days is generated with a first-order Markov-chain model in which the probability of rain on a given day is conditioned on whether the previous day was wet or dry. When a wet day is generated, the 2-parameter gamma distribution is used to generate the precipitation amount. Daily maximum temperature and solar radiation are sampled from normal distributions parameterized separately for wet and dry days, with sampling conditioned on precipitation occurrence. Distributions of solar radiation are truncated at 16 and 85% of extraterrestrial irradiance. Minimum temperature is sampled from a normal distribution independently of precipitation occurrence. Lag-1 auto- and cross-correlations among maximum and minimum temperatures and solar radiation are maintained by sampling random normal deviates from a trivariate autoregressive model (Richardson, 1984). The final values of the primary output variables are determined by adding the seasonal means and standard deviations to the generated residual elements. All parameters are estimated on a calendar-month basis.

Daily values are computed internally, using linear interpolation.

Using different random “seeds” to generate the initial vector of values used for the sampling, WGEN was used to generate 100 stochastic weather year realizations based directly on the statistics computed for the historical, 1972-2003, observed weather data for northern Sisaket. The resulting realizations provide 100 alternate stochastic future years of daily weather without any forced adjustment for an anthropogenic climate change signal. We refer to these weather realizations as describing a “neutral” scenario, assuming that future climate will be a direct, linear extension of the late 20th century within-year weather variability and multi-decadal daily amounts and monthly means for the key climate variables. These neutral scenario predictions were compared with predictions from the climate change scenarios.

To generate future likely weather with a forces SRES climate change scenario, the IPCC SRES predicted future changes to monthly precipitation and temperature for the Southeast Asia region were used to adjust the WGEN-calculated set of summary statistics for the 1972-2003 observed daily weather data. Then, WGEN was used to generate 100 multiple stochastic future weather years for each SRES scenario using the adjusted summary statistics to make the predictions. The result is likely future daily weather, conditioned directly on the means, variances and cross-probabilities of the observed 1972-2003 daily weather, but adjusted according to individual SRES scenario predictions for Southeast Asia.

Because of the uncertainty in future anthropogenic global changes (which may differ dramatically due to potential policy or technology changes) and their corresponding impacts on atmospheric emissions and pollution amounts, as well as to assess the range of likely possible impacts, we generated stochastic weather realizations for both the highest (A1F1) and lowest (B1) IPCC SRES emissions scenarios, using predictions for the Southeast Asia region, using predictions for the 2040-2069 time period.

The neutral and climate scenario realizations were then used as inputs to DSSAT, and rice yields were simulated for a stratified sample of 100 plots from our study area. These 100 plots were drawn at random from our larger sample of 1,030 plots, with equal share drawn from each of five years of actual data. This produced a distribution of 100 yields for each plot with variation in yields due to variation in the stochastic weather realizations. To assess the impact of climate change on yields, we used the climate change scenario-adjusted weather realizations, for the high and low emission scenarios, as inputs to DSSAT to again generate a distribution of 100 yields for each plot, for each scenario. This produced 300 yield realizations for each of 100 plots, with 100 realizations for each of neutral, high emissions and low emissions climate scenarios. Throughout these simulations, all non-weather inputs were kept the same for each plots, at values of the actual data from 1998-2003. In other words, no adjustment was made to inputs and timing from one weather realization to another. Thus, for a given plot, variation in assumed climate and weather realizations was the only source of difference in yields in the 300 DSSAT yield simulations for that plot.

The final step was to use the three generated weather scenarios together with corresponding DSSAT crop simulations as inputs into estimated economic model and use it to predict yields. For each plot, individual rain expectations were constructed for each of 300 weather realizations. Similarly, measures of intermediate stage one and stage two outputs were constructed for each of 300 DSSAT simulations for a given plot. Estimation then proceeded in four steps. In the first step, input levels for stage one were estimated. These estimates incorporated rain expectations for stage one and thus reflected variation in input usage due to difference in weather realizations. In the second step, estimates of levels of first stage inputs were used together with DSSAT indicators of stage one intermediate output and stage two rain expectations to estimate levels of stage two inputs. These estimates reflected variation in input usage due to both differences in weather realizations and adjustments made by the farmer in the first stage. In the same manner we estimated levels of stage three inputs. We then used estimates of all inputs together with rain realizations as inputs into composite production function and estimated final yields. These final yields estimates integrated models of climate change, weather variations within each climate scenario, plant's biological development as modeled by DSSAT, and estimation of farmer's production choices as modeled by economic model.

VI Results

We first provide a summary of the two alternative climate changes that we consider. These are high and low emission climates corresponding to middle range period as defined by the IPCC SRES. Table 1 uses the 100 weather realizations generated by WGEN for each climate scenario to compare high and low emission climate scenarios to the neutral scenario.

Panel A of table 1 compares amounts of daily precipitation and panel B compares average temperature during daylight hours. In each panel, second column contains mean daily values for each month under neutral climate. The next three columns address shift from neutral to high-emissions climate. Column three shows the corresponding change in mean daily values, column four expresses this change in percent, and column five shows the probability value of the test on the equality of daily precipitation under neutral and high-emissions climates. In the same manner, columns six through eight address shift from neutral to low emissions climate, and columns nine through 11 address shift from low emissions climate to high emissions climate.

Climate change is more extreme under high emissions scenario. While daily temperatures increase under both climate scenarios, the magnitude of increase under high emissions climate is about 40% higher. Daily precipitation increases throughout the year under low emissions climate. However under high emissions climate there is less rain in the second half of the year, starting in June, which is exactly the period of rice cultivation. Thus low emissions climate change brings moderate increase in temperature and more rain, while high emissions climate bodes both higher increase in temperature and less rain for rice cultivation.

DSSAT predictions are summarized in panel A of table 2 and in table 3. We first look at table 2, which provides aggregate yield comparisons across the three climate scenarios. Row one shows mean yield change, measured in kilograms per acre, and row two expresses this change as percent of aggregate mean yield under initial climate scenario. Row three shows p-value for the test of equality of means under initial and final climate scenarios. Compared to neutral climate, aggregate yields decrease under both high and low emissions scenarios, and these yield decreases are highly statistically significant. Yields are also lower under low emissions than high emissions scenario, despite the fact that low emissions climate is less extreme of the two. This may be due to the damaging effect on the crop of higher rainfall during the final production stage, when grain is mature and harvesting takes place.

Table 3 provides plot-level analysis of DSSAT predictions. First three rows of table 3 compare predicted yields, measured in kilograms per acre, when shifting from neutral to high emissions climate. For each plot in our sample of 100 plots, we test the equality of mean yields under neutral and high emissions climates. We then compute the percent of plots that have statistically significant change in yields. These numbers are reported in the first row of table 2, separately for increases and decreases in yields, for 1, 5 and 10% significance levels. Second row of table 3 reports the actual size of mean yields change over plots where the change was statistically significant. To give the idea of the scope of yield changes, third row expresses mean yields change of row two in percent. In the same manner, rows four to six compare predicted yields when shifting from neutral to low emissions climate, and rows seven to nine compare yields when shifting from low to high emissions climate.

DSSAT predicts lower yields for about a third of the plots under both low and high emission scenarios. For these plots, decrease in yields is severe, ranging from 30 to 50%. Decrease in yields is stronger when shifting to low emissions scenario, under which both more plots are affected and the scale of yield decrease is higher. Note also that, comparing plots with decreased yields under low and high emissions climates, plots affected under low emissions scenario were more productive under neutral climate than plots affected under high emissions scenario.

DSSAT predictions thus suggest that yields decrease more under the milder low emissions scenario. Despite the fact that high emissions climate has less rain during the second half of the year while low emissions climate has moderately more rain throughout the year, farmers fare worse in low emissions climate.

Model predictions are summarized in panel B of table 2 and in table 4. Panel B of table 2 provides aggregate results for model predictions. As is the case with DSSAT predictions, model predicts lower aggregate yields under both high and low emissions scenarios when compared to neutral scenario. These yield decreases are again highly statistically significant. Similarly, yields are lower under low emissions then under high emissions scenario, although model predicts much smaller gap between the two.

Table 4 provides plot-level analysis of model predictions and is constructed in the same manner as table 3. Rows one to three compare predicted yields, measured in kilograms per acre, when shifting from neutral to high emissions climate, rows four to six compare predicted yields when shifting from neutral to low emissions climate, and rows seven to nine compare yields when shifting from low to high emissions climate.

Model predictions are in stark difference with DSSAT predictions. First thing to note is that the fraction of sample experiencing statistically significant yield decrease under high emissions climate more than doubles compared to DSSAT. Yields go down for 68% of the plots, with the average decrease of about 13%. However, under low emissions climate yields actually increase for over 80% of the plots, albeit only by half a percent. For a small number of plots the crop has failed altogether under low emissions climate. Further, we also see that there is no difference in productivity for plots affected under low emissions scenario versus those affected under high emissions scenario.

Thus, according to model predictions, farmers manage to take advantage of the moderate increase in rainfall under low emissions climate. The majority of farmers do not experience large scale changes in yields. At the same time, there is a chance of complete crop failure. We next look if this risk is associated with soil quality or farmer's finances.

We look at the connection between yield changes and per capita income in farmer's household. We compute the probability of household's per capita income being below the median[16] given that the household experienced statistically significant increase (decrease) in yields. We also consider differences in soil quality between plots with and without statistically significant yield changes. We use two measures of soil quality. One is pH, which indicates the relative acidity or alkalinity of soil. Another is cation exchange capacity (CEC), which indicates soil's capacity to hold cation

[16]Household's per capita income is compared to the province median per capita income of all households in our larger sample of 137 households in each of five years in the sample. Our results hold when we do comparisons using village-specific median per capita income, and also when we use per capita consumption in place of per capita income.

nutrients. CEC is determined by amounts of clay and humus in the soil and is not easily adjusted. For both measures, we compute the difference in soil quality between plots with and without yield increase (decrease), expressed in percent. We also test for equality of mean pH and CEC values between plots with and without yield increase (decrease) and report the resulting probabilities.

These results are presented in table 5. Panel A contains results for yield changes significant at 1% level, panel B contains results for yield changes significant at 5% level, and panel C contains results for yield changes significant at 10% level.

Soil quality is not associated with yield changes no matter which climate change is considered. This is true for both DSSAT and model predictions. Household's income also does not correlate with yield changes, with one notable exception. We see that the few plots that experience crop failure under low emissions climate according to model predictions have a 70% chance of having per capita income below median. This result suggests that poorer households are incapable of coping with the moderate climate change that other farmers are able to adjust to.

We now compare model and DSSAT predictions for middle-range climate changes. To repeat, there are several differences between the model and DSSAT that are key to this analysis. DSSAT takes into account only amounts of non-labor non-equipment inputs such as fertilizer and seedlings that are applied to soil. When we simulated DSSAT under alternative climate scenarios, these input values were not adjusted from their actual levels reported under current climate. Thus changes in yields predicted by DSSAT are driven solely by changes in climate in which the crop is grown, with no adjustment to any inputs.

Changes in rainfall across different climate scenarios are taken into account in model prediction through adjustment of farmers' rainfall expectations. The model also incorporates results of DSSAT simulations though changes in measures of crop's intermediate states. Thus all inputs in model prediction incorporate adjustment to climate change through these two channels. In addition, we are able to utilize the multi-stage structure of our production function and adjust input levels in later stages according to adjustments made to inputs in earlier stages.

To summarize, DSSAT predictions of yield changes do not take into account any adjustments by farmers. Model predictions, on the other hand, make adjustments to all production inputs according to the estimates of farmer's input decision rules.

For the shift from neutral to low emissions climate, comparison of DSSAT and model predictions shows that taking into account farmer's response to climate change makes a substantial difference. Without input adjustments, we see statistically significant yield decrease of large magnitude in a third of our sample plots. Once farmer's responses to climate change are incorporated, the majority of plots do not experience yield decrease and even enjoy a slight increase in yields. Farmers are thus able to adjust to climate change from neutral to low emissions scenario.

The role of farmers' adjustment to climate change is also evident in the shift from neutral to high emissions climate. Without input adjustments, we see statistically significant yield decrease of around 30% in a quarter of our sample plots. Once farmer's responses to climate change are incorporated, the fraction of sample experiencing yield decrease more than doubles but the magnitude of average yield decrease more than halves. Farmers thus respond to this more severe climate change with adjustments that prevent large crop failures, at the cost of reducing their yields by about 13%. In other words, farmers are unable to fully neutralize the effects of the more severe climate change. However, by adjusting their crop cultivation routine they are able to mitigate the adverse effects of this more extreme climate change scenario.

It should also be noted that under milder climate change from neutral to low emissions scenario, farmers do not find it necessary to adjust their cultivation methods sufficiently to reduce the chance of crop failure. Our results thus suggest that various climate changes pose different challenges to the farmers. One is overall reduction in yields, when crops do not fail but are less productive. Another is crop failure on a large scale. It appears that there is a trade-off in adjustment techniques for these two challenges. Under less severe climate change large crop failure may be a result of bad weather draw, so farmers choose adjustment that maintains their yields but does not guard against crop failure. Under more severe climate change any weather realization can lead to large crop failure, and so farmers switch the adjustment technique to preventing large crop failure at the cost of lower yields.

VII Conclusion

In this paper we integrated models from several different disciplines to assess the effect of climate change on rice production in Thailand. We considered two alternatives for climate change, one more extreme with higher temperatures and lower rainfall, another more mild with smaller temperature increase as well as moderate rainfall increase.

Our results illustrate the complexity of climate change effects on rice yields. Milder climate change does not necessarily mean smaller adverse effect on yields. In addition, it appears that different climate changes call for different adjustment strategies by farmers, and these adjustment strategies are not necessarily complimentary. Our results also illustrate the scope of farmers' ability to counter climate change, and thus the importance of accurate modeling of farmers' decisions. Overall farmers are unable to neutralize the adverse effects of the more extreme climate change. However, they are able to cope with milder climate change and even benefit slightly from small increases in rainfall. We find that farmers' ability to adjust to climate change is not correlated with soil quality of their land or their incomes. One notable exception to this is that while most farmers manage to adjust to milder climate change, poor farmers are less able to do so.

It should be noted that in our analysis we consider only farmers' adjustment through input decision rules, namely, their choices of levels of production inputs. We do not model or incorporate possible changes in timing of input usage. We also do not consider broader adjustments such as changes in the type of crop grown or migration. As a result, our findings may overstate both yield changes and implied welfare effects due to climate change.

References

1. J. H. Christensen et al., *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, 2007.
2. M. Collins, S. F. B. Tett, and C. Cooper, "The internal climate variability of HadCM3, a version of the Hadley Centre coupled model without flux adjustments," *Climate Dynamics* 17, no. 1 (2001): 61-81.
3. J. Felkner, K. Tazhibayeva and R. Townsend, "Crop Production: Combining Socio-Economic and Biophysical Data and Models," working paper, University of Chicago, 2008.
4. F. Giorgi and L. O. Mearns, "Calculation of Average, Uncertainty Range, and Reliability of Regional Climate Changes from AOGCM Simulations via the Reliability Ensemble Averaging (REA) Method," *Journal of Climate* 15, no. 10 (2002): 1141-1158.
5. A. Mackay, "Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change," *Journal of Environmental Quality* 37, no. 6 (2008): 2407.
6. N. Nakicenovic et al., *Special Report on Emissions Scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change* (PNNL-SA-39650, Cambridge University Press, New York,, United States., 2000).
7. C. W. Richardson, "Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation," *WATER RESOURCES RES.* 17, no. 1 (1981): 182-190.
8. C. W. Richardson, "Weather simulation for crop management models," *Paper-American Society of Agricultural Engineers* (1984).

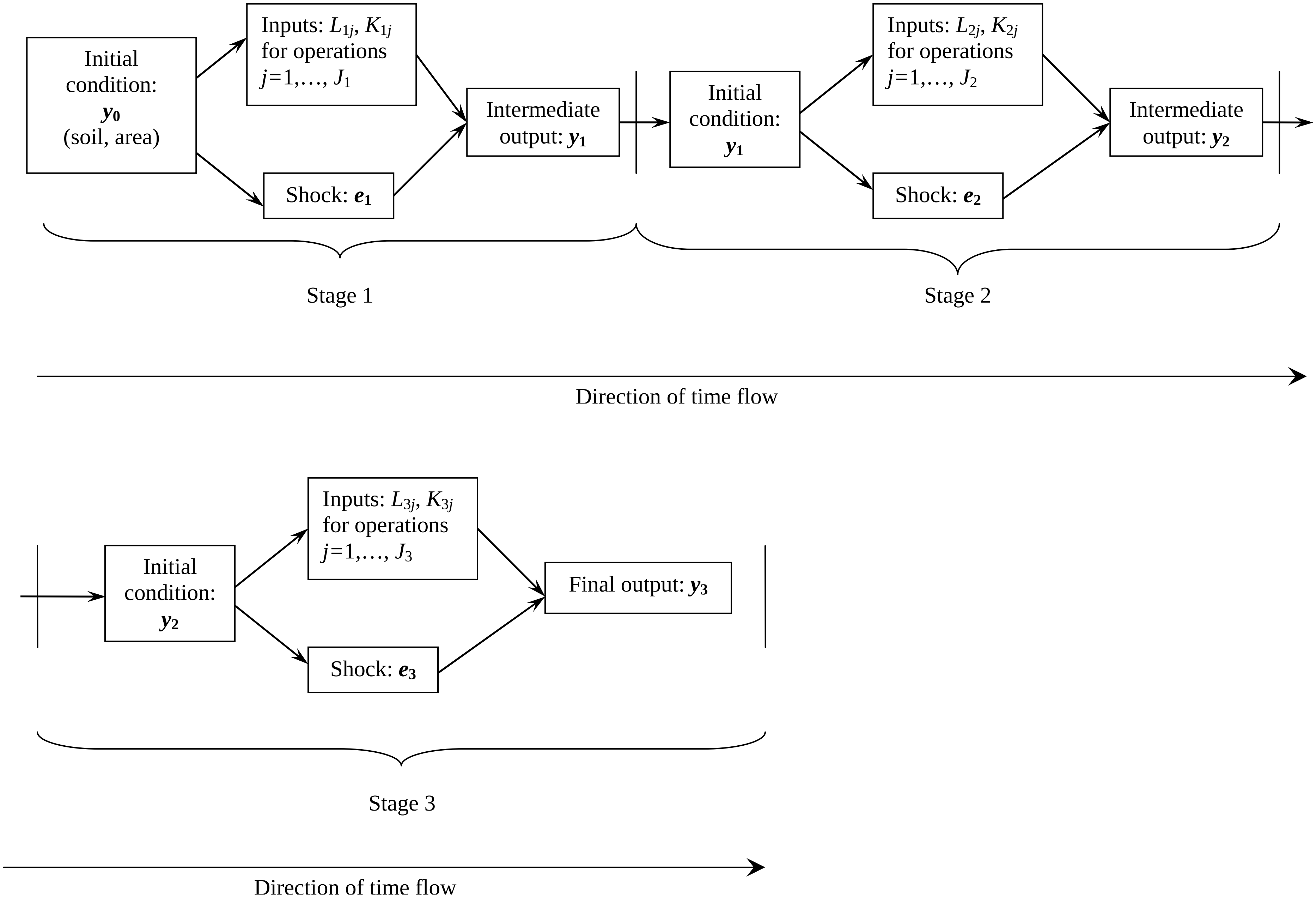

Figure 1 – Three-Stage Production Process

Table 1 – Comparison of Neutral to Alternative High and Low Emissions Climates

Panel A: Daily Amount of Precipitation, in mm

	Neutral	Neutral to high emissions shift			Neutral to low emissions shift			Low to high emissions shift		
Month	Mean	Mean change	Percent	P-value	Mean change	Percent	P-value	Mean change	Percent	P-value
January	0.123	0.003	2.285	0.01	0.005	4.413	0.01	-0.003	-2.038	0.01
February	0.226	0.003	1.342	0.00	0.007	3.252	0.00	-0.004	-1.850	0.00
March	1.119	0.035	3.157	0.00	0.034	3.062	0.00	0.001	0.092	0.00
April	3.329	0.102	3.053	0.00	0.102	3.053	0.00	0.000	0.000	0.00
May	4.882	0.152	3.111	0.00	0.150	3.066	0.00	0.002	0.044	0.00
June	6.402	-0.059	-0.914	0.00	0.024	0.375	0.00	-0.083	-1.285	0.00
July	5.068	-0.001	-0.021	0.01	0.050	0.984	0.00	-0.051	-0.995	0.00
August	5.691	0.030	0.522	0.00	0.055	0.967	0.00	-0.025	-0.441	0.00
September	8.127	-0.082	-1.013	0.00	0.080	0.990	0.00	-0.163	-1.983	0.00
October	4.391	-0.042	-0.967	0.00	0.042	0.967	0.00	-0.085	-1.915	0.00
November	1.160	-0.014	-1.210	0.00	0.007	0.629	0.00	-0.021	-1.827	0.00
December	0.023	-0.001	-3.467	0.00	0.001	5.270	0.00	-0.002	-8.300	0.00

Panel B: Average Daily Temperature during Daylight Hours, in degrees Centigrade

	Neutral	Neutral to high emissions shift			Neutral to low emissions shift			Low to high emissions shift		
Month	Mean	Mean change	Percent	P-value	Mean change	Percent	P-value	Mean change	Percent	P-value
January	26.697	2.300	8.615	0.00	1.300	4.869	0.00	1.000	3.572	0.00
February	29.083	2.300	7.909	0.00	1.300	4.470	0.00	1.000	3.291	0.00
March	31.391	2.300	7.327	0.00	1.300	4.141	0.00	1.000	3.059	0.00
April	32.357	2.300	7.108	0.00	1.300	4.018	0.00	1.000	2.971	0.00
May	31.339	2.327	7.426	0.00	1.300	4.148	0.00	1.027	3.147	0.00
June	30.464	2.078	6.821	0.00	1.300	4.267	0.00	0.778	2.449	0.00
July	29.894	2.100	7.024	0.00	1.300	4.349	0.00	0.800	2.563	0.00
August	29.414	2.199	7.478	0.00	1.300	4.420	0.00	0.899	2.928	0.00
September	30.350	1.205	3.971	0.00	1.300	4.283	0.00	-0.095	-0.300	0.00
October	28.434	1.298	4.567	0.00	1.300	4.572	0.00	-0.002	-0.005	0.00
November	27.191	1.172	4.311	0.00	1.300	4.781	0.00	-0.128	-0.449	0.00
December	25.733	2.420	9.405	0.00	1.300	5.052	0.00	1.120	4.144	0.00

Table 2 – Aggregate Yield Changes across Climate Scenarios

Panel A: DSSAT Predictions

	Neutral to high emissions	Neutral to low emissions	Low emissions to high emissions
Yield change	-53.521	-209.154	155.633
Percent change	-3.53	-13.79	11.91
P-value[a]	2.683E-02	1.030E-12	2.390E-09

[a] Corresponds to one-sided test in the direction indicated by sign of yield change in the first row: H_a is decrease in yields for columns one and two and H_a is increase in yields for column three.

Panel B: Model Predictions

	Neutral to high emissions	Neutral to low emissions	Low emissions to high emissions
Yield change	-71.152	-79.230	7.981
Percent change	-10.81	-12.04	1.40
P-value	0.000E+00	0.000E+00	1.170E-13

[a] Corresponds to one-sided test in the direction indicated by sign of yield change in the first row: H_a is decrease in yields for columns one and two and H_a is increase in yields for column three.

Table 3 – DSSAT Predictions of Yield Changes

		1 percent significance		5 percent significance		10 percent significance	
Climate shift	Variable	Increase	Decrease	Increase	Decrease	Increase	Decrease
Neutral	Percent of sample	4.21	20.00	10.53	26.32	13.68	36.84
to	Yield change	306.308	-272.687	325.976	-220.047	286.748	-260.302
High emissions	Percent change	102.50	-49.25	49.26	-33.98	38.51	-27.97
Neutral	Percent of sample	3.16	29.47	5.26	35.79	12.63	36.84
to	Yield change	119.723	-581.584	221.085	-605.151	206.053	-591.514
Low emissions	Percent change	123.43	-50.27	78.77	-43.57	36.42	-42.76
Low	Percent of sample	5.26	1.05	9.47	5.26	20.00	10.53
to	Yield change	2301.83	-61.71	1322.69	-75.67	690.29	-117.94
High emissions	Percent change	36.83	-100.00	21.45	-8.60	21.30	-7.68

Table 4 – Economic Model Predictions of Yield Changes

		1 percent significance		5 percent significance		10 percent significance	
Climate shift	Variable	Increase	Decrease	Increase	Decrease	Increase	Decrease
Neutral	Percent of sample	15.85	62.20	15.85	68.29	17.07	69.51
to	Yield change	2.427	-114.872	2.427	-104.719	2.396	-102.973
High emissions	Percent change	0.42	-14.08	0.42	-12.84	0.43	-12.62
Neutral	Percent of sample	79.27	12.20	81.71	12.20	81.71	12.20
to	Yield change	3.840	-675.937	3.898	-675.937	3.898	-675.937
Low emissions	Percent change	0.55	-98.20	0.55	-98.20	0.55	-98.20
Low	Percent of sample	4.82	84.34	4.82	85.54	4.82	85.54
to	Yield change	313.04	-8.32	313.04	-8.29	313.04	-8.29
High emissions	Percent change	0.83	-0.99	0.83	-0.98	0.83	-0.98

Table 5 – Soil Quality and Household Income in Yield Changes

Panel A: Yield Changes Significant at 1% Level

Yield change	Variable	DSSAT predictions: Neutral to high emissions	DSSAT predictions: Neutral to low emissions	DSSAT predictions: Low to high emissions	Model predictions: Neutral to high emissions	Model predictions: Neutral to low emissions	Model predictions: Low to high emissions
Increase	Below median per capita income	50.00	0.00	40.00	53.85	47.69	50.00
	pH mean change, in percent	-3.03	3.20	0.92	-4.94	2.98	-10.33
	pH mean change, P-value	0.665	0.691	0.884	0.223	0.333	0.136
	CEC mean change, in percent	73.56	-4.38	16.95	31.07	-7.71	41.63
	CEC mean change, P-value	0.186	0.903	0.620	0.199	0.577	0.363
Decrease	Below median per capita income	68.42	60.71	0.00	49.02	70.00	47.14
	pH mean change, in percent	-4.38	-0.74	0.00	2.32	-6.25	4.40
	pH mean change, P-value	0.207	0.810	0.000	0.416	0.168	0.181
	CEC mean change, in percent	16.14	7.22	0.00	-9.12	23.20	-11.24
	CEC mean change, P-value	0.385	0.634	0.000	0.470	0.370	0.438

Panel B: Yield Changes Significant at 5% Level

Yield change	Variable	DSSAT predictions: Neutral to high emissions	DSSAT predictions: Neutral to low emissions	DSSAT predictions: Low to high emissions	Model predictions: Neutral to high emissions	Model predictions: Neutral to low emissions	Model predictions: Low to high emissions
Increase	Below median per capita income	50.00	40.00	33.33	53.85	46.27	50.00
	pH mean change, in percent	-3.53	-2.05	4.30	-4.94	3.68	-10.33
	pH mean change, P-value	0.439	0.745	0.372	0.223	0.243	0.136
	CEC mean change, in percent	23.60	23.78	-8.33	31.07	-6.09	41.63
	CEC mean change, P-value	0.363	0.510	0.689	0.199	0.668	0.363
Decrease	Below median per capita income	60.00	55.88	60.00	50.00	70.00	46.48
	pH mean change, in percent	-3.93	-0.54	-2.42	3.46	-6.25	4.22
	pH mean change, P-value	0.212	0.853	0.701	0.235	0.168	0.205
	CEC mean change, in percent	8.62	8.74	23.91	-14.57	23.20	-9.07
	CEC mean change, P-value	0.588	0.547	0.508	0.246	0.370	0.540

Panel C: Yield Changes Significant at 10% Level

		DSSAT predictions			Model predictions		
Yield change	Variable	Neutral to high emissions	Neutral to low emissions	Low to high emissions	Neutral to high emissions	Neutral to low emissions	Low to high emissions
Increase	Below median per capita income	46.15	50.00	52.63	50.00	46.27	50.00
	pH mean change, in percent	-4.94	-2.32	8.20	-5.07	3.68	-10.33
	pH mean change, P-value	0.223	0.583	0.020	0.197	0.243	0.136
	CEC mean change, in percent	20.65	17.03	-11.07	33.12	-6.09	41.63
	CEC mean change, P-value	0.360	0.454	0.460	0.163	0.668	0.363
Decrease	Below median per capita income	60.00	54.29	70.00	49.12	70.00	46.48
	pH mean change, in percent	-2.03	-1.00	-3.34	3.65	-6.25	4.22
	pH mean change, P-value	0.483	0.730	0.465	0.211	0.168	0.205
	CEC mean change, in percent	-5.25	9.85	15.80	-14.08	23.20	-9.07
	CEC mean change, P-value	0.691	0.497	0.519	0.266	0.370	0.540