Smallholder farmers' adaptation to climate change and its potential contribution to UN's sustainable development goals of zero hunger and no poverty

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Abstract

Climate change is likely to worsen poverty, and agriculture-dependent groups and poorest countries are at the greatest risk. Farmers' have begun developing and implementing climate change adaptations. This study investigates the extent to which climate change adaptations by smallholder farmers have the potential to contribute to the UN's sustainable development goals of no poverty (SDG 1) and zero hunger (SDG 2). To this end, the study measures the impact of such adaptations on food production using farm-level survey data from Nepal. We utilize a matching technique and stochastic production frontier model to examine the productivity and efficiency of farmers. Results reveal that the group of farmers adopting adaptations exhibit higher levels of productivity and technical efficiency in food production as compared to the non-adopters. It is evident from the results that policy makers should encourage farming households in climate change adaptations, which have the potential to enhance farmers' productivity and efficiency in agriculture thereby contributing to two of the United Nations Sustainable Development Goals (SDGs) of eradicating hunger and poverty (SDG's target indicators 2.3).

Keywords: Adaptation; food security; production frontier; selection bias; sustainable development goals; Nepal.

1. Introduction

Agriculture is highly dependent on climatic conditions. Several studies have indicated that most crops yields negatively respond to increases in temperature (Lobell & Field, 2007; Peng et al., 2004; Ureta et al., 2020). Long term changes in climatic conditions is also likely to increase the occurrence of extreme weather events (Álvarez and Resosudarmo, 2019; Morton, 2007), can initiate and alter the timing of pest and disease outbreaks (Nelson et al., 2009), reduces water and nutrient use efficiency (Asplund et al., 2014) and increases yield variability (Torriani et al., 2007). Such effects are likely to further lower agricultural productivity (Coulibaly et al., 2020; Liu & Dai, 2020; Moriondo et al., 2011; Olayide & Alabi, 2018; Sarker et al., 2014) and can undermine global efforts to reduce two of the UN's Sustainable Development Goals (SDGs) of eradicating hunger and poverty.

Adaptation plans have been initiated against the impacts imposed by climate change. In the agricultural sector, farmers have been employing diverse adaptation plans and strategies. Major agricultural adaptations exercised by smallholder farmers include adjustments in farm operations timing, on-farm diversification, and soil-water management through improved irrigation, reduced tillage, contour farming, etc. (Below et al., 2012; Harmer & Rahman, 2014; Jawid and Khadjavi, 2019). It is uncertain how effective these plans and strategies are and will be in the future as little attention has been given on the monitoring and evaluation of smallholder farmers' adaptations. Although a few studies have begun analyzing the impacts of adaptations on agricultural production (Challinor et al., 2014; Di Falco et al., 2011; Huang et al., 2015; Khanal et al., 2018; Khanal et al.,2019; Rosenzweig & Parry, 1994; Waha et al., 2013), most analyses have considered only a few adaptation options and were focused on macro-level analysis.

Given this background, this study aims to investigate the extent to which climate change adaptations by smallholder farmers have the potential to contribute towards the sustainable development goals of zero hunger and no poverty. Specifically, the focus of this study is on the SDG target indicator 2.3 which is to double the small-scale framers' agricultural productivity and incomes by 2030. In doing so, we first investigate how farmers perceive changes in climatic parameters over the years, and how such changes impact in agriculture. Then, we analyze the impact of farmers' adaptation on farming households' efficiency and productivity in food production. Since smallholder farmers (less than 2ha) account for more than 80% of all farms worldwide (FAO, 2014), sustainable development goals of no poverty (SDG 1) and zero hunger (SDG 2) can be achieved if appropriate policies are designed to support these farmers to become more efficient and productive.

We use Nepal as a case study country. Smallholder farmers in poor economies like Nepal are comparatively more impacted by changing climatic parameters (Bandara & Cai, 2014; Morton, 2007; Dissanayake et al., 2019; Jawid and Khadjavi, 2019). In Nepal, agriculture contributes approximately one-third to the gross domestic product and employs about 70% of the country's population (MoF, 2014). Nevertheless, the food insecurity issue is serious in Nepal. As of 2011, approximately 38% of the population was in food deficiency conditions (NPC, 2013). According to the Global Hunger Index (GHI) report 2015, Nepal is in the 58th position. The vulnerability of the country's agricultural sector to climate change has been demonstrated by the severe effects of unfavorable weather conditions on crop production. In 2012/13, the rice cultivated area and production reduced by 7.1% and 11.3% respectively, as a result of limited monsoonal rains and longer periods of droughts. Likewise, inadequate winter rainfall resulted in a decline of maize production by 8.3% and millet by 3% (MoF, 2013). Rice could not be cultivated in about 50,000 hectares as a result of reduced rainfall in the year 2013/14 (MoF, 2014). A further effect of climate change is the trend of increasing temperatures – in Nepal's case a rise between 0.04-0.06°C per year (MoE, 2010). Several studies have shown that although such long-term rises in temperature have a marginally positive effect in Nepal's mountain regions, agricultural systems in most parts of the country are adversely affected (MoE, 2010). Thus, overcoming hunger and poverty in an agriculture dependent country such as Nepal needs minimizing the impacts of climate change and boosting agricultural productivity.

A few methods can be utilized to assess the impact on agricultural production of innovations in the form of adaptation practices. The difference-in-difference methodology is one analytical tool that can be used (Yorobe et al., 2011; Duong & Thanh, 2019). However, the approach needs information on before and after analysis. In the case of present study, farmers have been employing diverse adaptation options at different temporal and spatial level, thus no common period of time can be taken into account. Moreover, another limitation of this approach is its inability to capture all the observed changes to the treatment as various external variables are affecting the changes (Bravo-Ureta et al., 2012). A better approach, therefore, is to compare the performance between two groups of farmers that are similar in every respect except for the adoption of adaptation practices. This can be done by using matching techniques, such as propensity score matching (PSM) (Caliendo & Kopeinig, 2008; Duong & Thanh, 2019). However, such an approach assumes that once observable characteristics are controlled for, the uptake of technology is random and is not associated with the outcomes (Abdulai & Huffman, 2014). Moreover, this methodology fails to take into account the biases stemming from the unobservable factors (Mendola, 2007).

There are several studies that have analyzed technical efficiency (TE) in the agricultural sector (Coelli et al., 2002; Khanal et al., 2018b; Rahman & Rahman, 2009; Bidisha et al., 2018). An important issue prevalent in many such studies is that they compare the TE between two groups of farmers. However, farmers often self-select into a particular group (Bravo-Ureta et al., 2012; Rahman et al., 2009). Greene (2010) introduced a model that addresses the sample selection issue in the stochastic production frontier (SPF) framework. Several studies employ Greene's model to correct selection bias in the SPF (Rahman, 2011; Rahman et al., 2009). But while these models address the issue of sample selection, they do not take into account the biases arising from observable factors. Recently, a few studies have combined propensity score matching with the sample selectivity bias-corrected SPF developed by Greene (2010) to compare TE between treated and control samples (Bravo-Ureta et al.,2012; Villano et al., 2015; Abdulai & Abdulai, 2016). By combining the two techniques, these studies reported that both the observable and unobservable biases are controlled while comparing TEs between two groups.

This study contributes to the existing literature in three strands. First, this study examines the potential contribution of smallholder farmers' climate change adaptations on sustainable development goals of zero hunger and no poverty. While there are ample studies that assess the impacts of climate change on agriculture, only a few studies explicitly investigate the adaptations impact on agricultural outputs. Moreover, there are a few studies that have investigated whether on-farm climate adaptations by small holder farmers are effective in improving their efficiency and productivity in agricultural production. Second, we bring together the sample selectivity bias corrected SPF framework with PSM to compare technical efficiency and productivity of farmers who adopt and those who do not adopt adaptation practices. Finally, this study provides empirical evidence from Nepal on smallholder farmers' actions against climate change and impacts on their efficiency and agricultural productivity.

2. Materials and methods

2.1 Analytical strategy

We model the uptake of climate change actions and farmers' efficiency in agricultural production in a two-stage procedure. First, we utilized the PSM technique to select a sample of farming households that have adopted (adopters) and those who do not (non-adopters) of adaptation practices with comparable socio-economic characteristics, thus controlling for biases from observables. In the second stage, sample selectivity bias corrected SPFs[1] are employed to estimate TE scores for both groups of farmers. Here the objective is to control for biases stemming from unobservable factors. The sample selectivity corrected SPF models, together with their associated error structures, can be presented in the following three equations[2]:

Sample selection: $$d_i = 1[\alpha z_i + w_i > 0], w_i \sim N[0,1] \quad (1)$$

SPF model: $$y_i = \beta x_i + \varepsilon_i, \varepsilon_i \sim N[0, \sigma_\varepsilon^2] \quad (2)$$

(y_i, x_i) are observed only when $d_i = 1$

Error structure: $$\varepsilon_i = v_i - u_i \quad (3)$$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i|, where U_i \sim N[0,1]$$

$$v_i = \sigma_v V_i, where V_i \sim N[0,1]$$

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[1] Stochastic Production Frontier (SPF) Analysis and Data Envelopment Analysis (DEA) are the most commonly employed methods in analysing efficiency. The SPF is a parametric method that assumes a functional relationship between outputs and inputs. In contrast, DEA is a non-parametric method that utilizes mathematical programming methods to construct a piecewise frontier of the data. The DEA considers all deviations from the frontier are attributed to inefficiency whereas SPF analysis is able to separate technical inefficiency effect and random errors. In this study, the use of SPF analysis seems more appropriate, given that agricultural production is subject to heterogeneous environmental factors such as weather which are beyond the control of farmers.

[2] For a detailed model structure, refer Greene (2010) and Bravo-Ureta et al. (2012).

$$w_i v_i \sim N_2\left[(0,1),\left(1,\rho\sigma_v,\sigma_v^2\right)\right]$$

where d is a dichotomous variable that takes the value one for adopters and zero for non-adopters; y represents output; z represents a set of explanatory variables incorporated in the sample selection equation and x represents the set of inputs in the production process. ε is a composite error term. The coefficients α and β are the parameters to be estimated; v is the two-sided random error independent of the u, and u is a non-negative random variable representing inefficiency in production. Sample selection bias is said to occur when the noise in the stochastic frontier, v_i, is correlated with w_i in the sample selection equation. The parameter ρ indicates the presence or absence of selection bias. For detail explanation of the model see Greene (2010).

2.2 Study site and data collection

This study was conducted by selecting 720 farming households covering all three ecological regions in Nepal. First, two districts were purposively selected from each region. The selected districts are -Mustang and Rasuwa in the Mountain region; Kaski and Dhading in the Hill region, and Chitwan and Rupandehi in the Terai region. From each district, we selected two village development committees (VDCs)[3] by following random procedure. In the next step, we selected four wards from each VDC randomly. Finally, 15 farming households were selected from each ward through simple random sampling. Of the total 720, we discard 16 observations in the analysis as some of the information related to input and output variables were missing in those observations. The survey was undertaken from October 2015 to January 2016. The interview was done in the Nepali language. For each household, it took around one hour to complete the interview.

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[3] A VDC is a local level administrative unit that is similar to a municipality.

In addition to the household survey, focus group discussions (FGD) was carried out in each VDC to collect information related to village characteristics under study, farmers perceptions of long-term changes in the climatic condition and adaptation strategies. The identified adaptations were integrated into the survey questionnaire developed to investigate the actual adaptations by the farming households. For each stated impact of climate change, we asked if the particular farming household had made any adjustment or not. We also asked if farmers believe that employing adaptation practices in their farmlands helps to minimize the adverse impact of climate change on agriculture. We consider adapters as being only those households that had exercised a minimum of one of the identified adaptation measures and had stated that the adoption of the practices contributed to reducing the negative impacts of climate change and variabilities.

2.3 Empirical strategy

First, we employed PSM and obtained selection propensity scores. For this purpose, we implemented the nearest neighbor matching algorithms in which a maximum of five matches per adopter with maximum tolerance (caliper) of 0.01 is selected. Among the total observations of 704, the process resulted 433 matched observations, consisting 263 adopters and 170 non-adopters. The summary statistics are reported in Table 1. In the unmatched samples, we find significant differences in most of the variables. However, in the matched samples no significant differences are found between the means of observed variables of adopters and non-adopters. This suggests that the balancing condition of the covariates is satisfied (Leuven & Sianesi, 2015).

In the second step, we modelled the decision of the respondent to adopt adaptation practices or not. The behaviour of farmers in choosing adoption is described by an unobservable selection function, *Bi*, which is hypothesized to be a function of explanatory variables describing respondents' socio-economic characteristics. The model is expressed as:

$$B_i = \alpha_0 + \sum_{j=1}^{6} \alpha_j Z_{ji} + w_i \tag{4}$$

where *B* is a binary variable that reflects a respondent's choice to adopt adaptation practices (i.e., 1 for adopters and 0 otherwise), α_0 is a constant term, α_j is a vector of unknown parameters and *w* is the error term distributed as $N(0, \sigma^2)$. Z is a vector of exogenous variables that represent household socio-economic characteristics which explain the decision to adopt or not. The empirical studies on farmers' climate change adaptations indicate several factors affecting adaptation. Studies report that better education of the agricultural producers is related with improved access to information on better farm practices indicating a greater likelihood of adopting adaptation practices by better-educated farmers compared to less educated ones (Deressa et al., 2009). The effects of farmers' experience in farming on the adoption of improve agricultural practices are mixed, both positive (Hassan & Nhemachena, 2008) and negative (Anley et al., 2007; Nyangena, 2008). It has been discussed that farmers get information on better agricultural actions from agro-based groups and networks, consequently enhancing the possibility of adoption (Abdulai & Huffman, 2014). We included farm and household characteristics that are commonly used in the literature such as farming experience measured in years, households' heads level of education measured in years, market distance from households in kilometers, share of irrigated land measured as the ratio of irrigated land to the total land owned by the household, whether the household sold agriculture produce or not (dummy variable) and whether any member of the household has membership in an agricultural-related organization (dummy variable).

In estimating the SPF model, the Cobb-Douglas (C-D) functional form was chosen to characterize Nepalese agricultural technology. The relevance of the C-D form was tested relative to the commonly used translog function. However, the C-D specification resulted the more consistent outcomes for adopters and non-adopters. Moreover, the C-D production function has been commonly used due to its computational feasibility. Several studies have used C-D production function in analyzing TE in agriculture (Battese, 1992; Binam et al., 2004; Manjunatha et al., 2013; Mayen et al., 2010). The production behaviour postulating a Cobb-Douglas SPF function for the adopters is as follows:

$$LnY_i = \beta_0 + \sum_{j=1}^{4} \beta_j \, lnX_{ij} + v_i - u_i, \qquad \text{iff } B = 1, \tag{5}$$

where Y represents the output variable, $X_{1\text{-}4}$ are the inputs used in producing the output, v_i is the statistical noise and u_i represents the inefficiency in production. The same specification is utilized in estimating the selectivity bias corrected SPF for the non-adopters. However, the dependent variable in equation 4 takes the value 1 for non-adopters and 0 for adopters. The output variable is calculated as the total returns from agricultural produce of the farming households measured in Nepali currency (NRs). The input variables include area of farmland in hectare, labour in man days, chemical fertilizer in kilogram, and capital expenditure in agriculture production measured in Nepalese rupees. In the estimation, we follow the steps by Bravo-Ureta et al. (2012) which are summarized in Table 2.

3. Results and discussions

3.1 Farmers' perceptions of climate change, associated impacts and adaptations

Figure 1 shows the perceptions of sampled farming households regarding the trends in climatic parameters. Majority of the farmers reported that both the summer and winter season temperature have increased as compared to 15-20 years before. Similarly, most farmers perceived that duration of summer season and unpredictability of local weather have increased over the years. 60% of the responded sample experienced an increase in the winter season temperature in recent years. 95% perceived that the summer season temperature has increased.

Similar findings on farmers perceptions of increase in temperature in Nepal have been reported by other studies (Manandhar et al., 2011; Piya, Maharjan, et al., 2012). Moreover, farmers' perceptions are consistent with scientific observations which are reporting measurable temperature rises in Nepal (Chaudhary & Bawa, 2011). Farmers' perception of precipitation was measured in terms of their views on changes in rainfall and snowfall quantity. About 58% of the sampled farmers stated reduced precipitation in their locality in recent years. While 56% of respondents stated increased unpredictability of the weather patterns, 41% noticed no change in predictability.

When asked about the impacts of the above changes in agricultural outputs, most (95%) of the respondents reported that climate change has adversely affected their agriculture. A few of them (5%) reported that there was no impact of those changes. About 85% of the respondents said that they have experienced more drought and 80% reported that the water available for irrigation has been reduced over the years. Almost 78% of respondents stated an increased occurrence of flooding and landslides and a majority reported an increase in pest infestations in crops (83%). About 75% of the respondents experienced the encroachment of invasive species in their farmlands. Similarly, about 82% of them reported that their farm-land soil has been degraded. A total of 74% stated that there has been a decline in agricultural productivity over the recent years as a result of the climate-related changes and variability.

Farmers in the study area have undertaken several adaptation measures against impacts imposed by climate change and variability. The study findings revealed that approximately 91% of farms had employed a minimum of one measure against the impacts imposed by climate change (Figure 2). We find that 53% of farming households had made adjustments in their crop species and varieties, 51% had adopted agricultural practices related to soil and water management, 48% had made changes in fertilizer application, 45% had made changes in farm operations timing, and 18% had adjusted off-farm activities. This study’s expanded analysis encompassed three adaptation measures: crop/varietal adoption, farm operations’ time adjustments, and soil-water management. Farming households who practiced one or more of these three adaptation strategies in their farmlands and those who stated that the adoption of these strategies reduced the negative climate change impacts are termed as adopters, and otherwise non-adopters. Out of the 704 farming households, 468 belong to the adopter category. It is equally important to examine the impact of each adaptation type on the efficiency and productivity. However, most of the farmers had undertaken more than one adaptation simultaneously. Among the 263 adopters in the matched sample, about 8% had undertaken crop/varietal adoption only, 6% had undertaken soil-water management only, and 4% had undertaken farm operations’ time adjustments only. Moreover, 49% had adopted combinations of two adaptations and 33% had adopted all three adaptation measures (Figure 3). In cases where farmers had adopted more than one adaptation strategy, we believe that if we try to conduct the analysis using any one adaptation category at a given time, then we are likely to ignore those who adopted more than one of these three options. This is because analysing any one adaptation option implies that we are treating each adaptation as mutually exclusive. However, this is not the case as revealed by our survey results.

3.2 Econometric results

The results of the self-selection model using both unmatched and matched samples are reported in Table 3. The results show that the matching technique minimizes the variability between the adopters and non-adopters. This is indicated by the lower number of significant variables for the matched sample as compared to that of unmatched. The results indicate that both farming experience and educational levels are significant factors in farmers’ decisions to uptake adaptations. As expected, more experienced farmers are more likely to adopt adaptation measures. This finding is in line with that of Deressa et al. (2009) and Hassan and Nhemachena (2008). Our result supports the findings that, farming household heads with higher levels of education are more probable to uptake adaptation measures (Deressa et al., 2009; Seo & Mendelsohn, 2008). Furthermore, our findings reveal that households with a higher percentage of irrigated land and those which sold agriculture produce are more likely to adopt adaptation measures. Contrary to our expectations, households having any members associated with agro-based organizations is inversely related to the use of adaptation practices implying that agricultural-related groups and networks are not adequately supporting farmers to enhance skills and knowledge on climate change adaptation.

Table 4 presents the results of the conventional and sample selection bias-corrected SPFs for unmatched samples while Table 5 presents the same for the matched samples. In both cases, the coefficient for the selectivity variable, ρ, is significant for the adopters. This reveals the existence of selection bias in this analysis justifying the use of the sample selectivity bias-corrected SPFs. The estimates of 'sigma v' are significantly different from zero in all the models. The estimates of 'sigma u', is statistically significant for adopters in the matched sample implying the presence of an inefficiency component. The sum of the estimated parameters associated with all the inputs is less than one in all the frontiers, implying decreasing returns to scale (DRS). This indicates the use of some of the inputs surpass the scale efficient point for the existing technology. Since the farmers analysed in this study are smallholders with the average landholdings of 0.56ha, the DRS is most likely to be associated with labour use. This is indicated by the labour use rate of 105 man-days/ha in our study (Table 1) which is relatively greater than other studies on smallholder framers (e.g., Gedara et al., 2012; Villano et al., 2015). Nevertheless, the DRS has been reported in previous studies on small-scale farmers (e.g., Gedara et al., 2012; John and Seini, 2013) including for a study in Nepal (Shrestha et al., 2014).

We undertook three hypothesis tests in investigating the productivity differential between adopters and non-adopters. First, the mean output of the adopters was found to be significantly different than that of non-adopters (Table 1). Second, the pooled model results reveal significant differences between the two groups. This was indicated by the statistical significance of the parameter for adaptation. Third, we utilized a likelihood-ratio (LR) test to investigate whether the two groups of farmers share the same technology. The null hypothesis of the test is that stochastic production frontier models for the adopters and non-adopters are the same. The estimated LR test rejects the null hypothesis in both unmatched and matched samples, suggesting significant technological differences between the adopters and non-adopters. This justifies the necessity to estimate separate frontiers for each group of farmers.

Summaries of TE scores for all the estimated models are reported in Table 6. Average TE levels range from 0.71 for the non-adopters using conventional SPF to 0.88 for the adopters, also using the conventional SPF. The TE scores of farmers in this study are comparable to those from other studies in Asian countries. For instance, the mean TE of farmers is found to be 0.81 in Vietnam (Khai & Yabe, 2011), and ranges from 0.80 to 0.91in South-East China (Tan et al., 2010), 0.83 in India (Tadesse & Krishnamoorthy, 1997), 0.72 in Sri Lanka (Gedara et al., 2012) and between 0.74 and 0.67 in urban and rural areas in Nepal (Piya et al., 2012). The average TE score from the P-U model is 0.73. When comparing the TE scores from this model between the two groups of farmers, we found that, on average, adopters (0.78) are 11% more efficient than non-adopters (0.67). Similarly, the average TE score for the P-M model is 0.87. Comparing TE scores from this model show that adopters (0.84) are 5% more efficient than non-adopters (0.89). In both these models, the average TE score of adopters is found to be significantly (P<0.01) higher than that of non-adopters.

The results of the sample selectivity bias-corrected SPF models show higher estimates of TE of adopters in all cases. This implies that adopters are performing better than non-adopters when comparing TE scores within their own cohorts. The results further reveal that the implementation of the matching procedure minimizes the efficiency gap between adopters and non-adopters (Table 6). Moreover, the TE gap between the two groups reduces even further by the employment of the sample selectivity bias correction technique. Figure 4 depicts how correcting for both types of biases affect TE levels.

Finally, we compared the output between the two groups of farming households. This was done after both the observable and unobservable biases are controlled for. In doing so, we obtained the predicted frontier output using the sample selectivity corrected SPF. As presented in Table 7, the average output gap is 15% in favour of adopters. This suggests that adopters are not only performing better as indicated by higher TE scores, they are also operating at a higher level of output.

4. Conclusions and policy implications

The overarching objective of this study is to assess whether the adoption of climate change adaptation practices contributes to increased food production that supports the global efforts to eradicate hunger and poverty - two of the United Nations Sustainable Development Goals (SDGs). For this purpose, we first investigated farmers' perceptions of changes in the climatic parameters, the impacts of climate related changes in agriculture, and farmers' actions against those impacts. Then, we investigated whether adoption of adaptation practices impact on farming households' productivity and efficiency in agricultural production. We employed an emerging framework that combines impact evaluation techniques with the SPF model. A matched group of adopters and non-adopters of adaptation practices is obtained utilizing PSM method to correct for biases based on observed characteristics. In addition, the possible self-selection arising from unobserved characteristics are taken into account by employing Greene's (2010) sample selectivity corrected SPF method. The analysis confirms that selection bias was present; thus, suggesting for the combined framework.

The results reveal that Nepalese farmers have the potential to enhance agricultural production under existing technology and inputs levels. When biases arising from both observable and unobservable sources are ignored, on average adopters are found to be 11% more efficient than non-adopters. Moreover, when the biases stemming from observable sources only are addressed, the adopters are found to be 5% more efficient than non-adopters. Even after correcting for both sources of bias, average TE was consistently greater in the case of adopters than non-adopters. However, the TE gap between adopters and non-adopters is reduced in the matched sample. Additionally, the sample selectivity bias corrected SPF further decreases the TE gap between adopters and non-adopters. Even though the TE gap of the matched selectivity model is shown to be the narrowest, what is important is the net gap after controlling for all observable and unobservable biases. In brief, it is evident from the study that, even after correcting for both observed and unobserved sources of bias, farming households adopting adaptation practices are more technically efficient than households not adopting adaptation practices. Our analysis also suggests that adopters perform better than non-adopters in terms of agricultural output. In Nepal, about 80% of the population lives in rural areas whose main economic base is agriculture. Thus, in a country like Nepal where economic development greatly depends on its agricultural sector, alleviating hunger and poverty is likely to occur if priority is given to increasing agricultural productivity. In this context, our findings provide empirical evidence that adaptation to climate change make agricultural production systems more productive.

At a time when more than 800 million people suffer from chronic hunger and many of them being subsistence producers (FAO, 2014), this study demonstrates that there is significant potential to improve agricultural productivity if smallholder farmers are able to adapt to the impacts imposed by climate change. Regarding policy implications, this study suggests that policy makers should formulate policies to encourage farming households to undertake climate change adaptation practices which have the potential to enhance farmers' productivity and efficiency in agricultural production. There is, therefore, a need for additional investment to promote farmers' adaptation practices and to reduce the adverse impacts imposed by changes in the local climatic conditions. This needs to be demonstrated by conducting detailed studies and showing that existing adaptation practices are indeed contributing toward enhancing farmers' performance in agriculture production. In this regard, this study presents an empirical framework that can be employed in a range of developing countries in examining the impacts of climate change adaptations on food production. However, judging from the current and potential future contribution of farmers' adaptations to sustainable development goals of eradicating hunger and poverty, more effort will be required in monitoring and evaluating various adaptation strategies to support boosting agricultural production. In the case of the present study, adaptation was integrated into the models as a binary variable. However, different types of adaptation can have different levels of impacts on farmers' productivity and efficiency. Further research is, therefore, recommended to examine the impacts of particular adaptation practices on food production. The interest of farmers' adaptations for sustainable development is likely to increase because of the clear connection between sustainable development goals and what agriculture can contribute towards achieving them. Thus, farmers need to be involved to play active roles and their skills and knowledge need to be taken into account in climate adaptation planning.

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Table 1. Descriptive statistics of variables

Variables	Pooled		Adopters		Non-adopters		Test of means
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Unmatched sample							
Production (NRs/ha)	90584.93	83231.43	100745.1	80528.41	79904.04	68934.07	2.507***
Land (ha)	0.56	0.62	0.62	0.69	0.43	0.40	3.921***
Labour (man-days/ha)	105.52	86.73	116.13	98.55	96.72	83.78	3.813***
Fertilizer (kg/ha)	245.80	447.86	260.35	401.86	242.92	363.58	1.934**
Capital (NRs/ha)	7495.92	16060.93	7947.68	11931.26	6396.26	7409.23	1.822**
Farming experience (years)	24.15	13.42	24.93	13.47	22.58	13.22	2.213**
Education (years)	6.63	4.21	6.83	4.15	6.21	4.30	1.865**
Distance to market (km)	8.07	10.51	8.35	11.58	7.51	7.94	1.006
Share of irrigated land (%)	60.89	28.72	63.42	26.89	55.87	31.49	3.319***
Sold agriculture produce (dummy)	0.52	0.48	0.60	0.49	0.36	0.48	6.235***
Membership (dummy)	0.62	0.50	0.59	0.47	0.68	0.43	2.502***
Adaptation (dummy)	0.66	0.47					
Observations	704		468		236		
Matched Sample							
Production (NRs/ha)	94873.58	95396.58	97738.06	73258.67	93478.41	113129.2	0.777
Land (ha)	0.53	0.48	0.53	0.51	0.49	0.42	1.417
Labour (man-days/ha)	106.91	92.54	109.13	135.33	98.61	130.69	1.259
Fertilizer (kg/ha)	261.43	419.90	269.74	390.00	257.51	489.74	0.905
Capital (NRs/ha)	6245.08	7524.04	6425.72	7724.76	6029.33	7116.17	1.328
Farming experience (years)	24.18	13.20	24.48	13.03	23.71	13.48	0.593
Education (years)	6.72	4.14	6.80	4.07	6.58	4.24	0.540
Distance to market (km)	7.73	10.26	7.69	11.19	7.78	8.66	0.088
Share of irrigated land (%)	62.05	27.77	63.37	26.34	69.99	29.81	1.239
Sold agriculture produce (dummy)	0.48	0.50	0.49	0.50	0.45	0.49	1.028
Membership (dummy)	0.66	0.46	0.64	0.46	0.66	0.46	0.092
Adaptation (dummy)	0.61	0.49					
Observations	433		263		170		

*** and ** denote 1% and 5% level of statistical significance.

Table 2. Estimation steps

Step no.	Action	Outcome
1	All available data are used to estimate a pooled unmatched SPF model (P-U) where the dichotomous factor adaptation (1 for adopters, 0 for non-adopters) is included as a regressor.	The overall farm performance examined, accounting for technological change attributable to the adoption of adaptation practices. The model ignores any type of bias.
2	Two separate SPF models are estimated using the unmatched subsamples, one for adopters (U-A) and the second for non-adopters (U-N).	TE score distribution within each group of farmers compared. These models also ignore any type of bias.
3	Two separate SPF models are re-estimated with correction for selectivity bias, one for adopters (U-A-S) and the other for non-adopters (U-N-S).	TE scores compared among farmers in each category where biases arising from unobservable characteristics are taken into account.
4	All available data are used to implement the propensity score matching.	Propensity scores calculated which were the basis for matching adopters and non-adopters.
5	Re-estimated the pooled SPF model but using only the matched subsamples (P-M) and adaptation dummy variable is included as a regressor.	The overall farm performance analyzed, accounting for the biases arising from observed sources.
6	Two separate SFP models are estimated using the matched subsamples; one for adopters (M-A) and the other for non-adopters (M-N) without correction for selectivity bias.	TE scores distribution among farmers within each category compared, accounting for biases arising from observed sources.
7	Two separate selectivity bias corrected SPF models are estimated using the matched subsamples; again one for adopters (M-A-S) and the other for the non-adopters (M-N-S).	TE scores distribution among farmers within each category compared correcting for biases stemming from both observed and unobserved sources.

Table 3. Estimations from the probit selection equation

Parameter	Unmatched sample		Matched sample	
	Coefficients	S.E.	Coefficients.	S.E.
Constant	-0.615**	0.245	-0.330	0.329
Farming experience	0.012***	0.004	0.007	0.006
Education	0.043***	0.013	0.034*	0.018
Distance to market	0.006	0.005	0.001	0.006
Share of irrigated land	0.004**	0.002	0.002	0.002
Sold agriculture produce	0.541***	0.103	0.244*	0.126
Membership	-0.253**	0.112	-0.048	0.135
Log likelihood	-418.103		-286.522	
Chi-square	61.84***		13.07**	
N	704		433	

***, ** and * denote 1%, 5% and 10% level of statistical significance

Table 4. Parameter estimates for the conventional and sample selectivity bias corrected SPF models: unmatched sample

Variables	Conventional SPF						Bias-corrected SPF			
	Pooled (P-U)		Adopters (U-A)		Non-adapters (U-N)		Adopters (U-A-S)		Non-adopters (U-N-S)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	0.771***	0.255	8.173***	0.485	6.329***	0.493	8.410***	0.498	6.383***	0.515
Land	0.259***	0.044	0.263***	0.053	0.275**	0.089	0.258***	0.041	0.347***	0.083
Labour	0.295***	0.051	0.205***	0.063	0.287***	0.075	0.221***	0.056	0.283***	0.074
Fertilizer	0.090***	0.024	0.117***	0.019	0.059	0.053	0.112***	0.029	0.081	0.068
Capital	0.208***	0.039	0.168***	0.052	0.237**	0.083	0.149***	0.036	0.161***	0.033
Adaptation	0.137**	0.066								
Returns to scale	0.852		0.753		0.858		0.740		0.873	
Log Likelihood	-802.395		-481.205		-289.946		-665.345		-547.951	
Gamma	0.785***	0.054	0.322***	0.058	0.519***	0.140				
Sigma square	2.167***	0.501	0.476***	0.032	1.154***	0.296				
Sigma u							0.281	0.484	0.334	0.268
Sigma v							0.680***	0.053	0.656***	0.127
RHO (ρ)							-0.509***	0.092	0.207	0.516
N	704		468		236		468		236	

*** and ** denote 1% and 5% level of statistical significance

Table 5. Parameter estimates for the conventional and sample selectivity bias corrected SPF models: matched sample

Variables	Conventional SPF						Bias-corrected SPF			
	Pooled (P-M)		Adopters (M-A)		Non-adopters (M-N)		Adopters (M-A-S)		Non-adopters (M-N-S)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Constant	7.142***	0.748	7.542***	2.321	6.428***	0.596	7.794***	0.537	6.912***	1.485
Land	0.269***	0.068	0.243**	0.096	0.272**	0.105	0.263***	0.059	0.291***	0.076
Labour	0.315***	0.089	0.184***	0.047	0.307***	0.081	0.237***	0.084	0.365***	0.112
Fertilizer	0.102**	0.036	0.084***	0.016	0.084	0.070	0.085**	0.043	0.093	0.086
Capital	0.217**	0.106	0.272	0.197	0.215**	0.084	0.219***	0.055	0.167**	0.058
Adaptation	0.115*	0.059								
Returns to scale	0.903		0.783		0.878		0.804		0.916	
Log Likelihood	-501.508		-263.401		-212.415		-398.589		-375.075	
Gamma	0.556***	0.161	0.453***	0.133	0.394***	0.112				
Sigma square	0.613***	0.051	0.420***	0.112	0.803***	0.185				
Sigma u							0.5224*	0.262	0.482	0.421
Sigma v							0.667***	0.056	0.893***	0.172
RHO (ρ)							0.451***	0.121	-0.294	0.730
N	433		263		170		263		170	

***, ** and * denote 1%, 5% and 10% level of statistical significance

Table 6. TE levels and differentials across models

Category	Index	Conventional SPF							Sample selection SPF				
		Pooled		Adopters		Non-adopters		Test of TE distribution[a]	Adopters		Non-adopters		Test of TE distribution
		Mean	SD	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Unmatched sample	TE	0.73	0.11	0.88	0.09	0.71	0.15	P = 0.000	0.84	0.02	0.77	0.12	P = 0.000
	Differential[b]	23.94%							9.09%				
Matched sample	TE	0.87	0.06	0.88	0.09	0.74	0.14	P = 0.000	0.86	0.02	0.82	0.03	P = 0.000
	Differential	18.91%							4.88%				

[a]A Kruskal-Wallis test was used to determine if TE distributions are significantly different between the adapters and non-adapters. We also used a t-test to compare the TE scores between adopters and non-adopters. The mean TE scores were found significantly different in all four cases

[b]TE differential was measured as the percentage increase in TE between adapters and non-adapters.

Table 7. Predicted frontier output after bias correction for matched sample

Category	Mean output (NRs/ha)	Std. dev
Adopters	108664.78	74414.92
Non-adopters	94229.53	69780.81
Percent differential	15.32	

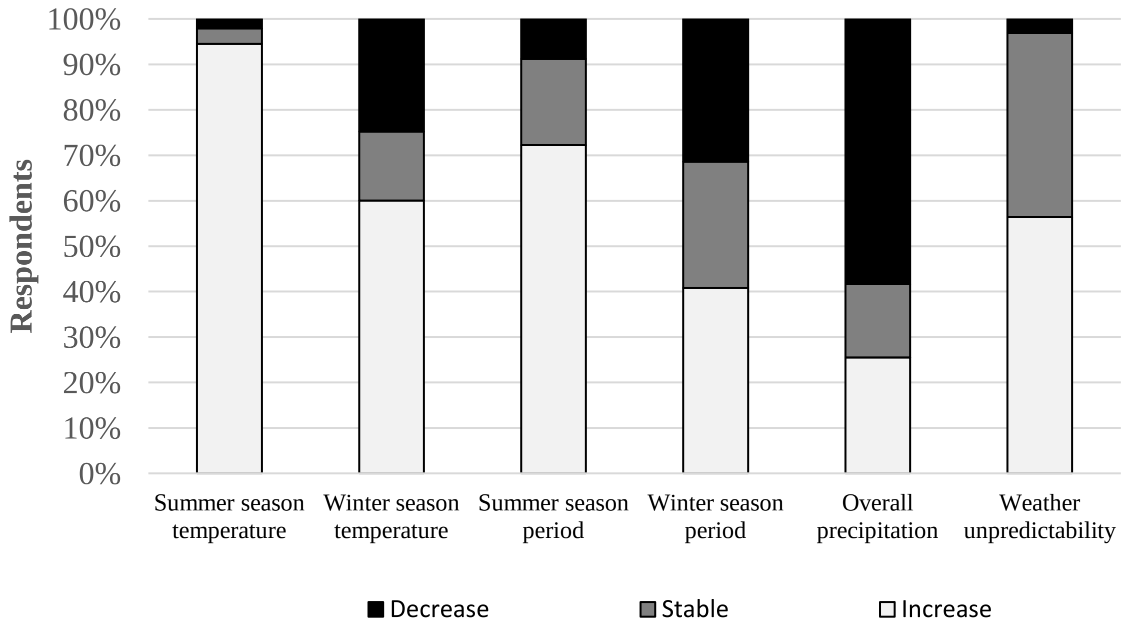

Fig 1. Respondents' perceptions of local climatic conditions

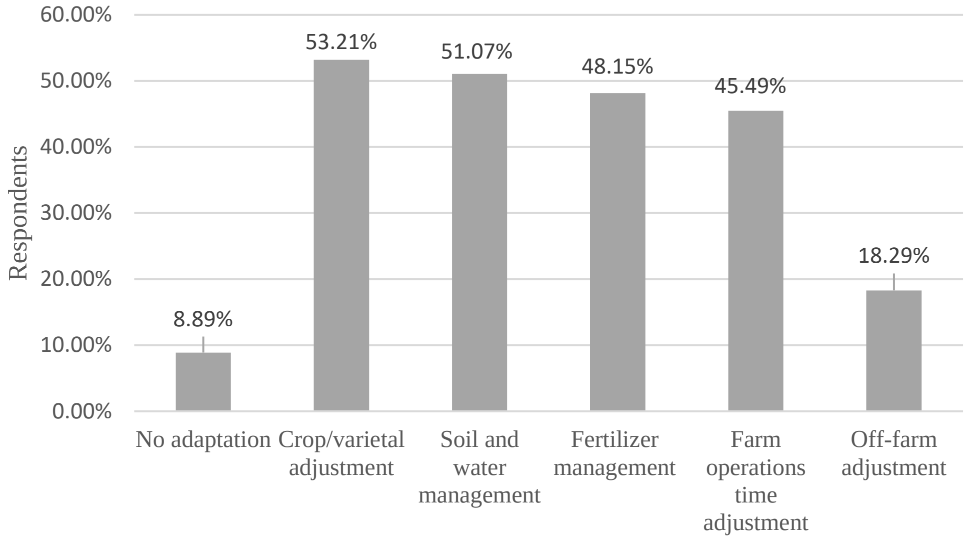

Fig 2. Adaptation strategies

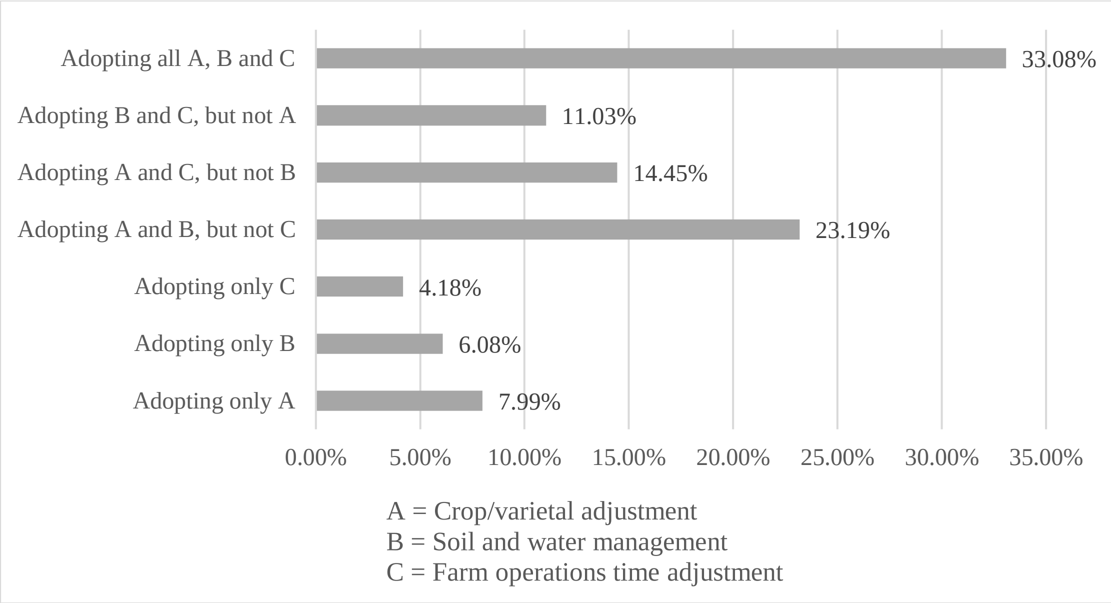

Fig 3. Extent of adaptations amongst the matched adopters (n = 263)

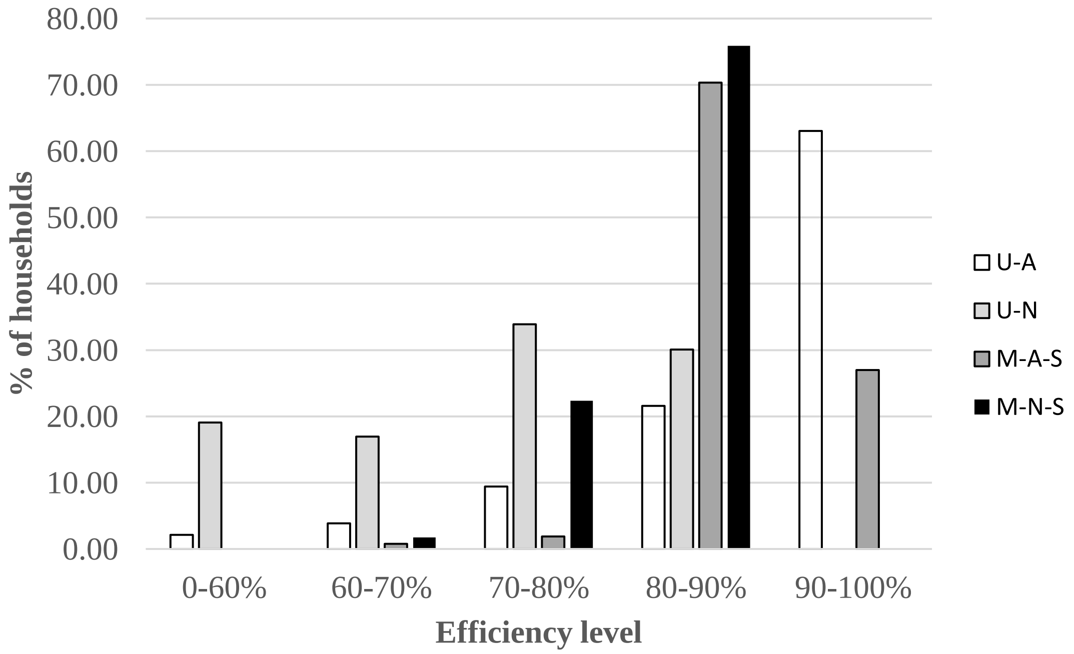

Fig 4. Distribution of efficiency scores for extreme models