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ORIGINAL PAPER

The Impact of Climate Change on Rice Production in Nepal

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Abstract
Using panel data from Nepal Living Standard Surveys (NLSSs) from 2003 and 2010, this study investigates the impact of climate change on rice production in Nepal. Specifically, we use stochastic frontier model and incorporate both technical inefficiency and spatial filtering technique to estimate the impact of increases in average and extreme rainfall and temperatures on annual rice production. Our central finding is that a 1°C increase in average summer temperature results in a 4183 kg reduction in rice production. However, we find no evidence of such impact for increases in extreme temperature days. On the other hand, although we do not find a direct link between increases in average monsoon rainfall and rice production, our results show that extreme rainfall variation hurts productivity. Moreover, we find that a large majority of agricultural households in rural Nepal practice technically inefficient production methods. Households in districts with higher road and river densities are more technically efficient despite climate challenges, which suggests that improved irrigation and market access are needed for climate adaptation.

Keywords Climate change · Rice production · Spatial filtering · Technical inefficiency · Nepal

JEL Classifications Q54 · Q56 · Q58 · Q12 · Q15

The disproportionate impacts of climate change on the poor living in rural areas of developing countries are well documented (Hallegatte et al. 2015; Burgess et al. 2017; Hallegatte and

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Rozenberg 2017; Barbier and Hochard 2018; Hsiang et al. 2019). These impacts are particularly severe among populations living in less-favored agricultural areas (LFAAs), characterized by difficult terrain, poor soil quality, or limited rainfall and with limited market access. As such, less-favored agricultural areas are prone to low agricultural productivity and severe soil degradation (Barbier and Hochard 2018, p. 27, 35). Two broad categories of factors, namely lack of access to credit and technology as well as the non-linearity in damage functions, result in larger marginal damages among the poor populations (Hsiang et al. 2019). Because the poor in LFAAs face marginal environmental conditions and are land-dependent, any exogeneous changes in environmental conditions can push them into poverty-environmental traps (Carter and Barrett 2006; Barbier 2010).

Nepal's mountainous terrain, poor access to infrastructure and markets, and excessive dependence on subsistence agriculture and ecosystem services place the rural Nepalese poor among the most climate vulnerable groups within the LFAAs (Pender and Hazell 2000; Pender 2007). Climate models show steady increases in both temperature and precipitation in South Asia and the Hindu-Kush region, where Nepal is situated (Im et al. 2017; Janes et al. 2019). High altitude regions including in the hill and mountains of Nepal bear the brunt of these changes (Shrestha and Aryal 2011; Gentle et al. 2018). While there is evidence that long-term adaptation can mitigate some of the negative impacts of climate change in the developed economies (Burke and Emerick 2016), tools and resources for effective long-term climate adaptation require higher upfront investments that are not readily available to poor households in developing countries, such as Nepal (Anttila-Hughes and Hsiang 2013; Rayamajhee and Bohara 2019a). Moreover, Nepal's unique physiographical and topographical distribution and enormous climatic and ecological diversity add additional vulnerabilities (Shrestha and Aryal 2011).

Nepal has long been a predominantly agriculture-based subsistence economy, with over 70% households directly relying one or more forms of agriculture to meet their daily needs (Joshi and Bohara 2017; Joshi et al. 2017). Land is among the few productive assets that most households own. Rice is the most preferred staple crop, grown by 76% of all agricultural households in Nepal (Sanogo and Maliki Amadou 2010). Despite its special significance, rice productivity remains poor and uncertain (MoF 2013; Khanal et al. 2018). This is because nearly two-thirds of total cultivation relies on red-fed farming methods, which are highly sensitive to climate fluctuations (MoAD 2012). Given the sensitivity of rice yields to climatic conditions and the subsistence nature of the Nepalese economy, climate change induced changes in rice production can have devastating impact on household food security and overall wellbeing.

As successful collective action toward climate mitigation at the global scale remains elusive, significant barriers also exist for "small but positive steps" from private and public actors at lower levels (Ostrom 2012). First, there is only limited research that quantifies the impact of climate change on the livelihoods of agricultural households in Nepal (Eriksson et al. 2009; Kunwar and Bohara 2017). The lack of relevant research is well-reflected by the fact that a majority (50.67%) of Nepalese households have not even heard about climate change (CBS 2017). This is disconcerting considering a large volume of studies examines the impact of climate change on agricultural production outside Nepal[1] (Schlenker et al. 2006; Schlenker and Lobell 2010; Fisher et al. 2012; Lobell et al. 2013; Lobell et al. 2014; Moore et al. 2017; Baldos et al. 2018; Baldos et al. 2019). This lack of knowledge presents major hurdles for

[1] For an overview of the debate on different approaches to assessing climate impact on agriculture, see Blanc and Reilly (2017).

rational policymaking at the local or regional levels and prevents private actors from adopting long-term adaptation strategies. Second, although evidence suggests that some households have adapted to climate change (Chhetri et al. 2012; Gentle and Maraseni 2012), the extent and nature of the trade-offs involved in adaptation and the resulting new sources of vulnerabilities are still unclear. Thus, quantifying the impact of climate change on the livelihood of farming households and identifying the sources of technical inefficiency should go hand in hand to effectively reduce climate-vulnerability among Nepalese households.

This study estimates the impact of climate change on food production in Nepal using the Stochastic Frontier Model based on the Cobb-Douglas production function theory (henceforth referred to as the SFP model). The SFP model considers crop production (rice in this case) as a function of agricultural inputs such as labor, capital, raw materials, and weather variables (Isik and Devadoss 2006). SFP models generally offer more reliable estimates compared to the traditional hedonic approaches, whose estimates are highly sensitive to the choice of control variables, sample selection, and weight assignments (Deschênes and Greenstone 2007). Moreover, it allows us to account for spatial correlations of climate variables across districts and to integrate technical inefficiency model within the same framework to jointly identify factors that could improve agricultural production.

We use panel data from Nepal Living Standard Survey data from the years 2003/2004 and 2010/2011 that are publicly available from Nepal's Central Bureau of Statistics. Climate data gathered from 36 ground weather stations was acquired from Nepal Study Center's data repository. We construct four climate indices based on the available temperature and precipitation data: a) extreme temperature during cropping seasons (days with temperatures above 32°C), extreme rainfall during cropping seasons (days with rainfall 3 standard deviation above the long-run average), average monsoon temperature, and average monsoon rainfall. Because the length of climate data varies across the weather stations, we base extreme climate indices on the percentage of the days. Data on rice production, costs of production inputs, and other variables come from NLSS. We use maximum likelihood estimation methods to run our models.

We address a number of shortcomings in the extant empirical literature on the impact of climate change on agriculture in South Asia and the Hindu-Kush region. First, we allow for the spatial correlation of error terms using the spatial filtering technique. The spatial distribution of agricultural land within and across districts affects the error term structure thus resulting in an underestimation of the true variance-covariance matrix and an overestimation of climate change impacts (Schlenker et al. 2006). Second, we incorporate technical inefficiency into our stochastic frontier model to account for inefficiencies in households' rice production methods. This allows us to examine technological and related factors that may hinder a firm (or a farming household) from reaching its technological frontier (Movshuk 2004). Third, we use spatial analysis to provide additional insights regarding the distribution of technical inefficiency by district. The purpose is to show which districts are ahead or behind in adopting technical changes and track their progress overtime.

We find that the rise in extreme precipitation has adverse effects on rice production. The extreme climate conditions model suggests that a 1 % increase in the number of days with extreme rainfall variation (i.e. 3 standard deviations above or below the long-term average) decreases rice production by 0.28%, which amounts to 5.34 kg per household. However, we do not find evidence of similar impacts of the rise in extreme temperature days. On the other hand, results from the average climate conditions model indicate that an increase in long-term average monsoon temperature has significant negative impacts on rice production. We find that a 1°C increase in average summer temperature results in a 0.48% (4183 kg) reduction in rice production each season. This effect decreases with further increases in average temperatures. However, we find no evidence linking rise in average monsoon precipitation with rice production.

Log-likelihood ratio tests for both extreme and average climate conditions models confirm the presence of technical inefficiency. Results from the best-fitting extreme climate model show that road and river densities, availability of agricultural extension services, and education significantly improve technical efficiency, but these variable estimates are not robust to alternate model specifications. Nonetheless, we find that they jointly explain technical inefficiency across all models (at 5% significance level). Thus, although we are unable to identify definitively what factors lead to technical inefficiencies, we conclude that technical inefficiency is present across all models. Comparisons of technical efficiency scores across districts in the years 2003 and 2010 tell us that households did not make progress in adopting technical improvements over the years. 12 districts in the sample had better technical efficiency scores in 2010 (compared to 2003), whereas 13 districts slipped to lower scores.

The paper proceeds as follows. The next section presents theoretical model that forms the basis of our analysis. Then, we provide the econometric model derived from the theoretical model. The next section describes the data, variables, and hypotheses. Then, we discuss results from extreme climate conditions model, average climate conditions model, and technical inefficiency model. The concluding section summarizes results and discusses policy implications.

Theoretical Model

Stochastic Frontier Model with Technical Inefficiency for Panel Data

We follow Battese and Coelli's (1995) model for technical efficiency in a stochastic production function for panel data. First, we begin with a deterministic production model of the following form:

$$y_{it} = f(x_{it})TE_{it} \tag{1}$$

where y_{it} is the actual agricultural output of household i at time t; x_{it} is a vector of agricultural inputs used by household i at time t; $f(x_{it})$ is the maximum feasible output using x_{it}; TE_{it} is the technical efficiency of production for household i at time t. TE_{it} is defined by Eq. (3.2):

$$TE_{it} = \frac{y_{\mathrm{it}}}{f(x_{it})} \tag{2}$$

Since the actual output is less than or equal to the maximum feasible output, we write: $TE_{it} \in [0, 1]$. $TE_{it} = 1$ represents maximum feasible agricultural output for household i at time t. $TE_{it} < 1$ indicates technical inefficiency; that is, the actual agricultural output is less than what is technically feasible if produced at the production possibility frontier curve.

In order to capture the effect of the random shocks, we add the effect of random shocks and rewrite Eq. (3.1) as:

$$y_{it} = f(x_{it})\exp\{v_{it}\}TE_{it} \tag{3}$$

The expression $f(x_{it})$ exp $\{v_{it}\}TE_{it}$ on the right-hand side is the stochastic production frontier, where $\exp\{v_{it}\}$ represents the effect of random shocks (Angelici 2011). Since $TE_{it} \leq 1$ and nonnegative, we use an exponential term $\exp\{-u_{it}\}$, to represent it, where $u_{it} > 0$. We rewrite Eq. (3.3) as:

$$y_{it} = f(x_{it})\exp\{v_{it}\}\exp\{-u_{it}\} \tag{4}$$

For empirical estimation purposes, we take the linearized version of the logarithm of the production function in Eq. (3.4) and specify it as:

$$\ln y_{it} = \beta_0 + \sum_1^t \sum_1^i \beta_{it} lnx_{it} + \beta_c CC_{jt} + v_{it} - u_{it} \tag{5}$$

where y_{it} is the production of rice in the t^{th} period (t = 2003, 2010) for the i^{th} household; X_{it} is a vector of inputs; CC_{jt} captures the climatic conditions for the j^{th} district. Note that, although temperature and precipitation are direct inputs in agricultural production (Deschênes and Greenstone 2007), most applications of stochastic production models based on standard Cobb-Douglas assumptions do not include them. For brevity, the remainder of this section assumes x_{it} also represents CC_{jt}. The first random error v_{it}, is assumed to be independently identically normally distributed with zero mean and constant variance $N(0, \sigma_v^2)$. It is also assumed to be independent from u_{it}. The second random error term, u_{it}, is associated with technical inefficiency of production. We write u_{it} as a function of z_{it}, a vector of explanatory variables affecting technical inefficiency:

$$u_{it} = \gamma z_{it} + \varepsilon_{it} \tag{6}$$

where γ is the associated vector of parameters; ε_{it} is a vector of random errors that captures the random part unexplained by the variables included in the model. Following Battese and Coelli (1995), ε_{it} is assumed to be truncated, normally distributed with zero mean and constant variance, σ_u^2.

Spatial Filtering

We use spatial filtering technique to capture the spatial correlation in climate conditions among adjacent districts. Compared to traditional spatial analysis models, such as spatial autoregressive models and spatial error models, the spatial filtering approach offers more flexibility (Griffith 2000; Getis and Griffith 2002; Tiefelsdorf and Griffith 2007). It avoids restrictive assumptions of traditional linear models, incorporates spatial effects, and provides more robust estimates (Patuelli et al. 2006). The procedure of spatial filtering is straightforward. We split the variable (initially spatially correlated) into spatial and non-spatial components and filter out spatially auto-correlated patterns to reduce the stochastic noise in the residuals (Patuelli et al. 2006, p. 2). Spatial filtering is done by using weight-matrix eigenvectors, which are synthetically created variables to represent the data's spatial structure (Wang et al. 2013). As a first step, we create eigenvectors to generate a spatial weight matrix, *W*, which is developed from a contiguity or a distance-based weight matrix. We utilize a distance-based weight matrix since our data do not consistently include adjacent districts. Distance is chosen (39,240 m.) such that all districts are included within at least one neighborhood. If districts *i* and *j* are within (outside) the chosen distance threshold, a value of 1 (0) was assigned to generate a 46-by-46 regular symmetrically binary matrix. Next, a transformation matrix Ω is generated from the spatial weight matrix *W* following Griffith (2000):

$$\Omega = \left(\mathrm{I}-ll^T/n\right)W\left(\mathrm{I}-ll^T/n\right) \tag{7}$$

where W is the binary spatial weight matrix; I is an n-by-n identity matrix. l is an n-by-1 vector of 1 s, T denotes transpose operator, and n is the number of neighborhoods. Then, we decompose the matrix Ω to generate 46 eigenvectors that are associated with 46 eigenvalues (Griffith and Chun 2014). The eigenvectors and eigenvalues are denoted as $E = (E_1, E_2, \ldots, E_n)$ and $\delta = (EV_1, EV_2, \ldots, EV_n)$ respectively. Since the eigenvectors are orthogonal and uncorrelated (ibid.), we could apply more than one eigenvector in our regression analyses.

Cobb-Douglas Frontier Model Incorporating Spatial Effect

After incorporating spatial correlation, the Cobb-Douglas Frontier model can be rewritten as:

$$\ln y_{it} = \beta_0 + \sum \beta_{it} \ln x_{it} + \delta_k E_k + v_{it} - u_{it} \tag{8}$$

$$u_{it} = z_{it}\gamma + \varepsilon_{it} \tag{9}$$

where E_k is a vector of spatial filtering eigenvectors, and δ_k is a vector of corresponding parameters. In the above model, E_k accounts for the spatial autocorrelation between the residuals and constants across the years 2003 and 2010.

Finally, to incorporate technical change influencing agricultural production across different years, we add another year dummy variable T in Eq. (8) (Battese and Coelli 1995). The revised model is of the following form:

$$\ln y_{it} = \beta_0 + \sum \beta_{it} lnx_{it} + \delta_k E_k + \delta_{k+1} T + v_{it} - u_{it} \tag{10}$$

Econometric Model

Our econometric analyses are based on Eqs. (8), (9), and (10), which are specified in this section to fit our data and context. We analyze how a set of agricultural inputs (e.g. land, labor, capital, irrigation, etc.), climate variables, and technical factors (road, river, extension services, etc.) affect agricultural production in rural Nepal.

Basic Econometric Model

The following base econometric model is used to define the stochastic frontier rice production function considered in this paper:

$$\begin{aligned} \ln agri_{ijt} = {} & \beta_0 + \beta_1 lnlab_{it} + \beta_2 lnfert_{it} + \beta_3 lnseed_{it} + \beta_4 irrig_{it} + \beta_5 lnland_{it} + \beta_6 cc_{jt} \\ & + \beta_7 E_{kj} + v_{it} - u_{it} \end{aligned} \tag{11}$$

In Eq. (11), $\ln agri_{ijt}$is rice produced by household i residing in district j at time t; lab, $fert$, $irrig$, and $seed$ are inputs of labor, fertilizer, irrigation, and seed, respectively; cc represents climate condition variables such as temperature and rainfall; and, E_{kj} is eigenvector k decomposed from the spatial weight matrix for district j. All inputs except for irrigation and climate conditions are expressed in logarithms. Because spatial variation is not explained by the eigenvectors whose MC values (for eigenvector, $E_j = \frac{n}{l^T Cl} * \delta_j$) approach their expected MC values, we exclude the eigenvectors with a MC value of less than 0.25, resulting in 14 feasible eigenvectors (Griffith and Chun 2014). Therefore, following Griffith and Chun (2014), we select the eigenvector that provides the best model fit, which is E_3 in this case. Substituting E_{kj} in Eq. (11) by E_{3j}, we can rewrite it as:

$$\begin{aligned} \ln agri_{ijt} = \beta_0 + \beta_1 lnlab_{it} + \beta_2 lnfert_{it} + \beta_3 lnseed_{it} + \beta_4 irrig_{it} + \beta_5 lnland_{it} + \beta_6 cc_{jt} \\ + \beta_7 E_{3j} + v_{it} - u_{it} \end{aligned} \tag{12}$$

Technical Inefficiency Model

To analyze technical inefficiency in agricultural production, Eq. (9) is further specified as:

$$\begin{aligned} u_{ikjt} = \varphi_1 river_{jt} + \varphi_2 road_{jt} + \varphi_3 roadsq_{jt} + \varphi_4 scfarm_{jt} + \varphi_5 agrixt_{kt} + \varphi_6 hedu_{it} \\ + \varphi_7 hgender_{it} + \varepsilon_{it} \end{aligned} \tag{13}$$

where i, j, k, and t denote household, district, village development committee (VDC), and time, respectively. Factors influencing the technical inefficiency included in the model are: total river length (*river*), total road length (*road*), social capital index for farmer groups (*scfarm*), access to agricultural extension services (*agrixt*), and household demographics (e.g. education, gender of household head).

Data, Variables, and Hypotheses

The main dataset employed for this study comes from 2003 and 2010 Nepal Living Standard Surveys (NLSSs). Although NLSS's panel-data for 1996 were also available, we do not include the year 1996 in our analysis. Only half of the observations from the later waves were included in 1996, which would reduce observations by a half. Rainfall and temperature records from 36 ground weather stations in Nepal were accessed through Nepal Study Center's data repository.

Dependent Variable: Rice Production

The dependent variable is the amount of rice produced by each household in the years 2003 and 2010. Prior to analysis, we took the following steps to prepare our data. We converted all units to kilograms for uniformity and dropped the outliers (less than 10 kg and greater than 15,000 kg). Urban households were excluded for our analysis for two reasons: urban agriculture is relatively minimal in Nepal and rural agricultural households in the mountain regions are particularly vulnerable to climate change impacts (Hussain et al. 2016; Shrestha and Nepal 2016). This results in a total sample size of 946 households (473 for each year). An average rural household's annual rice production was 1869.7 kg, with a significant variance ranging from 19.2 kg to 14,929.6 kg. Figure 1 presents the distribution rice production, which shows a clear right-tailed skewness. The overall rice production per household in 2010 (mean of

2028.13 kg) is slightly higher than that in 2003 (1854.45 kg). Our primary interest is to investigate the factors influencing rice production patterns.

Inputs in the Rice Production Function

We categorize variables in the production function into two groups: climate conditions and other inputs. We first describe climate conditions, as they are of primary interest. Then we proceed to conventional Cobb-Douglas inputs such as investments in capital, labor, fertilizers, seeds, irrigation, and cultivated land area. In the subsequent subsection, we describe factors effecting technical inefficiency separately.

Climate Conditions

We construct climate indices using rainfall and temperature records from 36 ground weather stations which cover 28 districts in Nepal. The original data include daily mean rainfall, as well as daily maximum and minimum temperatures. To circumvent data limitation issues arising from missing climate information in other districts, we employ the following data extrapolation technique. First, we compute means of weather indices for each district with more than one weather stations. These 28 districts (here, we denote them as i) are assigned the mean values of these indices. Second, using ArcGIS tools, we identify adjacent districts i (with climate data) for each district j (without climate data) and conduct data imputation. Specifically, if a district j has only one adjacent district i, it is automatically assigned that climate data. In cases with multiple adjacent districts i, spatial analysis based on the average rainfall and temperature values is conducted to compute climate data for each j. Although this process does not impute data for all 75 districts, we are able to gain significant information through the imputation process described. The map in Fig. 2a illustrates districts with original weather data (color coded in blue/darker shade), whereas that in Fig. 2b shows data available to us after imputation (imputed data color coded in lime green/lighter shade).

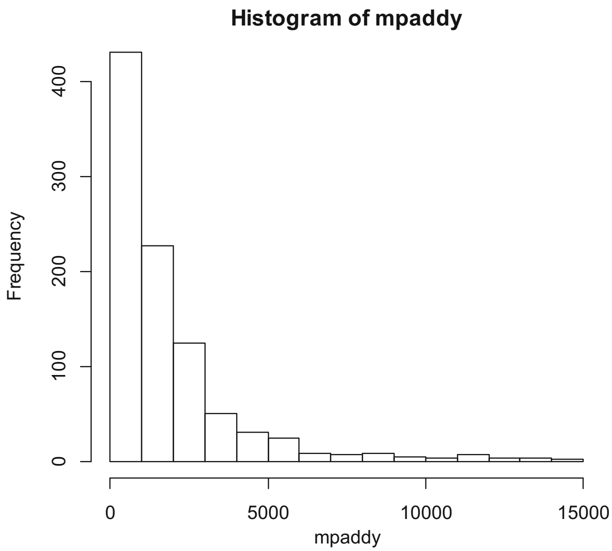


Fig. 1 Distribution of Rice Production. (x-axis: quantity in kilograms; y-axis: number of households)

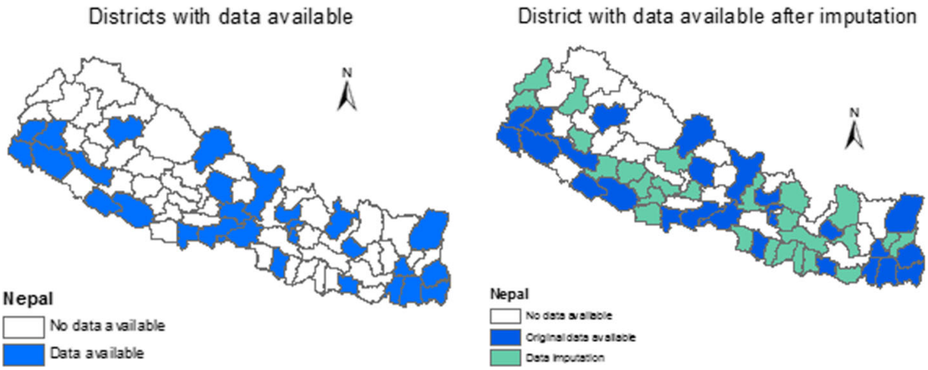
We construct four climate indices for rainfall variation and extreme temperatures during cropping seasons and average rainfall and temperatures during the monsoon seasons. We observe a significant variation in availability of extreme weather data across weather stations, ranging from 13 years (1996 to 2008) to 28 years (1971 to 2008). Therefore, to avoid heteroskedasticity problems stemming from this variation, we use the percentage of days to represent extreme temperature and rainfall conditions. For districts with data available for more than 25 years, the most recent 25 years before 2003 and 2010 were considered. Following similar studies in the region, we define extreme temperature days as those days with temperatures greater than 32°C. This is consistent with generally agreed upon definitions of extreme temperature (heat) as those that hover above the 90th percentile from the long-term baseline temperature (Revadekar et al. 2013; Shrestha et al. 2017). Also, consistent with established conventions, an extreme rainfall day in a given district is defined as the day with rainfall the exceeds three standard deviation from the long-run average (ibid.).

The first guiding hypothesis is that extreme climate events reduce total agricultural production.

$$\begin{aligned} \text{Hypothesis 1 :} \quad & \beta_{RainExtreme} = 0 \ v.s. \beta_{RainExtreme} < 0 \\ \& \quad & \beta_{TempExtreme} = 0 \ v.s. \beta_{TempExtreme} < 0 \end{aligned}$$

Traditional rice-growing practices (called *Ropain*) in the Hindu-Kush region including Nepal involve flooding the land once temperatures get warm enough (not hot). We hypothesize that increase in average monsoon rainfall will serve that purpose, thereby increasing rice production. On the other hand, increases in average summer temperature may disrupt traditional practices. Thus, we expect that can reduce overall rice production, particularly if cultural traditions dictating *Ropain* timeline are not adapted to changing external conditions.

$$\begin{aligned} \text{Hypothesis 2 :} \quad & \beta_{RainAverage} = 0 \ v.s. \beta_{RainAverage} > 0 \\ \& \quad & \beta_{TempAverage} = 0 \ v.s. \beta_{TempAverage} < 0 \end{aligned}$$



(a) (b)

Fig. 2 (**a**) Districts with original weather data and (**b**) Districts with original and imputed weather data

Other Inputs

Other inputs for rice production include capital, labor, fertilizers, and seeds. In our model, we incorporate these inputs using the log of costs incurred per input category within the household, which are reported in Nepalese Rupees[2] (NRs).

Because NLSS does not provide direct measure of capital, we construct an aggregated capital measure following a similar study conducted in Nepal (Devkota and Upadhyay 2013). Capital measure is computed by summing up several types of capital investments included in the survey: namely, the cost of agricultural machinery; payments for tractors, threshers, and other rented equipment; investments toward the improvement and maintenance of land, machines, and buildings. As reported in Table 1, the average cost of capital is NRs. 1734.

With respect to labor, we sum up the costs of home-labor and hired-labor. The mean value for labor costs is NRs. 4480. The information on irrigation costs is not available in the NLSS dataset; therefore, following Battese and Coelli (1995), we use the portion of irrigated land area as a proxy for irrigation input. A mean of 0.551 irrigation input indicates that, on average, more than half of the agricultural land is irrigated. Although land area allocated for rice growth is not reported in the data, we have information on all vegetables planted within specific plots of land. We construct the land area variable by summing up all these areas. Finally, we convert all input costs (if reported in NRs.) to their logarithmic values.

Technical Inefficiency Factors

In our analysis, we include three potential sources of technical inefficiency in agricultural production relevant to rural Nepal: namely, natural and physical infrastructures, community attributes, and household characteristics. The following section describes how we construct these key variables.

Natural and Physical Infrastructures

Recent literature confirms that roads and rivers are critical to Nepal's agricultural development (Joshi et al. 2017; Bucheli et al. 2018). Proximity to rivers determine the agricultural potential of land, whereas roads ensure agricultural products reach viable markets. So, we include the total length of roads (*Road*) and rivers (*River*) within a district.

We calculate the total length of roads (categories: main trail, foot path, graveled road, highway, metaled, and railway) from publicly available shapefiles data (2000 and 2009) provided by the Nepal government (GON). We find negligible change in road density in that decade. We expect that road density contributes to technical efficiency in agricultural production; that is, it is negatively correlated with technical inefficiency.

Hypothesis 3:

$$\beta_{Road} = 0 \ v.s. \beta_{Road} < 0$$

[2] At the time of the study, I USD = NRs. 98.

Table 1 Summary Statistics

Variable	Definition	Mean	Standard Deviation	Minimum	maximum
Dependent Variables					
Rice	Quantity of rice production (in Kilogram)	1869.7	2255.091	19.2	14,929.6
Independent Variables					
Labor	Labor input: cost of labor in the household (in logarithm)	4.711	4.176	0	12.143
Capital	Capital input: cost of capital in the household (in logarithm)	4.913	3.230	0	11.149
Fertilizer	Fertilizer input: cost of fertilizer in the household (in logarithm)	6.085	3.138	0	11.562
Seed	Seed input: cost of seeds in the household (in logarithm)	3.780	3.291	0	9.881
IrrigatedLand	Irrigation input: Portion of land irrigated.	0.572	0.430	0	1
Land	Input of amount of land in the household (in logarithm)	−.0.814	1.118	−6.158	2.411
TempExtreme	Percentage of days in which maximum temperature exceeds 32°C over 1971 to 2008 (at the district level)	0.259	0.240	0	0.814
RainExtreme	Percentage of days in which average rainfall exceeds triple of standard deviation over 1971 to 2008 (at the district level)	0.032	0.013	0.007	0.072
TempAverage	Average monsoon temperature at the district level over 1971 to 2008 (June to August)	26.484	3.515	19.471	30.014
RainAverage	Average monsoon rainfall over 1971 to 2008 at the district level (June to August)	18.569	8.553	5.626	30.014
Female	Dummy variable. Coded as 1 if gender of household head is female, 0 otherwise	0.147	0.354	0	1
Read	Dummy variable. Indicator for education. Coded as 1 if household head can read, 0 otherwise	0.541	0.499	0	1
SocialCapital	Indicator for social capital. Farming association membership engagement at the district level	0.508	0.582	0	2.540
AgriExtension	Dummy variable. Coded as 1 if there is agricultural extension service existing in the ward, 0 otherwise	0.108	0.310	0	1
River	Total length of river at the district level (in kilometer)	821.316	307.625	281.8	1607.3
Road	Total length of road at the district level (in kilometer)	558.978	199.83	26.456	1143.74
Observation	912				

Data source: Nepal living standard survey 2003/2004 and 2009/2010, Nepal shape files

Note: the summary statistics are average values of panel data

Proximity to a river increases access to irrigation. In places where *kulos* (traditional irrigation systems) are technically infeasible, closer proximity can substantially reduce costs toward the construction of modern irrigation systems. We calculate total river length for each district. The mean river length is 821.3 km. We hypothesize that river density leads to increased technical efficiency (or decreased technical inefficiency).

Hypothesis 4:

$$\beta_{River} = 0 \; v.s. \beta_{River} < 0$$

Community Characteristics

Extant research finds that community-level features and resources such as social capital (*SocialCapital*) and agricultural extension services (*AgriExtension*) play central role in increasing farmland productivity and household food security in Nepal (Adhikari and Nepal 2016; Rayamajhee and Bohara 2019a). Therefore, we include them in our technical inefficiency model. Social capital is calculated using membership size in farming associations at the district level. This is consistent with recent empirical studies on social capital from Nepal (Rayamajhee and Bohara 2020; Rayamajhee and Bohara 2019a). The variable for availability of agricultural extension services is at the village level. We code *AgriExtension* as 1 if farmers can access extension services such as training experience and weather information in the village. If no such service is available, we code it as 0. We find that the mean value of the variable is 0.11, which indicates that such services are scarce. We hypothesize that community social capital and agricultural extension services both increase technical efficiency (i.e. decrease technical inefficiency).

Hypothesis 5:

$$\beta_{SocialCapital} = 0 \; v.s. \beta_{SocialCapital} < 0$$

Hypothesis 6:

$$\beta_{AgriExtension} = 0 \; v.s. \beta_{AgriExtension} < 0$$

Household Characteristics

We also include household characteristics that influence technical efficiency in agricultural production. Based on data availability, we include the gender of the household head (*Female*) and their education (*Read*). The gender variable is coded as 1 if the household head is female (0 otherwise). The education variable (*Read*) is coded as 1 "if the head of household can read," and 0 otherwise. Although more granular data on the education level was included in the survey questionnaire, the actual data has too many missing observations. *Read* has a mean value of 0.541, which shows that 45.9% households are illiterate.

Results and Discussion

We use the maximum likelihood estimation method to estimate the Stochastic Frontier Production (SFP) Models. We conduct two separate analyses for extreme climate conditions during cropping seasons and changes in average rainfall and temperatures during monsoon seasons.

Extreme Climate Conditions Model

First, we run the SFP models for extreme climate conditions. Results are presented in Table 2. The base model results are presented in column 2 (labeled Model 2a). In Model 2b, we add climate variables and the corresponding spatial filtering eigenvector. Model 2c accounts for

Table 2 Estimation Results (Extreme Climate Indices)

		Model 2a	Model 2b	Model 2c	Model 2d	Model 2e
	Basic Frontier Production Model					
Inputs	Labor	0.029***	0.029***	0.032***	0.032***	0.033***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
	Fertilizer	0.113***	0.110***	0.108***	0.11***	0.109***
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
	Seed	0.016*	0.011	0.019**	0.018**	0.015*
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	Capital	0.052***	0.053***	0.040***	0.040***	0.039***
		(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
	IrrigatedLand	0.368***	0.371***	0.405***	0.383***	0.391***
		(0.072)	(0.071)	(0.066)	(0.064)	(0.064)
	Land	0.892***	0.888***	0.923***	0.924***	0.912***
		(0.088)	(0.088)	(0.079)	(0.080)	(0.078)
Climate	TempExtreme		−0.012	−0.097	−0.033	−0.051
			(0.187)	(0.167)	(0.153)	(0.165)
	RainExtreme		−29.484**	−23.235***	−27.527***	−27.583**
			(11.405)	(9.124)	(9.015)	(9.485)
	Eigenvector (E_3)		0.676**	0.748***	0.713***	0.693***
			(0.232)	(0.193)	(0.184)	(0.190)
	Time (tech Δ)	−0.105	−0.090	−0.152	−0.125	−0.117
		(0.104)	(0.124)	(0.079)	(0.068)	(0.074)
	Constant	5.847***	6.799***	6.569***	6.716***	6.713***
		(0.113)	(0.387)	(0.306)	(0.310)	(0.322)
	Technical Inefficiency Model					
Infrastructure	River			−7942.200	−7374.100	−8666.100*
				(7162.700)	(5064.300)	(5005.600)
	Road			−3310.400	−2856.600	−3939.500*
				(2985.100)	(1960.700)	(2272.100)
Community	SocialCapital				−205.780	−219.790
					(140.710)	(161.280)
	AgriExtension				−265.260	−75.339***
					(180.590)	(25.051)
Household	Female					644.170
						(435.860)
	Read					−96.682***
						(36.687)
	Constant2			−276.160	−265.260	−75.339
				(262.420)	(180.590)	(25.051)
Variance Parameters	SigmaSq	1.268***	1.213***	1066.300	1203.300	1085.9*
		(0.146)	(0.144)	(944.370)	(821.720)	(632.450)
	Gamma	0.600***	0.581***	0.992***	0.993***	0.992***
		(0.055)	(0.059)	(0.001)	(0.001)	(0.001)
	Log-likelihood	−1148.834	−1141.331	−1128.152	−1116.501	−1109.308
	AIC	2319.669	2310.662	2290.304	2271.003	2250.616
	N	921	921	912	912	912

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; and * denotes significant at the 10% level. Numbers in the parentheses are standard deviations. The rice production and inputs except for portion of irrigated land are in logarithm. The river and road variables are in logarithm divided by 100 technical inefficiency but only natural and physical infrastructures are considered. In Model 2d, we expand the technical inefficiency model to include additional community characteristics. Finally, in Model 2e, we add household characteristics into the technical inefficiency model. Comparisons of AIC and the log-likelihood values for Models 2a-2e show that model specifications in 2e provide the best fit. Therefore, we choose that as the final model. Discussions that follow mainly focus on Model 2e.

With respect to extreme climate indices, the negative coefficients for *TempExtreme* (percentage of days with high extreme temperatures) across Models 2a-2e indicate that high extreme temperatures negatively affect rice production. However, the effect is not statistically significant. Our results are consistent with previous studies conducted in the Hindu-Kush region (Peng et al. 2004; Nagarajan et al. 2010). In addition, we find that the frequency of extreme precipitation (excessive rainfall or droughts) adversely impacts rice production. These impacts are statistically significant and consistent across all model specifications (2b-2e). We find that a 1% increase in the number of days with variant rainfall corresponds to a 0.28% (5.34 Kg per household) decrease in rice production. Additionally, highly significant coefficients of the eigenvector (*E3*) across all models confirm spatial correlation between adjacent districts.

The signs of the coefficients of all inputs are consistent with the hypotheses discussed in the previous section. The coefficients for investments in labor, fertilizers, seed, capital, irrigation, and land are all positive and statistically significant, indicating that they contribute positively to rice production. Land is the most important input, with an elasticity of 0.912. This indicates that land area is a *decreasing-returns-to-scale* input. That is, a 1 % increase in land area results in a less than 1 % (0.912%) increase in rice production (18.14 kg). All other inputs also exhibit decreasing returns to scale, with even lower elasticities. 1% increases in labor (42.7 NRs) and capital (17.13 NRs) increases rice production by 0.033% (0.64 kg) and 0.039% (0.76 kg) respectively. These effects are robust across the five models, including both magnitudes of coefficients and statistical significance levels.

This study accounts for factors affecting technical inefficiency in rice production. Results from the best-fitting model (2e) show that road and river densities, availability of agricultural extension services, and education significantly improve technical efficiency. Coefficients for *River* and *Road* variables are as hypothesized. The negative coefficient for *River* implies that the districts with higher river density have higher technical efficiency of production. This may be because farmers living closer to water sources face lower irrigation costs and more paddy choices (Edmonds 2002). On the other hand, the negative coefficient for *Road* indicates that road network improves technical efficiency of rice production. This can occur through improved access to durable goods or through human capital channel such as access to better education and training (Bucheli et al. 2018).

As for the community characteristics, we do not find a statistically significant relationship between technical inefficiency and social capital. This is possibly due to the fact that part of the effect may have been captured by education and road variables. However, we find a positive relation between availability of agricultural extension services and technical efficiency. The is consistent with Elias et al. (2016), who point out that extension services should focus on technology choices to improve agricultural production. Gender appears to play a part in technical efficiency. Female-headed households have lower technical efficiency. This hints to gender disparity that hinders agricultural production. As expected, we also find that educated households are more technically efficient than their non-educated counterparts. Estimates for factors determining technical inefficiency are sensitive to alternate specifications, which prevents us from deriving definitive conclusions. Nonetheless, we find the presence of technical inefficiency across all models (H_0: $\gamma = 0$ is rejected throughout).

Average Climate Conditions Model

Next, we run SFP models to estimate the impact of changes in long-term average climate conditions on rice production. We consider average climate conditions (average monsoon rainfall and average monsoon temperature) over the period of 1971 to 2008 during the rice growing seasons. Table 3 presents the results. We find that results for various input costs (labor, capital, fertilizer, seeds, irrigation, and land) are very similar to those in the previous models. We estimate five model specifications (shown as Models 3a-3e). Model 3a is the base model without climate variables and technical inefficiency, hence identical to model 2a in the previous section. Models 3b-3e follow similar modeling approaches as 2b-2e but with different climate variables. That is, we include long-term average climate variables instead of extreme climate variables. To capture the potentially nonlinear relationship between long-term climate conditions and rice production, we also include square terms of the long-term rainfall and temperature averages. Model comparisons based on AIC and log-likelihood values show that the final model (2e) provides the best fit. So, we base our analysis on Model 2e.

The variables of interest in these models are climate change indices. We find positive coefficient for average monsoon (summer) rainfall (*RainAverage*), whereas its squared term (labeled *RainAverageSqr*) has negative coefficients. This indicates that increase in monsoon rainfall is beneficial for rice production up to a threshold, beyond which the effect becomes negative. However, these results are not statistically significant. On the other hand, we find that increases in long-term average monsoon temperature (*TempAverage*) decreases rice production significantly. *TempAverage* has a coefficient of −0.480 (0.157), significant at 1% level. This indicates that a 1°C increase in average summer temperature decreases rice production by 0.48%. Crude calculations show that this translates to a 4183 kg reduction in net rice produced per season. The positive sign for the squared term for *TempAverage* (i.e. *TempAverageSqr*) means that this impact decreases with further increases in average summer temperatures.

We find that estimates from the technical inefficiency models are not robust to model specifications in models 3c-3e. Although the signs of all coefficients are consistent with results in models 2a-2e, their effects fade away.

Finally, although not directly relevant to rice production in the region, we rerun SFP models for long-term average climate conditions with average climate variables for all three cropping seasons (Spring, Summer, and Fall). Results are presented in Table 4. We find that effects of summer climate conditions appear insignificant. However, we find significantly positive effects of spring temperatures and fall rainfall, and adverse effects of fall temperatures. As one would suspect, we find that these unexpected results were due to very high correlation among seasonal averages. Average temperatures across seasons are almost perfectly correlated (shown in Table 5).

Technical Efficiency Analysis

In order to examine technical inefficiency in rice production, we test the following hypothesis:

$$H_0 : \gamma = \varphi = 0$$

Table 3 Estimation Results (Average Rainfall and Temperature during Monsoon Season)

		Model 3a	Model 3b	Model 3c	Model 3d	Model 3e
	Basic Frontier Production Model					
Inputs	Labor	0.029***	0.030***	0.033***	0.034***	0.034***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
	Capital	0.052***	0.051***	0.038***	0.037***	0.037***
		(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
	Fertilizer	0.113***	0.103***	0.101***	0.103***	0.102***
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
	Seed	0.016**	0.009	0.016*	0.015*	0.013**
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	IrrigatedLand	0.368***	0.345***	0.373**	0.352***	0.358*
		(0.072)	(0.072)	(0.064)	(0.064)	(0.063)
	Land	0.892***	0.902***	0.936***	0.938***	0.927***
		(0.088)	(0.088)	(0.077)	(0.079)	(0.078)
Climate	RainAverage		0.004	0.020	−0.013	0.013
			(0.032)	(0.033)	(0.031)	(0.029)
	RainAverageSqr		−0.0003	−0.001	−0.001	−0.001
			(0.0008)	(0.001)	(0.001)	(0.001)
	TempAverage		−0.491***	−0.458***	−0.484***	−0.480***
			(0.214)	(0.159)	(0.169)	(0.157)
	TempAverageSqr		0.010**	0.010***	0.010***	0.010***
			(0.004)	(0.003)	(0.003)	(0.003)
	Eigenvector (E_3)		0.819***	0.852***	0.849***	0.832***
			(0.242)	(0.190)	(0.197)	(0.199)
	Time (tech Δ)	−0.105	0.021	0.002	0.063	0.071
		(0.102)	(0.186)	(0.171)	(0.176)	(0.164)
	Constant1	5.847***	11.488***	10.915***	11.287***	11.229***
		(0.113)	(2.604)	(21.915)	(2.040)	(1.883)
	Technical Inefficiency Model					
Infrastructure	River			−5145.500	−2039.600	−4326.400
				(4613.400)	(1671.000)	(3126.800)
	Road			−2195.400	−829.130	−2085.200
				(1966.700)	(678.200)	(1506.200)
Community	SocialCapital				−64.156	−104.050
					(54.386)	(71.419)
	AgriExtension				−164.140	−196.330
					(127.650)	(136.120)
Household	Female					411.360
						(286.500)
	Read					−69.142
						(50.410)
	Constant2			−657.720	−164.140	−196.330*
				(577.260)	(127.650)	(136.120)
Variance Parameters	SigmaSq	1.404***	1.202***	1030.900	470.930	776.920
		(0.127)	(0.141)	(914.260)	(376.320)	(552.780)
	Gamma	0.641***	0.583***	0.998***	0.989***	0.993***
		(0.042)	(0.058)	(0.002)	(0.002)	(0.034)
	Log-likelihood	−1148.834	−1138.601	−1124.202	−1112.69	−1105.24
	AIC	2319.669	2309.202	2286.404	2267.38	2256.480
	N	921	921	912	912	912

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; and * denotes significant at the 10% level. Numbers in the parentheses are standard deviations. The rice production and inputs except for portion of irrigated land are in logarithm. The river and road variables are in logarithm divided by 100

Table 4 Estimation Results (Average rainfall and temperatures during cropping seasons)

Model 4

	Basic Frontier Production Model			Technical Inefficiency Model			
		Coefficient	S.E			Coefficient	S.E.
Inputs	Labor	0.036***	0.007	Household	River	−2670.700	2720.200
	Fertilizer	0.101***	0.011		Road	−1454.200	1480.400
	Seed	0.010	0.009	Community	SocialCapital	−59.868	63.109
	Capital	0.039***	0.010		AgriExtension	−277.500	273.860
	IrrigatedLand	0.313***	0.063		Female	360.170	374.680
	Land	0.885***	0.076	Infrastructure	Read	−80.120	76.481
Climate	SpringRain	−0.018	0.381		Constant2	−277.500	273.860
	SpringRainSqr	0.031	0.107				
	SpringTemp	0.826***	0.218				
	SpringTempSqr	−0.019***	0.005				
	SummerRain	0.008	0.038				
	SummerRainSqr	0.000	0.001				
	SummerTemp	−0.210	0.512				
	SummerTempSqr	0.006	0.009				
	FallRain	0.470***	0.087				
	FallRainSqr	−0.024***	0.005				
	FallTemp	−1.180**	0.553				
	FallTempSqr	0.022**	0.011				
	Eigenvector (E_3)	0.517**	0.255				
	Time (tech Δ)	−0.017	0.190				
	Constant1	12.487***	2.862				
Variance Parameters	SigmaSq	701.450	699.740				
	Gamma	0.996***	0.000				
	Log-likelihood		−1079.528				
	AIC		2221.055				
	N		912				

Note: *** denotes significant at the 1% level; ** denotes significant at the 5% level; and * denotes significant at the 10% level. The rice production and inputs except for portion of irrigated land are in logarithm. The river and road variables are in logarithm divided by 100

where φ is the variance parameter of the inefficiency model, and γ is a vector of parameters of the factors influencing technical efficiency. This null hypothesis states that technical inefficiency is not present in the model.

Following Battese and Coelli (1995), we conduct likelihood-ratio tests to compare the two chosen models for extreme (Model 2e) and average climate (Model 3e) conditions. In both cases, we compare the models with and without their corresponding technical inefficiency models. The results, presented in Table 6, show that the null hypothesis was rejected at the 5% significance level in both models, leading us to conclude that technical inefficiency exists. This suggests that,

Table 5 Correlation between the average temperature during cropping seasons

	Spring Temperature	Summer Temperature	Fall Temperature
Spring Temperature	1	0.91	0.91
Summer Temperature	0.91	1	0.99
Fall Temperature	0.91	0.99	1

Source: Authors' Calculation

Table 6 Technical Inefficiency Tests

	Null Hypothesis	Chi-square value	Conclusion
Model 2e	No inefficiency effect ($\gamma = \varphi = 0$)	94.769	Reject Null
Model 3e	No inefficiency effect ($\gamma = \varphi = 0$)	101.31	Reject Null

Source: Authors' Calculation

although variables in the technical inefficiency model do not seem to have any independent effects in Model 3e, natural and physical infrastructures, community features, and household characteristics jointly explain technical inefficiency in rice production in both models.

Next, we look at the frequency distribution of technical efficiency (TEF) scores for 2003 and 2010 separately to analyze technical progress overtime. Table 7 reports the results for extreme weather model (average weather model results are near identical). We find that average TEF scores are similar for both years. That is, households had not made significant progress in the years we studied. For instance, the mean TEF score in 2003 is 0.637 for the extreme weather model.[3] In 2010, the score dropped slightly to 0.622. We find that the range increased from 0.024 to 0.885 in 2003 to 0.019 to 0.911 in 2010. This indicates that more households moved to the extreme (lowest and highest) efficiency score categories. Frequency distribution shows that additional households shifted to the least technically efficient production category in 2010. The percentage of households with TEF scores below 0.5 increased from 15.9% in 2003 to 20.3% in 2010. On the other hand, we find that the percentage of households with highest efficiency scores (>0.8) decreased from 10.5% in 2003 to 7.7% in 2010. In both years, this category includes fewest percentage of total households. We also find that the percentage of households in the 0.5–0.6 efficiency score category remained steady (13.7% in 2003 versus 13.2% in 2010), whereas that in the 0.7–0.8 category increased slightly (32.7% in 2003 to 36.9% in 2010).

Finally, we look at the district-wise distribution of TEF scores in 2003 and 2010. Figure 3 presents results from spatial analysis. Of the 44 districts covered in the sample, 12 districts climbed to higher efficiency score categories, whereas 13 slipped to lower categories. Mahottari district (market M) experienced the largest improvement, whereas Kailali district (marked K) had the largest decline in TEF scores.[4] Only one district (Surkhet, marked S) had maintained an efficiency score above 0.8 in both periods. The technical efficiency scores across the 44 districts in the sample range from 0.339 to 0.866 in the year 2003 and from 0.262 to 0.868 in the year 2010.

Conclusion and Policy Implications

Our findings make it abundantly clear that rural agricultural households in Nepal are vulnerable to the impacts of climate change. We find that changes in average and extreme

[3] The mean technical efficiency score for the average weather model is 0.627 (full results not reported).

[4] Mahottari's technical efficiency score jumped from below 0.5 in 2003 to 0.6–0.7 in 2010. Kailali's score declined from 0.7–0.8 in 2003 to 0.6–0.7 in 2010.

Table 7 Frequency distribution of technical efficiency scores

Efficiency Score	Year 2003		Year 2010	
	No. of households	Percentage	No. of households	Percentage
0–0.5	73	15.9	92	20.3
0.5001–0.6	63	13.7	60	13.2
0.6001–0.7	125	27.2	99	21.9
0.7001–0.8	150	32.7	167	36.9
>0.8	48	10.5	35	7.7
Mean	0.637		0.622	
Max	0.885		0.911	
Min	0.024		0.019	
Observations	459		453	

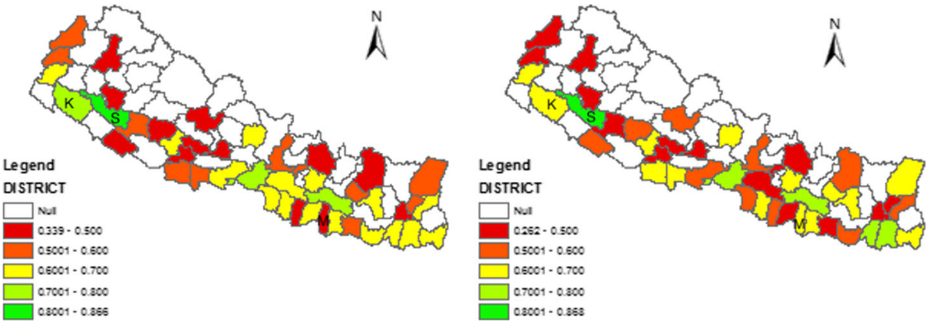
Source: Authors' calculation

precipitation and temperatures have significant negative impacts on rice production. In particular, we find that increasingly aberrant extreme rainfall patterns and long-run rise in average temperatures are significant threats to rice production. Back-of-the-envelope calculations based on temperature projections from Janes et al. (2019) in the Himalayas suggest that temperature rise will result in 27.6 tons to 36.8 tons annual loss in rice production in the next 50 to 100 years.[5] They also project a 10–40% increase in average monsoon precipitation in central India. A similar increase in the Himalayan region can result in a considerable rise in extreme precipitation days. We estimated that a 1% increase in extreme precipitation days results in a 5.34 kg loss in rice production per household. Based on this, we can conclude that the effects will be significant.[6] In light of the already high food insecurity levels in Nepal and the significance of rice for the livelihood of rural households, these findings are disconcerting (Sanogo and Maliki Amadou 2010; Rayamajhee and Bohara 2019a). Moreover, changes in land use pattern resulting from low agricultural productivity are likely to result in the deterioration of forests, watersheds, and other common pool resource systems, which provide vital ecosystem amenities to rural households (Field et al. 2012). When climate change threatens land productivity and the sustenance of other critical resource systems, the result is an increased threat of vicious poverty-environment traps that are only reinforced by further environmental shocks and asset depletion.

Extant studies show that technical efficiency in rice production can be improved significantly (Huang et al. 2015). We also find that much of the detrimental impacts of climate change on rice production can be explained by technically inefficient production methods. This points to some low hanging fruits for effective climate adaptation in Nepal and the Hindu-Kush region. Much of the climate impact on agriculture that could be mitigated by diverting resources from broader, less certain mitigation policies toward improving technical efficiency in agricultural production. We find some evidence to suggest that access to roads and river may minimize technical inefficiencies. Other studies show that access to irrigation facilities can reduce the severity of climate change impacts on crop production (Mendelsohn and Dinar 2003). Crop-insurance programs such as weather-indexed micro-insurance may help alleviate some of the food security issues from reduced crop production (Ranganathan et al. 2018;

[5] Janes et al. (2019) model projects that the Himalayas/Tibetan Plateau region will experience warming of between 6 and 8 °C in the next 50–100 years. Projections for other parts of South Asia vary considerably.

[6] Calculations assume no improvement in technical efficiency.



(a: Technical Efficiency scores 2003) (b: Technical Efficiency scores 2010)

Fig. 3 Technical Efficiency Scores by district in 2003 and 2010. (Source: Authors' Calculation)

Sibiko and Qaim 2020). Because different districts face different production opportunities and technology sets owing to differences in resource endowments, factors that can improve technical efficiency are likely to vary across districts. Focused microeconomic studies are needed to shed more light on this issue.

Research shows that Indo-Nepal trade has partly compensated for the loss in domestic agricultural production (Pyakuryal et al. 2010). However, the benefits from trade are mostly confined to the Terai plains, with mountains and hills receiving little to no fruits of market liberalization. One reason for this is the land ownership issue. Land ownership is among the most strong determinant of food security in Nepal (Pyakuryal et al. 2010, p. 22, 27). However, a number of institutional issues such as patrilineal inheritance traditions and vestiges of *jamindari-pratha* (feudal system) preclude equal ownership rights, particularly for women and many indigenous groups (Allendorf 2007; Mishra and Sam 2016). This has led to wide differences and hierarchies in land ownership structures across Terai, hills, and mountains. Moreover, the lack of transportation infrastructure in Nepal, especially in hills and mountains, continue to raise transaction costs and hinder trade (Sanogo and Maliki Amadou 2010; Chand 2018). One set of policy suggestions is to work toward mitigating institutional and infrastructural barriers and further easing Indo-Nepal commodity trade to compensate for agricultural production loss.

However, implementing such broader policy reforms requires strong political will and consensus. The decade-long Maoist insurgency and political instability that ensued have resulted in the weakening and fragmenting of public institutions needed to implement effective climate (and food) policies (Rayamajhee and Bohara 2019b). The seemingly more pressing ethnic and social issues continue to divert economic resources and political attention away from environmental challenges. Therefore, a more feasible second set of policy suggestions could be to facilitate greater participation of the private sector or voluntary local institutions in addressing many of these challenges. There is a strong public preference for community-based management of common resources in Nepal (Kunwar et al. 2020). A heap of studies from Nepal, particularly from the common pool resource and disaster literature, shows that bottom-up approaches from local self-governing institutions are better equipped to address many environmental problems (Benjamin et al. 1994; Ostrom et al. 1994; Varughese and Ostrom 2001; Shivakoti and Ostrom 2002; Rayamajhee and Joshi 2018; Rayamajhee 2020; Rayamajhee et al. 2020a; Rayamajhee et al. 2020b; Rayamajhee and Paniagua 2020). Therefore, "small but positive steps" from private and public actors, as Ostrom (2012) suggested, may in fact bear more fruits.

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