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Does Adoption of Soil and Water Conservation Practice Enhance Productivity and Reduce Risk Exposure? Empirical Evidence from Semi-Arid Tropics (SAT), India

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Abstract: This paper assessed the impact of soil and water conservation practices on farm productivity and risk exposure using data from 1204 plots in the semiarid tropics of India. A probit model was used to assess the determinants of adoption of soil bunds. We employed a moment-based approach for estimating crop revenue, its variability and downside risk exposure, i.e., crop failure. Furthermore, we also used a doubly robust method for assessing the impact of soil bunds on crop revenue, its variability and downside risk. Matching and propensity-based methods were also used to check robustness. The results show that training, access to credit and extension services are key determinants of adoption of soil bunds. Furthermore, the results also suggest that soil bunds not only improve the crop revenue but also reduce its variability. Most interestingly, we show that soil bunds also reduce the chances of downside risk, i.e., crop failure. Therefore, in view of increasing climate change and variability in the semiarid tropics, it can be suggested that soil bunds could be an important adaptation strategy for improving productivity and reducing risk exposure. This paper supports the investment in soil and water conservation technologies for sustaining the livelihood of resource-poor farmers of ecologically fragile regions such as the semiarid tropics.

Keywords: soil and water conservation; soil bund; impact; risk exposure; semiarid tropics

1. Introduction

The negative impacts of climate variability and change on agriculture are being witnessed all over the world, particularly in the countries like India, which is highly vulnerable because of its high dependence on agriculture and excessive pressure on natural resources [1,2]. Rainfed agriculture, which accounts for 67% of the net sown area, contributing 44% of food grains and supporting 40% of the population, is highly vulnerable to climate variability and change. Its high vulnerability can be attributed to fact that rainfed agriculture suffers numerous climatic (low and erratic rainfall, extreme rainfall variability, occurrence of unpredictable droughts, high temperatures), biophysical (land degradation, poor soil fertility) and socioeconomic constraints (inadequate infrastructure, high population pressure, high levels of poverty, low levels of input use and technology adoption, resource-poor farmers and inadequate credit availability, etc.) adversely affecting the productivity of the farming system [3,4]. Moreover, it is projected that the frequency of extreme weather, particularly droughts, is increasing [2,5]. However, sustaining crop production in rainfed areas is of critical importance to maintain India's food

security [6] since even after achieving full irrigation potential, nearly 50% of the net cultivated area will remain dependent on rainfall [7]. In the SAT (semiarid tropics) region, variability of rainfall is a principal source of production risk [8]. Production risk in the form of crop failures is a major barrier to making rainfed agriculture sustainable. Moreover, the incidence of crop failure is on the rise as the frequency of droughts over the years has been on the rise in the semiarid areas. Production risks influence agricultural production decisions, particularly a farmer's technology adoption decisions [9,10], and can worsen the sustainability of crop production systems through their downside (crop failure) effects [9,11]. Farmers understand the risks and uncertainties of production risk and try to manage it by taking up appropriate practices, including soil and water conservation measures. In this regard, empirical evidence shows that farmers are risk-averse [12], suggesting that suitable technologies can help in reducing farmers' exposure to production risk. Furthermore, there is evidence that most of the farmers exhibit decreasing absolute risk-aversion [13]. This implies that farmers are averse to "downside risk" [14], implying that farmers are especially averse to being exposed to unexpectedly low crop yields or returns.

To improve the productivity, stabilize the yields and to reduce the chances of crop failures, soil and water conservation (SWC) practices are considered one of the key strategies. Moreover, in the rainfed areas, SWC practices are crucial to sustain crop production in view of growing water shortages, deteriorating soil health and increasing incidence of drought and desertification, and also to moderate the negative effects of climate change and variability [15]. The common in situ moisture conservation practices for the region are broad beds and furrows, contour bunding, graded bunding, compartment bunding, ridges and furrows, tied ridging, contour cultivation, set-furrow cultivation, etc. [16–18]. Among these measures, contour bunding is the most widely practiced soil conservation measure in the semiarid tropics in India having medium- to low-rainfall areas (<700 mm) and on permeable soils with <6% slope [16,19]. Bunding helps in reducing the soil loss and runoff and improving the soil moisture, which in turn leads to higher productivity [20,21]. Keeping this in view, soil bunds or bunding was chosen for detailed investigation in this paper. This is an earthen embankment constructed on a contour to intercept runoff and hold the rainwater for conserving soil moisture.

A substantial literature has examined the impact of SWC practices on productivity, but very few studies attempted to examine the impact of SWC practice adoption on crop yield variability and downside risk exposure, i.e., crop failure. Most importantly, the influence of SWC practices on downside risk exposure (on the probability of crop failure) remains poorly explored in the rainfed areas [13]. To fill this research gap, this paper investigates how adoption of soil and water conservation practices, i.e., soil bunds, can contribute to improving farm productivity and how it affects the variability of crop production/yields and the risk of crop failure. In addition, the paper also identifies the key determinants of adoption of soil bunds. The paper employed the probit model for explaining the factors affecting the adoption behavior of soil bunds. For assessing the impact of soil bunds on the crop revenue, variance and skewness, inverse-propensity-weighting regression adjustment (IPWRA) is used as a main method. Furthermore, IPW (inverse propensity weighting) and propensity score matching (PSM) approaches (coarsened exact matching, optimal and nearest-neighbor matching) were used to confirm the robustness of the results. We followed the moment-based approach for estimating the mean-variance and skewness of crop revenue using the plot-level data. This paper will provide useful insights for policy makers for improving the adoption of SWC practices and also provide empirical evidence of how SWC not only sustains crop production in drought-prone semiarid areas and in degraded lands, but also it could be instrumental in reducing the risk exposure, which is expected to be increasing in view of increasing climate variability and droughts.

2. Materials and Methods

2.1. Data and Sampling Procedure

We collected data from 530 households and 1204 plots, of which 44.4% and 55.8% of farmers were adopters and nonadopters, respectively. Karnataka is a state in the southwestern part of India, which is one of the most drought-prone areas of the country. Around 77% of the area of the state is arid and semiarid, facing severe climatic and resource constraints. The occurrence of drought is common [22], and rainfall is less than 750 mm per annum, which is also erratic and uncertain, with higher spatial and temporal variability. In the region, most of the farmers are resource-poor, having limited capacity to invest in soil and water conservation. Consequently, the region is in the grip of a vicious circle of land degradation, hunger, and poverty. The region having drought-prone districts of the Karnataka state was purposively selected. Then, from the drought-prone districts, four districts (Tumkur, Bidar, Koppal and Gadag) were randomly selected; then, from each selected district, two subwatersheds were again randomly selected. From each selected subwatershed, adopters, and from the adjacent area, nonadopters were chosen for detailed survey. With the help of a pretested and well-structured questionnaire, plot-level data on soil and water conservation practices, socioeconomic and physical characteristics and institutional aspects were collected.

2.2. Analytical Tools

Econometric Model of Adoption of Soil Bunds

The plot having soil bunds was assumed as an adopter or a nonadopter otherwise. For each plot, i th, the latent variable y_i^* was assumed to be a linear function of the vector of observable household, plot and institutional characteristics as follows:

$$y_i^* = \beta Z_i + \varepsilon_i \quad (1)$$

where β is the coefficient vector, ε_i is a random error term and Z_i is the set of explanatory variables. The linkage between y_i^* and y_i is as follows:

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0 \\ 0, & \text{if } y_i^* < 0 \end{cases} \quad (2)$$

Then, the probability of adoption of soil bunds is given by

$$Prob[y_i^* = 1] = Prob[y_i^* > 0] \quad (3)$$

$$= Prob[\beta Z_i + \varepsilon_i > 0] \quad (4)$$

$$= 1 - Prob[\varepsilon_i \leq -\beta Z_i] \quad (5)$$

$$= F(\beta Z_i) \quad (6)$$

where $F(\cdot)$ is the cumulative distribution function (CDF) of the error term ε_i . We assume that ε_i follows the standard normal distribution, and the above equation was estimated by probit regression.

2.3. Choice of Explanatory Variables Used in Probit Model

Drawing upon the literature on technology adoption and particularly on the adoption of SWC measures [23–27], the required variables for the paper were chosen. Adoption of SWC practices is determined by synergic and interactive effects of numerous socioeconomic factors, availability and access to financial and capital resources, physical features of the land/plot and institutional support. Accordingly, factors determining adoption of SWC practices can be categorized into groups: (a) household-specific characteristics, (b) economic and institutional factors and

(c) biophysical/plot-level feature characteristics. Following this, we also collected the plot-level information on variables relating to household-specific characteristics, viz., age, education, family size, farm assets, livestock, size of landholding and off-farm income. In view of results from previous studies, we hypothesized that older farmers would have a higher likelihood of taking up SWC practices [26,28,29]. The level of education was measured in terms of the number of schooling years, and we expected a positive effect on the adoption of SWC practices. This is due to the fact that better education helps in developing a better understanding relating to detrimental consequences of soil erosion and land degradation, and it also facilitates and improves access to information and technologies. Most importantly, it brings about a desirable change in attitude and behavior about conserving natural resources [30–32]. Soil and water conservation measures are highly capital-intensive; therefore, adoption of these practices is inadequate in scale and intensity (rate of adoption and its intensity) due to financial hardships and liquidity constraints, which are common in the SAT region, as a majority of farmers are resource-poor. Therefore, we also included variables such as access to credit and off-farm income. Taking indications from earlier studies [33], we supposed that access to credit will have a positive impact on adoption by overcoming financial constraints. Furthermore, we believed that having a source of off-farm income will also affect positively the adoption of SWC practices. Size of landholding is often used a proxy for farm income and wealth, indicating relatively higher capacity to invest in SWC measures. It was reported to have a positive effect on the adoption of conservation measures [28,29,34]. Another set of explanatory variables is pertaining to physical features of the plot/land, viz., slope, soil erosion and fertility levels. It was reported that the higher the slope of the plot, the higher the probability of adoption since steeper slopes are more prone to soil erosion [35,36]. Furthermore, it was noticed that higher soil erosion also had a positive association with the taking up of SWC measures [23,37]. This can be attributed to the fact that soil erosion is greater on the plots having higher slopes, and soil erosion removes the top layers of soils [36], leading to a decline in the productive capacity of the soil [24,38]. Extension service is measured in terms of the number of visits of farmers to local extension agencies such as KVKs and RSKs (KVK and RSK stand for the Krishi Vigan Kendra (Farmer Science Centre) and Raita Sampark Kendra (Farmer Contact Centre), which are involved in agricultural extension services). We believed that if farmers are in contact with extension service centers, then they have more access to information and advisories about soil and water conservation and their expected benefits [29,39]. Use of such services also helps in developing a better understanding of potential consequences of soil erosion [40]. A positive impact of extension services was reported by many researchers [24,28,29,31]. Lack of technical support negatively affects the adoption of conservation measures [28,41]. We supposed that training of farmers has a positive influence on the adoption. If farmers participate in training on SWC measures, then they are expected to have more technical knowledge about the use and implementation, leading to a higher probability of adoption. Social capital is critical as far as adoption of agricultural innovations is concerned [42]. It encourages cooperative behavior, reduces transaction costs, and facilitates information sharing [43,44]. We tried to measure the social capital in the form of interaction and its perceived usefulness and supposed a positive effect on adoption.

2.3.1. Econometric Model of Mean Yield, Risk and Downside Risk

Following Antle (1983), we used a moment-based approach that allows a flexible representation of the production risk [11]. This approach has been widely used in agricultural economics to model production risk [13,45]. A moment-based approach (the mean-variance-skewness analysis) was used in a number of studies pertaining to production risk [45]. We wanted to estimate the impact of soil and water conservation practices, i.e., soil bunds, on crop revenue as well as on risk exposure. Since data was from different crops, to see the impact of soil and water conservation practices on farm performance, we used crop revenue as an indicator of farm performance instead of crop yield. Risk was measured by the second central moment (variance) and third central moment (skewness) of the error distribution of crop revenues after controlling for differences in inputs, household and plot-level

features. The flexible moment-based production function divides the variation in revenue into two parts. First, differences in inputs and other observable characteristics explain part of the variation in revenue, which is the mean effect of the explanatory variables on revenue. Second, the unexplained variation of revenue (the error distribution) is modeled as an economic structure reflecting the riskiness of agricultural production [11,46]. The distribution error of the revenue function provides relevant information for analyzing farmers' risk exposure. Skewness measures the extent of farmers' downside risk exposure (i.e., crop failure) by distinguishing unexpected bad and good events, which cannot be done by variance [45]. However, we used both variance and skewness as measures of risk exposure. An increase in skewness implies a reduction in downside risk exposure, which implies, for example, a reduction in the probability of crop failure. We preferred the moment-based approach because it imposes relatively fewer restrictions than the conventional production function specifications [11]. Since we had different crops (maize, sorghum, ragi and redgram), we estimated the net revenue function. Here, net revenue is gross income over the variable cost. Thus, net revenue is defined as follows:

Net revenue = Gross income (yield $\times$ price) – variable cost (cost of inputs).

Furthermore, the net revenue function is defined as

$$R = f_1(X\beta, Z\alpha, D\gamma) + \mu_1 \quad (7)$$

where R is net revenue, measured in INR (Indian National Rupee) per ha, X is input expenditure (INR per ha), Z includes socioeconomic and plot-level features and D is a dummy variable indicating adoption of soil bunds. β , α and γ are parameters to be estimated.

$$\varepsilon_1 = R - f_1(X\hat{\beta}, Z\hat{\alpha}, D\hat{\gamma}) \quad (8)$$

where ε_1 is the residual estimated from Equation (7).

Then, estimated residuals are used to estimate higher-order moments of production:

$$(\varepsilon_1)^j = E[R - f_1(X\hat{\beta}, Z\hat{\alpha}, D\hat{\gamma})]^j + v_j; j = 2, 3 \quad (9)$$

For the estimation of the mean net revenue equation, different alternative functional specifications, viz., linear-log, quadratic, Cobb–Douglas and translog-log, were estimated. Then, the econometric performance of each specification was evaluated using Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Accordingly, among these, the best model was used for analysis. Following Judge et al.'s (1988) procedure [47], in the first step, we estimated the mean function using ordinary least squares (OLS); in the second step, we predicted the residuals and then constructed squared residuals; and in the third step, we used the squared residual as the dependent variable for the variance function estimation using OLS. If the coefficient in the variance function is positive, it implies risk-increasing effects, and conversely, a negative coefficient implies a risk-decreasing effect of the input on outcomes. Similarly, the skewness equation was estimated by taking the cube of the residuals. In the skewness equation, a positive coefficient indicates that the distribution is positively skewed. In other words, it indicates a reduction in the downside risk, i.e., crop failure.

2.3.2. Impact Estimation Technique

Assuming the axiom of rationality, given resource constraints, a farmer will adopt soil bunds in the plot if it leads to higher revenue than cost. Therefore, it is assumed that a profit-maximizing farmer will adopt a technology/practice if expected net utility from adopting (U_i^A) is higher than that from nonadoption (U_i^{NA}). In other words, a farmer adopts if the expected net utility is greater than zero ($U_i = U_i^A - U_i^{NA} > 0$). In order to estimate the impact of soil bund technology adoption on a farmer's outcome, we estimate it as

$$Y_i = \beta_0 + \gamma D_i + \beta X_i + \alpha Z_i + \mu_i \quad (10)$$

where Y_i denotes the different dependent variables (net revenue, variance and skewness); D_i is the binary variable taking the value 1 if a plot has soil bunds and 0 otherwise; Z is a vector of farm-level socioeconomic and plot-level characteristics and institutional variables, which are expected to influence the outcomes; X is input variables; and μ_i captures the error terms. The results of OLS estimation of the above equation will be inconsistent and biased, as adoption of soil bunds is endogenous. Furthermore, when we use nonexperimental data, wherein individuals choose their adoption rather than being randomly assigned, this introduces self-selection bias. This is due to the fact that adoption of soil bunds may be strongly correlated with observable farm, plot and institutional features. Therefore, self-selection must be accounted for while estimating the impact of adoption of soil bunds. Additionally, there is a problem of missing data since the counterfactual outcomes cannot be observed. Furthermore, unobservable characteristics of the farmers, such as managerial skills, may influence households' decisions to adopt the technology as well as their outcomes, resulting in inconsistent and biased estimates.

In a regression approach (RA), the average treatment effect on the treated (ATT) is estimated as

$$ATT = E[Y_i(1) - Y_i(0) | D_i = 1] \quad (11)$$

where $Y_i(1)$ is the unit of outcome when the i^{th} individual has adopted ($D_i = 1$) the SWC practice and $Y_i(0)$ is the unit of outcome when the i^{th} individual has not adopted ($D_i = 0$) the SWC practice. This represents the calculated effect of taking into consideration only the units that received treatment. In regression adjustment (RA), two separate regression analyses ($\mu_0(x)$ when $D_i = 0$ and $\mu_1(x)$ when $D_i = 1$) were employed, each for treatment level, and then averages of predicted outcomes were used for estimating the ATT. Wooldridge (2010) suggested that a combination of the RA with the propensity score, that is, IPWRA. The IPWRA estimator has a “double robust” property because it combines the regression adjustment (RA) and the inverse probability weighting (IPW) estimators [48]. The IPWRA estimator simultaneously estimates treatment and outcome equations to account for selection bias. It uses weighted regression coefficients to compute treatment effects, and the weights used are inverse probabilities of treatment [48]. The IPWRA estimator estimates the impact of adoption of SWC practices in the following three steps:

(1) Let us say the outcome model for SWC practice adoption is specified as a linear regression function of the form $Y_i = \alpha_i + \beta_i X_i + \varepsilon_i; i = \{0, 1\}$ and the propensity scores estimated using probit regression $P(X, \hat{Y})$.

(2) In the second step, linear regression is employed to estimate the parameters (α_0, β_0) and (α_1, β_1) using inverse-probability-weighted least squares as follows:

$$\min_{\alpha_0, \beta_0} \left[\sum_i^N \frac{(Y_i - \alpha_0 - \beta_0 X_i)}{P(X, \hat{Y})} \right] \text{ if } D_i = 0. \quad (12)$$

$$\min_{\alpha_1, \beta_1} \left[\sum_i^N \frac{(Y_i - \alpha_1 - \beta_1 X_i)}{P(X, \hat{Y})} \right] \text{ if } D_i = 1 \quad (13)$$

(3) The third step involves calculating the average treatment effect on the treated (ATT) by

$$\min_{\alpha_1, \beta_1} \left[\sum_i^N \frac{(Y_i - \alpha_1 - \beta_1 X_i)}{P(X, \hat{Y})} \right] \text{ if } D_i = 1 \quad (14)$$

The IPWRA approach, being doubly robust, was treated as the main estimation approach; additionally, other approaches, namely, matching approaches and IPW, were also used to assess the impact of SWC practices to check the robustness of findings. For analysis, the packages, namely, PSweight [49], WeightIt [50], Matching [51] and MatchIt [52] were used in R-3.6.3.

3. Results and Discussion

3.1. Descriptive Summary of the Variables

The average age of the sample famers was 51 years; when segregated, it was 49 and 52 years for the adopters and nonadopters, respectively (Table 1).

Table 1. Descriptive statistics of the sampled farm households in the study area.

Variables	Definition	Full Sample	Adopters	Nonadopters
BUND	Soil bunds (1 if adopted; otherwise 0)	1204	532 (44.2)	672 (55.8)
AGE	Age (years)	51 (13.51)	49 * (12.87)	52 (13.93)
EDU	Education (number of schooling years)	4.91 (4.78)	5.06 (4.82)	4.8 (4.74)
OFFFARM	Off-farm income (1 if yes; otherwise 0)	561 (46.6)	303 *** (57.0)	258 (38.4)
FAMILY	Family size (numbers)	5.0 (2.3)	5.0 (2.3)	5.0 (2.3)
LIVESTOCK	Livestock (numbers)	3.35 (2.2)	3.29 (2.08)	3.4 (2.29)
LANDHOLDING	Size of landholding (ha)	2.59 (2.11)	2.64 (2.21)	2.55 (2.03)
CREDIT	Access to credit (1 if yes; otherwise 0)	811 (67.4)	394 ** (74.1)	417 (62.1)
FAI	Farm asset index (index scores)	0.11 (0.16)	0.14 * (0.19)	0.09 (0.13)
TENURE	Tenure (1 if owned; otherwise 0)	795 (66.0)	369 ** (69.4)	426 (63.4)
SLOPE	Slope of plot (1 if slope; otherwise 0)	693 (57.6)	362 *** (68.0)	331 (49.3)
EROSIONHIGH	Soil erosion (1 if high; otherwise 0)	362 (30.1)	208 ** (39.1)	154 (22.9)
EROSIONHIGHMED	Soil erosion (1 if medium; otherwise 0)	358 (29.7)	109 ** (20.5)	249 (37.1)
FERTIHIGH	Fertility (1 if high; otherwise 0)	399 (33.1)	221 *** (41.5)	0.27 (0.44)
FERTIMEDIUM	Fertility (1 if medium; otherwise 0)	570 (47.3)	196 *** (36.8))	374 (55.7))
BPI [#]	Benefit perception index	3.41 (0.78)	3.58 ** (0.73)	3.27 (0.79)
EXTENSION	Extension services (number of visits)	2.7 (1.4)	2.9 * (1.6)	2.4 (1.2)
TRAIN	Training (1 if yes; otherwise 0)	577 (47.9)	305 *** (57.3)	272 (40.5)
TALK	Interaction with others (1 = no interaction, 2 = often and 3 = frequently)	1.77 (0.81)	1.96 * (0.84)	1.63 (0.75)
USEFUL	Perceived usefulness of interaction (1 = not useful, 2 = useful, 3 = very useful)	2.41 (0.59)	2.4 (0.58)	2.43 (0.6)
EXPHL	Expenditure on human labor (INR/ha)	12,185 (4347)	12,482 ** (4579)	11,950 (4142)

Table 1. Cont.

Variables	Definition	Full Sample	Adopters	Nonadopters
EXPBL	Expenditure on bullock labor (INR/ha)	3758 (2722)	4050 *** (2927)	3528 (2527)
EXPSEEDS	Expenditure on seeds (INR/ha)	1130 (993)	1083 * (1030)	1181 (962)
EXPMACHINE	Expenditure on farm machinery (INR/ha)	3171 (2150)	3179 (2097)	3165 (2193)
EXPFERTI	Expenditure on fertilizers (INR/ha)	3041 (2788)	3253 ** (2825)	2873 (2748)
NETRETURN	Net return (000'INR/ha)	27.5 (23.4)	32.4 *** (24.6)	23.6 (21.6)
TUMKUR	Tumkur	211	80	131
BIDAR	Bidar	326	151	175
GADAG	Gadag	316	152	164

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively. For continuous and binary variables, figures in parentheses are standard deviation and percentage to total, respectively. For the continuous and binary variables, the difference between the adopters and nonadopters was tested using the t-test and chi-square test, respectively. BPI[#] is the benefit perception index, which indicates perceived benefits of soil and water conservation measures of farmers in terms of effects of soil and water conservation on improving the soil fertility, moisture, groundwater and reducing soil loss and runoff.

For variables, viz., education, family size, livestock, and size of landholding, statistically, there was no difference between the adopters and nonadopters. However, adopters were significantly different from nonadopters in terms of access to credit, off-farm income, and farm assets. More specifically, around 57% of the adopter farmers had a source of off-farm income, whereas this was only 38% for the nonadopters. Similarly, about 74% and 62% of adopter and nonadopter plots, respectively, had availed credit facilities in the study areas. Furthermore, in case of the plot-level features, nearly 69% and 63% of plots were being cultivated by farmers themselves, respectively, for adopters and nonadopters. Overall, about one-third of farmers perceived a higher level of soil erosion at their plots. After segregating, around 39% and 23% of the adopter and nonadopter farmers, respectively, stated that their plots were suffering the problems of relatively higher levels of soil erosion. The adopters opined that soil and water conservation were relatively more beneficial in terms of reducing soil erosion and runoff and improving soil fertility. This is evident from the relatively better benefit perception index (BPI) scores (3.58) of adopters in comparison to nonadopters (3.27). Finally, in terms of input usages, adopters, in comparison to nonadopters, were incurring more expenditure on human labor, bullock labor and fertilizers, whereas expenses were lesser on seeds. A two-sample t-test ($t = 6.55$, p -value < 0.001) showed that net revenue from adopters (INR 32.46 thousand per ha) was statistically higher than that of nonadopters (INR 23.55 thousand per ha). Further, a two-sample Kolmogorov–Smirnov test showed that cumulative distribution functions (CDF) of adopters and nonadopters were different from each other, i.e., the CDF of adopters lay below that of nonadopters. From the summary of the explanatory variables, it can be stated that the adopters were systematically different from nonadopter farmers. Therefore, the influence of these explanatory variables on outcomes needs to be controlled while assessing the impact.

3.2. Determinant of the Adoption of Soil Bunds

The probit model was statistically significant at the significance of level of 1%, as indicated by the p -value of the likelihood ratio chi-square (Table 2). The age of the decision maker influenced the adoption of soil bunds negatively, and it was statistically significant at 5% level of significance. This implies that younger farmers are more willing to adopt soil bunds. This result is in line with that of other studies [24,53]. Higher probability of adoption of younger farmers can be attributed to the fact that, generally, benefits of soil and water conservation cannot be realized within a short time period;

therefore, older farmers do not have much incentive for investing in conservation efforts [31]. In the study area, we noticed that younger farmers were more educated, had more access to the required information and technologies and also had a better understanding of negative consequences of soil erosion and land degradation, resulting in a higher probability of adoption. Furthermore, we also observed that younger farmers wanted to pursue market-oriented farming and were also aware about the importance of sustaining natural resources. Contrary to our expectation, education had a negative albeit statistically insignificant influence, and similar findings were also reported by many researchers [54]. For this, it was argued that better education might offer opportunities for alternative livelihood options, making for less interest in farming and thereby reducing the chances of investment in soil and water conservation. As per prior expectations, family size and farm size had a positive influence on the adoption, but it was statistically insignificant. As anticipated, CREDIT had a positive effect on adoption of SWC practices. In the study areas, most of the farmers were resource-poor, having a limited capacity for investing in conservation efforts. Therefore, having a source of off-farm income helps with overcoming the liquidity constraints. The result is in agreement with previous studies showing a positive effect of access to credit on the decision to take up soil and water conservation measures [33].

Table 2. Determinants of soil bunds in the study area.

Variables	Estimate	Std. Error	Marginal Effects	Std. Error
Intercept	−3.817 ***	0.438	–	–
AGE	−0.008 **	0.003	−0.003 **	0.001
EDU	−0.013	0.010	−0.005	0.004
FAMILY	0.006	0.020	0.002	0.008
LANDHOLDING	0.002	0.023	0.001	0.009
FAI	1.199 ***	0.309	0.464 ***	0.120
LIVESTOCK	−0.014	0.021	−0.005	0.008
CREDIT	0.295 ***	0.104	0.112 ***	0.039
OFFFARM	1.564 ***	0.104	0.527 ***	0.027
TENURE	0.014	0.098	0.005	0.038
SLOPE	0.398 **	0.095	0.152 **	0.036
EROSIONHIGH	0.312 **	0.112	0.122 **	0.044
EROSIONHIGHMED	−0.405 ***	0.112	−0.152 ***	0.040
FERTIHIGH	−0.087	0.130	−0.034	0.050
FERTIMEDIUM	−0.376 **	0.123	−0.144 **	0.047
BPI	0.377 ***	0.063	0.146 ***	0.024
TALK	0.468 ***	0.061	0.181 ***	0.024
USEFUL	−0.024	0.077	−0.009	0.030
TRAIN	0.518 *	0.033	0.199	0.035
EXTENSION	0.168 **	0.032	0.065 **	0.013
TUMKUR	−0.234 *	0.139	−0.089 *	0.052
BIDAR	−0.041	0.120	−0.016	0.047
GADAG	0.124	0.125	0.048	0.048

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively, likelihood ratio test: −632.07 ***, ($p < 0.001$).

Now, turning to plot level features, TENURE, as expected, had a positive influence on the adoption of SWC practices, although it was insignificant. This is due to the fact that ownership confirms the future use of the same land and, therefore, provides incentives for investment in conservation efforts [25] for harnessing its long-term benefits. Many studies reported a positive effect of tenure security on the adoption of soil conservation practices [24,42,55]. As anticipated, both the slope of the plot as well as the level of soil erosion were associated with a higher probability of adoption of SWC practices. These results are in conformity with earlier studies, in which it was reported that the likelihood of adoption was higher if a cultivator was able to recognize the negative effects of soil degradation on crop yields [23,24,37,38,54]. Furthermore, as a matter of fact, expected benefits of technologies are critical for increasing the adoption rates [24,31,38]. Similarly, we also found that farmers having higher perceived benefits of SWC practices were taking up and using conservation measures. In line with our prior anticipations, we noticed that social networks (frequency of interaction) had a favorable bearing on the decision to use SWC practices. This facilitates the exchange of views and experiences and also facilitates sharing of resources, which is essential for community-based soil and water conservation efforts/programs. A positive role of social capital on the adoption of agricultural technologies was reported [42–44]. Training also had a positive effect on adoption, and this finding is in line with earlier studies [56,57]. Lastly, EXTENSION had a positive effect, as anticipated, on decision to adopt SWC practices. Similar findings were also reported by many researchers [24,28,29,31]. These studies suggested that access to an effective extension service helps not only realize the detrimental effects of land degradation but also sensitize about the availability of suitable technologies.

3.3. Impact of Soil Bunds on Net Revenue, Variance and Down-Side Risk

The AIC criterion was 2684.9, 2688.8, 9583.8 and 2693.6 for linear-log, Cobb–Douglas, quadratic and translog-log specifications, respectively. The corresponding BIC criterion was 2837.7, 2843.3, 9767.2 and 2877.0, respectively. Therefore, the linear-log specification was the chosen model for the mean function. To manage the heteroscedasticity in the model, the robust standard error (Huber–White estimator) was used. In the chosen model, multicollinearity was not a serious issue, as is evident from VIF (variance inflation factor) values for all the explanatory variables, which were ranging between 1.02 and 3.5. Firstly, the ordinary least square (OLS) was used to determine the effect of soil bund adoption on mean return, variance and skewness. OLS is the simplest approach to investigate the effect of adoption that includes a dummy variable equal to 1 if the farm household adopted it and 0 otherwise. Results from OLS suggest that soil bund adoption had a positive, statistically significant effect on returns and skewness and negative effects on the variance (Table 3). These results indicate that soil bund adoption increased the crop revenue by INR 9.26 thousand per ha, and it was significant at a significance level of 1%. Furthermore, adoption of soil bunds reduced the variability in crop revenue indicated by the negative coefficient (−49.37) of BUND in the variance equation (p -value < 0.05), which also amounts to saying that it reduced variability in crop yields, as prices are assumed to be given. This has an important implication in rainfed areas, which suffer from the higher variability of the crop yields. Moreover, the coefficient of BUND in the skewness model was positive, showing that adoption of soil bunds reduced the downside risk, i.e., crop failure. As the region frequently faces moderate to severe droughts, consequently, crop failure is also common. Therefore, it can be stated that adoption of soil bunds not only enhanced returns but most importantly served as insurance for farmers by reducing the variability and minimizing the risk of crop failure. However, OLS results are not reliable, being biased and inconsistent estimates. This is due to the fact that OLS assumes that soil bund adoption is exogenously determined, although it is a potentially endogenous variable. To surmount the challenges of sample selection bias and missing data, we used IPWRA, PSM and IPW.

Table 3. Ordinary least square (OLS) estimation of mean, variance, and skewness equations.

Variable	Mean Equation		Variance Equation		Skewness Equation	
	Estimate	Robust Std. Error	Estimate	Robust Std. Error	Estimate	Robust Std. Error
Intercept	100.314 ***	13.260	406.016	411.116	0.282	2.909
BUND	9.26 ***	0.730	−49.37 **	20.53	0.255 **	0.162
AGE	0.001	0.028	0.799	0.858	0.000	0.006
EDU	−0.023	0.080	−1.250	2.478	−0.003	0.018
FAMLIY	−0.090	0.167	−6.154	5.169	−0.062 *	0.037
LANDHOLDING	0.795 ***	0.187	7.571	5.811	0.023	0.041
CREDIT	5.749 ***	0.844	43.173 *	26.173	0.226	0.185
FAI	1.621	2.340	−83.433	72.564	−0.634	0.513
LIVESTOCK	−0.350 **	0.168	−7.288	5.194	−0.068 *	0.037
TENURE	2.309 ***	0.782	39.827	24.261	0.230	0.172
Slope	1.714 **	0.790	33.370	24.492	0.023	0.173
EROISONHIGH	1.101	0.902	42.337 *	27.956	0.312 *	0.198
EROISONMED	−5.241 ***	0.906	−19.793	28.100	−0.061	0.199
FERTIHIGH	5.242 ***	1.068	44.471	33.121	−0.076	0.234
FERTIMEDIUM	−2.225 **	1.003	−30.797	31.101	−0.353 *	0.220
TRANI	0.350	0.745	17.427	23.085	0.079	0.163
BPI	1.527 ***	0.495	3.484	15.353	−0.061	0.109
EXTENSION	1.227 ***	0.256	−0.997	7.951	−0.026	0.056
Log EXPHL	−1.649	1.126	−3.256	34.907	−0.052	0.247
Log EXPBL	2.304 ***	0.560	55.225 ***	17.365	0.390 ***	0.123
Log EXPMACHINE	−1.394 **	0.560	−21.593	17.365	−0.037	0.123
Log EXPSEEDS	−5.647 ***	0.711	−4.661	22.043	−0.009	0.156
Log EXPFERTI	−1.667 **	0.514	−21.596	15.949	−0.111	0.113
TUMKUR	−1.633	1.153	−18.516	35.736	−0.287	0.253
BIDAR	1.550	1.490	20.290	46.193	0.199	0.327
GADAG	3.731 **	1.411	41.014	43.747	0.258	0.310
F-statistic	103.6 ***		8.201 ***		2.334 ***	

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively. Skewness was rescaled by dividing by 100,000.

Before discussing the results, first, there is a need to examine the quality of balancing of covariates. It can be seen from Figures 1 and 2 that after matching, there was a good overlap and common support in propensity scores.

Similarly, after weighting, the standardized mean differences (for continuous variables) and differences in proportion (for binary variables) were less than 0.05 for all the covariates, indicating that all the covariates achieved a good balance.

ATT results in IPWRA indicate that soil bunds helped in increasing the revenue by INR 8.05 thousand per ha. From the results of different approaches, it can be stated that an increase in net revenue could be between INR 7.31 and 9.25 thousand per ha (Table 4).

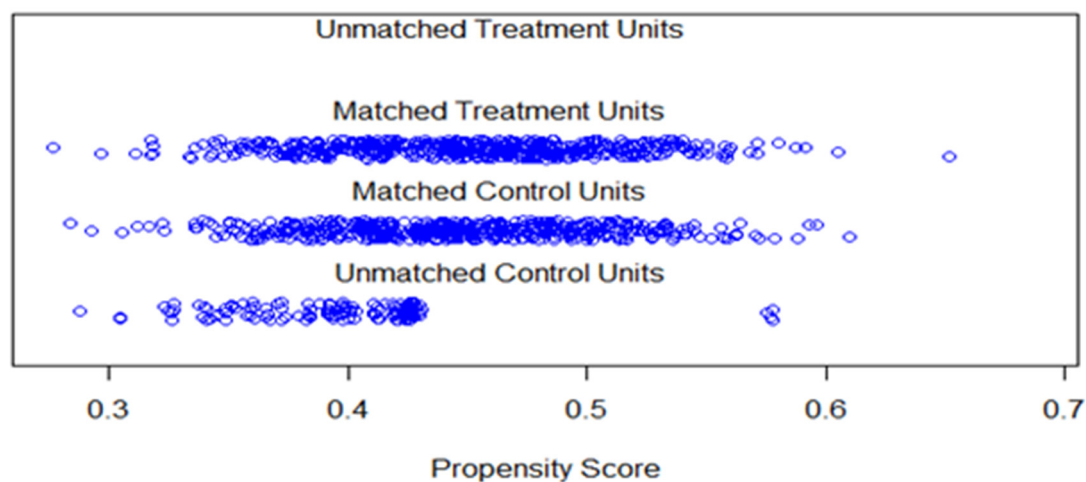


Figure 1. Distribution of propensity scores of treated (adopters) and controls (nonadopters).

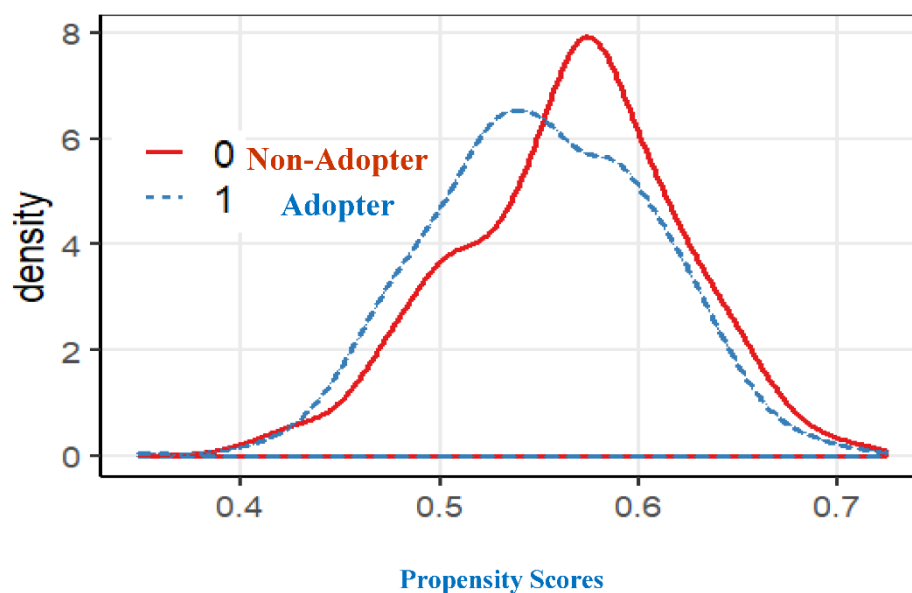


Figure 2. Distribution of propensity scores of treated (adopters) and controls (nonadopters) showing the common support.

The significant effect of soil bund technology on productivity is in accordance with other studies [58–60], which showed that soil and water conservation had a positive impact on productivity. Furthermore, the coefficient of variance was negative and statistically significant, which implies that adoption of the soil bunds reduces the variability of the crop revenue. Soil bunds reduced the variance between 30% and 50% points. This finding confirms earlier findings by [15] that soil bunds improved productivity and reduced the risk particularly in the low-rainfall areas. Moreover, adoption of soil bunds was positively and strongly related to the skewness, indicating that adoption of soil bunds hedged against the risk of crop failure. To check the robustness of the results, other approaches, viz., matching and IPW, also confirmed the findings of the IPWRA. Soil bund adoption was associated with significant positive skewness, increased crop revenue and reduced production risk, contributing to an improvement in sustaining crop production in the semiarid drought-prone areas, which are also facing the challenges of increasing climate variability. Therefore, this has important policy implications for encouraging the adoption of soil bunds in particular and soil and water conservation practices in general as an important risk-mitigation option.

Table 4. Impact of soil bunds on mean crop revenue, variance and skewness.

Methods	Treatment Effects	Mean		Variance		Skewness	
		Estimate	Robust SE	Estimate	Robust SE	Estimate	Robust SE
Matching (CEM [#])	ATE	8.88 ***	1.52	−29.16	27.72	0.27 *	0.15
	ATT	8.40 ***	1.69	−32.05	28.55	0.27 *	0.15
Matching (OPT [#])	ATE	7.12 ***	1.44	−45.33 *	24.65	0.25 *	0.14
	ATT	7.31 ***	1.31	−47.65 **	22.88	0.27 *	0.15
Matching (NNM [#])	ATE	8.73 ***	1.29	−45.56 *	24.82	0.34 **	0.15
	ATT	9.25 ***	1.41	−51.07 **	23.02	0.31 **	0.14
IPW	ATE	8.14 ***	1.40	−47.15 **	22.15	0.29 **	0.14
	ATT	7.93 ***	1.34	−43.29 *	24.17	0.32 **	0.15
IPWRA	ATE	7.97 ***	1.22	−46.82 **	21.75	0.30 **	0.14
	ATT	8.05 ***	1.26	−44.32 *	23.41	0.32 **	0.15

Note: ***, ** and * represent significance levels at 1%, 5% and 10%, respectively. CEM[#], OPT[#] and NNM[#] stand for coarsened exact matching, optimal and nearest-neighbor matching, respectively. IPW and IPWRA stand for inverse propensity weighting and inverse-propensity-weighting regression adjustment, respectively.

4. Conclusions

This paper illustrates an impact of soil and water conservation practices, i.e., soil bunds, on net revenue, its variability and downside risk, i.e., crop failure. We used primary data from 1204 plots of the semiarid tropics of India, which is facing environmental challenges of frequent droughts, soil erosion, land degradation and climate change and variability. We used the probit model for identifying the key determinants of adoption of soil bunds. The results show that for achieving a widespread adoption of soil bunds in the semiarid tropics, the younger farmers are to be targeted for training programs on soil and water conservation. Furthermore, there is a need to expand the extension services and training facilities, particularly focusing on the benefits of the conservation efforts to encourage farmers to take up soil and water conservation measures. As a majority of the farmers in the study area are resource-poor, for improving their financial capacity, there is a need for expanding credit facilities. Moreover, soil and water conservation programs should emphasize strengthening social networks for successful conservation outcomes. We also used the moment-based approach for estimating the crop revenue, its variability and downside risk exposure. Furthermore, we used a doubly robust method (IPWRA) for assessing the impact of soil bunds on crop revenue, its variability and downside risk. We found that soil bunds not only improved the crop revenue but also reduced its variability, leading to more stability in yields. This has an important implication for the semiarid tropics (SAT) witnessing erratic rainfall and frequent droughts. Most interestingly, we have also observed that soil bunds also reduced the chances of downside risk, i.e., crop failure. Therefore, in view of increasing climate change and variability in the semiarid tropics, it can be suggested that soil bunds could be an important adaptation strategy for sustaining crop production. To sum up, this paper supports the investment in soil and water conservation technologies for sustaining the livelihood of resource-poor farmers dwelling in the ecologically fragile regions such as the semiarid tropics.

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