Soil and Water Conservation Measures and Rainfed Agriculture in Telangana, India: Role of Community and Neighborhood Conservation Measures

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Abstract

Soil erosion is a significant problem in rain-fed areas in India. The study attempts to evaluate the causal effects of on-farm soil and water conservation (SWC) measures on farm profit and yield. The study uses the inverse-probability-weighted regression adjustment (IPWRA) method to assess the causal impact of SWC measures on agriculture output while controlling socioeconomic, institutional, and village-level characteristics. The results suggest a significant difference in overall agricultural profit, crop-wise profit, and crop-wise yields among the adopters and non-adopters of the SWC measures. The study highlights that there is a complementarity between the causal impact of community-level SWC measures and individual SWC measures on agricultural outcomes. Further, the neighbor's adoption of SWC measures plays a pivotal role on farmer's agricultural profits. The study highlights that farmer's profit for rainfed crops such as maize further increases if their adjacent neighbors also undertake SWC measures. Such complementary effects, however, are not observed in case of irrigated crops such as paddy.

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JEL Classification: Q24; C21; C11

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1. Introduction

A healthy land ecosystem is the backbone for the rural livelihoods in developing countries. Over the last few decades, unsustainable land management practices have led to extensive land degradation worldwide (MEA, 2005; Brevik et al., 2015; Tesfayohannes et al., 2022). Regarding on-site impacts, it is widely acknowledged that soil erosion will reduce agricultural yield and productivity and pose a significant challenge in India (Kumar et al., 2019; Dayakar, 2021). Moreover, beyond a certain threshold, soil erosion can make the soil cover regeneration process difficult and affects future livelihood options. Therefore, the link between on-farm soil erosion and agricultural productivity has intra-generational and intergenerational implications. Soil erosion also leads to significant negative externalities such as water pollution, soil water carrying capacity reduction, and disturbs hydrological cycles (Somanathan, 1991; Mbaga-Semgalawe & Folmer, 2000).

In economic terms, India's land degradation cost is estimated to range from 0.25% to 2.54% of GDP in 2019 (Mythili & Goedecke, 2016; TERI, 2018; Dayakar, 2021). Within India, Telangana is one of the states that witnessed significant land degradation over the years. According to the Desertification and Land Degradation Atlas of India (SAC, 2016), Telangana ranked 4th among major Indian states, with 25% of the total geographic area (TGA) classified as degraded. Soil erosion is a significant contributor to cropland degradation in Telangana and accounts for US$ 835 million in the cost of degradation (Dayakar, 2021). Biswas et al. (2015) show that Telangana witnesses moderate soil erosion rate of around 5-10 Mg ha-1 yr-1. With rainfed agriculture being Telangana's dominant mode of cultivation, the state is vulnerable to soil erosion and declining agricultural productivity.

However, the soil erosion problem can be addressed through proper on-site and off-site soil and water conservation (SWC) measures. Over the past four decades, successive governments have undertaken several SWC measures at the sub-watershed or community level to prevent land degradation caused by soil erosion in India. The growing body of literature suggests that farmers are the main stakeholders of soil conservation and undertake on-site SWC measures based on their perceived level of soil erosion on their plots[2] (Dayakar and Kavi Kumar, 2021).

[2] The literature on farm-level conservation measures adopted by the farmers to prevent soil erosion refers to such measures interchangeably as 'soil conservation measures' and 'soil and water conservation measures', given the close linkages between conservation of soil and water resources. Keeping this in view, the present study refers to farm-level conservation measures as soil and water conservation measures.

Similar to SWC measures undertaken at the community level, the conservation practices adopted by the individual farmers could benefit their neighbors and lead to significant positive externalities. The SWC measures provide benefits ranging from local (*crop yield improvement*), and regional (*flood control*) to global level (*carbon sequestration*) and can be both short-term and long term in nature (Lal et al., 2001; Bouma et al., 2007).

Against this background, the present study attempts to analyze the causal impact of SWC measures on agriculture output in rainfed areas of Telangana in India. The analysis is based on data collected through a primary survey undertaken in two sub-watershed areas of Siddipet district in Telangana, India. The rest of the paper is organized as follows: A brief literature review is provided in the next section. Section 3 provides details about the study area and data collection. The methodological framework is discussed in section 4. Section 5 provides the data description and summary statistics. The following section discusses the results. Finally, section 7 concludes the paper.

2. Review of Literature

A large body of literature acknowledges that adopting SWC measures improves crop revenues across the globe (Abebe and Bekele, 2014; Datta, 2015; Meaza et al., 2016; Singha. C, 2019; Siraw et al., 2020; Suresh Kumar, 2020; Tesfayohannes et a., 2022; Adere et al., 2022; Abrham Belay, 2023; Adebayo Isaiah Ogunniyi et al., 2023). Theoretically, farmers implement SWC measures by comparing the cost of SWC investment with the benefits of avoiding soil erosion losses. The profitability of SWC measures is site-specific and depends on adopted technologies, input costs, and output prices. Lutz et al. (1994) argue that the farmers' choice can be viewed as a choice between two different agricultural practices– for instance, practicing a traditional agricultural system where conservation practices are limited or choosing an alternative system, which involves a greater number of SWC measures. From the farmer's perspective, higher profits under the new agricultural system than those under traditional agricultural practices would justify incurring additional costs of implementing SWC measures.

Investing in appropriate technologies to prevent soil erosion will improve soil fertility and agricultural outcomes. Bizoza and Graaff (2012) conducted a study in hilly areas of Rwanda to examine whether adopting bench terracing improves productivity in agriculture and found that bench terracing improves soil fertility and increases net benefits at the farm level. Kumar et al. (2020) conducted a study in the semi-arid tropics of India to examine whether adopting soil bunds improves farmers' profitability in agriculture and found that soil bunds improve crop revenue and reduce the chances of downside risk. Singha C (2019) highlighted that vegetative soil conservation practices (afforestation/bamboo planting) improved farm profit and reduced variable cost in the Darjeeling district of West Bengal, India. Ogunniyi et al. (2023) in a study based in Nigeria argued that SWC practices improved crop productivity and household welfare respectively, by 28 and 38 percent. Similarly, Tesfayohannes et al. (2023) found that adoption of SWC practices increased average household income by 422 ETB in southern Ethiopia. Further, Meena et al. (2020) found that adopting SWC measures not only improves farm income, but also helps in enhancing water use efficiency, soil fertility, and biological regime. The impact of onsite SWC measures may have differential effects on different crops, which the studies based on aggregate outcomes often fail to capture.

Empirical literature has identified that predominant factors, including plot-level and household characteristics, community level, and neighbors' activities, influence farmers' decisions to adopt SWC measures. The impact of SWC measures on agriculture productivity may also differ in the presence of community (i.e., watershed) level conservation activities (Datta N, 2015; Nyssen et al., 2015; Yaebiyo et al., 2015; Gebregziabher et al., 2016; and Meaza et al., 2016; Singha C, 2019; Siraw et al., 2020). Agricultural crop yields depend on various localized factors, including soil type, soil quality, and land topography (Dayakar & Kavi Kumar, 2021). The SWC practices are also location specific, with some SWC practices more suitable for certain land categories. Thus, farmers operating on adjacent fields may exhibit similar behavior regarding adoption of SWC measures (Holloway & Lapar, 2007; Singha C, 2019; Dayakar & Kavi Kumar, 2021). However, neighborhood influence is often not measured, resulting in biased estimations. A set of empirical works explored the role of neighborhood conservation practices on farm level agricultural outcomes. These studies largely analyzed the role of neighbors on farmer's decisions to adopt a given technology by using statistical techniques (Abdul B.A. et al., 2011; Wang et al., 2013; Teklewold et al., 2014; Lapple & Kelly, 2015; Singha C, 2019; Xu-Chao Zhu et al., 2019). However, empirical literature did not comprehensively address the extent of influence the neighborhood SWC practices would have on agricultural outcomes.

Keeping these aspects in view, the present study attempts to assess the impact of SWC measures on crop profit and yield. It explores the role of community interventions and neighbors' conservation practices on agricultural outcomes. The inverse-probability-weighted regression adjustment (IPWRA) approach is adopted to measure the impact of SWC measures on farm-level agricultural profit and crop-wise profit and yield. These objectives are analyzed using the data sourced from a primary survey of farmers in the rainfed watershed areas of Telangana, India.

3. Study Area and Data Collection

31. Study Area[3]

The study was undertaken in two mandals of Siddipet district in Telangana, India (see Fig. 1). The selected area falls within the region highly vulnerable to drought with annual average rainfall of 650 mm, over 80% of which is received during the monsoon months June to September (Government of Telangana, 2015). The area is the part of Godavari River basin with moderate level of soil erosion reported based on satellite data (Bhuvan & Department of Land Resources, 2017). Purposive sampling method was followed to select study area and villages, to account for wide variation across villages in terms of soil and water conservation technology experience, soil erosion status and socio-economic heterogeneity. Twelve villages were selected from two mandals[4] (viz., *Chinnakodur* and *Dubbak*) of Siddipet district for the field study; six villages are located in the sub-watershed area of these mandals and are part of integrated watershed management program (IWMP)[5]. Other six villages are also located in the same sub-watershed areas, but not covered by the IWMP program. Biophysical, topographical, and hydrological conditions are broadly similar among selected villages. Selected villages are dominated by red loamy, red sand loamy, saline, and black soils. Paddy, maize, cotton, red gram, and vegetables are major crops cultivated in the area.

Soil erosion leads to nutrient loss, which ultimately reduces agriculture productivity and yield. Therefore, farmers traditionally practice SWC measures to control their perceived level of soil erosion (Kumar et. al, 2015). Field level observations in the study area reveal that farmers adopt *contour ploughing, grass bunds, soil bunds, drainage ditches, silt application (i.e., collected from tanks) and plantations (example, woody vegetation)* to prevent soil erosion.

[3] More details on the study area and data collection process are provided in Dayakar and Kavi Kumar (2020, 2021).

[4] Mandals are administrative subdivision of district in a state.

[5] Under IWMP program numerous activities are undertaken to restore the ecological balance by harnessing, conserving, and developing degraded natural sources such as soil, vegetation cover and water.

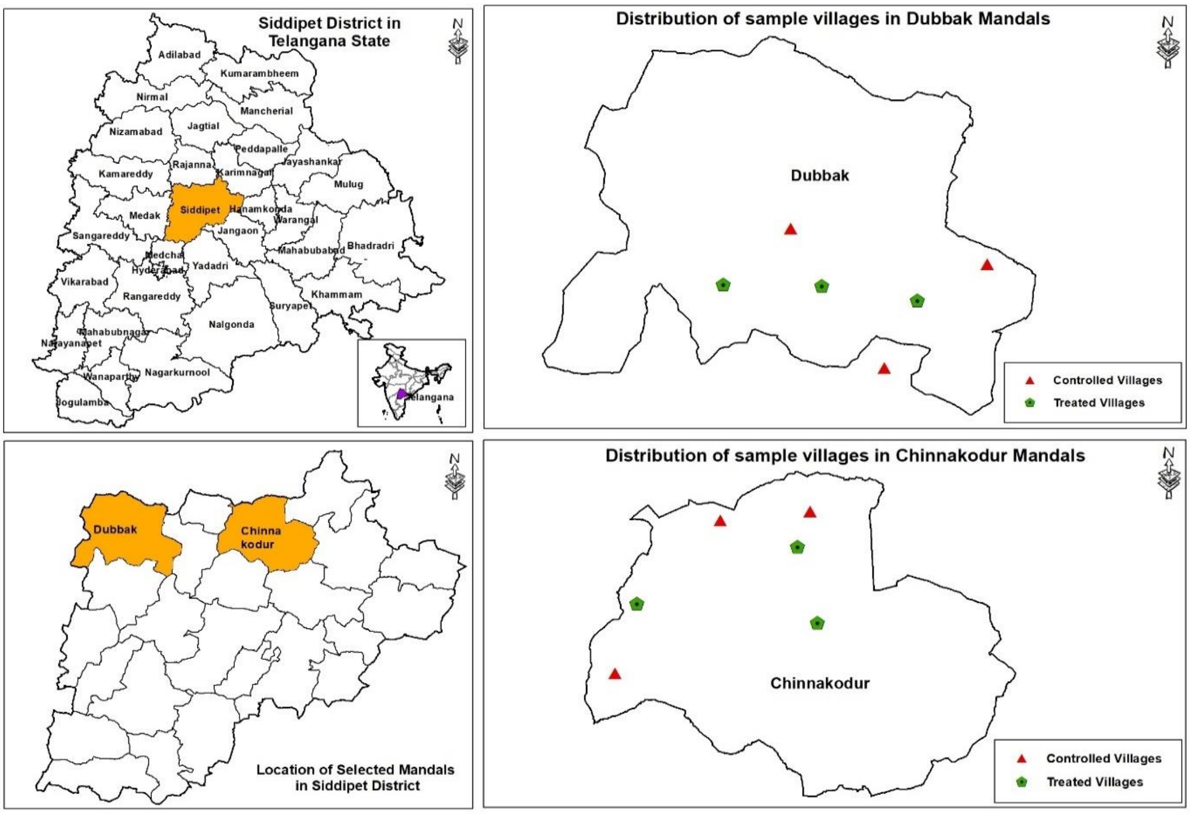

Figure 1: Location of Study villages in Telangana

3.2. Data sampling

The data used in the study came from household and plot level surveys of around 400 farmers in two mandals of Siddipet district in Telangana. The survey was conducted during January-March 2018. The Census data (2011) showed that the geographical and population characteristics differ across the villages. The number of households selected for survey in the villages is based on the proportion of households in each village to the aggregate number of households across all the selected villages. Thus, the total number of sampled households from the villages ranged between 13 and 67. In each village the list of households has been compiled from revenue and agricultural departmental data sets. Once the number of households was determined, the specific survey households were selected based on simple random sampling. The final sample consists of 206 households from the IWMP-covered villages, and 197 households from non-IWMP villages.

4. Methodological Framework

Farmers' decision to adopt SWC measures can be assessed using a random utility framework followed in earlier studies (e.g., Becerril & Abdulai, 2010; Kassie et al., 2015; Khonje et al., 2015; Zheng et al., 2021). The "fundamental problem of causal inference is that it is not possible to observe each individual having received the treatment and not having received the treatment from the observational data, and only one of the two potential outcomes is observed at any given time" (Holland, 1986). The randomized control trails (RCT) approach is the best suited framework for causal inference analysis, in which SWC measures are assigned randomly to a group of farmers while a control group of farmers cultivate without those specific interventions. Despite being the most appropriate approach, RCT is rarely implemented in practice in the context of SWC practices (Holland, 1986). In the absence of randomization in the observational data, empirical literature often employs the Propensity Score Matching (PSM) and Inverse-Probability-Weighted Regression Adjustment IWPRA methods (Singha C, 2019; Dayakar, 2021; Zheng et al., 2021). The present study adopts IPWRA approach to deal with the missing counterfactual problem. The main components of IPWRA are individuals (i.e., farmers here), potential outcome and treatment effect. Here, adopters are specified as those who have undertaken at least one SWC measure among seven possible measures[6]. In the case of binary framework treatment is specified as follows:

$$T_i = 1 \; if \; the \; farmer \; 'i' is \; an \; adopter \; of \; SWC \; measures$$

$$T_i = 0 \; if \; the \; farmer \; 'i' is \; non \; adopter \; of \; SWC \; measures$$

The treatment effect for adopter *i* can be written as:

$$T_i = Y_i\,(1) - Y_i\,(0) \;\ldots\ldots\ldots\; (1)$$

The only potential outcome is the differential between $Y_i\,(1) - Y_i\,(0)$. However, here we observe only potential outcome for adopter *i*. The counterfactual outcome comes from unobserved non-adopter *i*. The individual treatment effect is not possible here. The average treatment effects are the difference between expected farm outcomes between adopters and non-adopters.

$$ATE = E[(Y_{\mathrm{i}}(1)|\mathrm{T_i} = 1)] - E[(Y_{\mathrm{i}}(0)|\mathrm{T_i} = 0)] \ldots \ldots \ldots (2)$$

where Y_{i} is the outcome variable of farmer, i.e., aggregate farm profit, crop wise profit and crop wise yield. Adoption of SWC and the realization of outcome variables may get influenced by several explanatory variables (Heckman *et al.,* 1999; Caliendo and Kopeinig, 2008; Zheng et al., 2021). Therefore, the estimation based on equation 2 leads to biased results. Ideally, outcomes on farms with SWC measures do not represent the outcomes on farms without SWC measures due to the non-random and voluntary nature of adoption and which leads to selection

[6] Through focus group discussions, it was observed that in the field study area farmers have been practicing eight SWC measures including, contour ploughing, *silt application, construction of grass bunds and stone bunds, drainage ditch, farm ponds, slope leveling, and growing woody perennials*. Since most of the farmers (more than 58 percent) practice counter ploughing, it has been excluded from the set of SWC measures considered for the analysis.

bias (Caliendo and Kopeinig, 2008). The matching approach is one possible way to overcome selection bias. The adoption decisions based on observables, once accounted for makes it possible to construct for each adopter of SWC measures a comparable group of non-adopters who have similar characteristics. The IPWRA method relies on *conditional independence assumption (CIA), or stable unit treatment value assumption (SUTVA)*, and *common support assumption* in estimating the treatment effects (Caliendo and Kopeinig, 2008). The probability of adoption lies between '0' and '1' for both adopters and non-adopters. The common support assumption ensures that the farmer with the same observable covariates, can be both adopter and non-adopter with a positive probability. The implication of above assumptions are that no unobservable factors influence adoption and agricultural outcomes (viz., farm profit and crop wise yield) (Caliendo and Kopeinig, 2008). Another implication is that one farmer's adoption of SWC measures does not exclusively depend on another farmer's adoption. Once these assumptions are satisfied, the matching technique can be used to match adopters and non-adopters and create counterfactuals. The Average Treatment on Treated Approach (ATT) is written as:

$$ATT = E[(Y_{\mathrm{i}}(1)|\mathrm{T_i} = 1, X)] - E[(Y_{\mathrm{i}}(0)|\mathrm{T_i} = 1, X)] \dots\dots\dots (3)$$

However, since there are a large set of covariates, matching on covariates could be difficult and it can be resolved with the use of propensity scores (Hahn, 2010). The IPWRA estimator for ATT can be specified as follows:

$$ATT = E[(Y_i(1)|T_i = 1, P(X)] - E[(Y_i(0)|T_i = 0, P(X)] \dots\dots\dots (4)$$

where, $P(X) = P(\mathrm{T_i} = 1|X)$ is the propensity score, i.e., the conditional probability for a farmer to adopt SWC measures given his observed covariates 'X'. Due to large number of observed covariates, the problem arises while matching. The literature refers to this as "the curse of dimensionality" (Caliendo and Kopeinig, 2008; Hahn, 2010). This can be resolved "if we can control scalar value function of observable covariates, namely, propensity score" which is generated from all covariates in vector X, to create counterfactual (Hahn, 2010). Here the propensity score is a function of plot level, socio-economic, village and community level characteristics. Therefore, ATT is the mean difference of agricultural outcome (i.e., *aggregate profit, crop wise net profit and crop wise yields*) between adopters and non-adopters.

4.1. Estimation Method

The study utilized an inverse-probability-weighted regression adjustment (IPWRA) approach to analyze the causal impact of SWC measures on agricultural aggregate profit (i.e., profit accrued through cultivation of major crops paddy, maize, and cotton), crop-wise profit (i.e., profit obtained by cultivating paddy, maize and cotton separately) and crop-wise yields. The IPWRA approach utilizes weighted regression coefficients to estimate treatment effect, in which the "weights are the estimated inverse probabilities of treatment" (Wooldridge, 2010). The IPWRA approach involves three steps while estimating treatment effects. First, the probability of adopting SWC practice (i.e., the treatment model) is estimated using a simple logit regression model. The predicted probabilities are utilized in estimating the inverse-probability weights. The potential predictors are based on detailed review of the literature, and these include (a detailed description is provided below) plot level, household socio-economic, village level characteristics, and market and institutional variables (i.e., watershed activities). Second, the model used kernel matching technique to compare adopters and non-adopters (Caliendo and Kopeinig, 2008; Crump et al., 2009). Finally, the average outcomes for adopters and non-adopters are estimated, and the difference between these average outcomes provides the estimate of the treatment effects. The 'IPWRA' estimators combine models for the outcome and treatment status and 'IPWRA' estimators emerge naturally from a robust approach to missing-data methods. The 'IPWRA' estimators are also known as double-robust estimators (Wooldridge, 2007; Wooldridge, 2010).

5. Data and Descriptive Statistics

As shown in Table 1, paddy, maize, and cotton are the main crops cultivated in both rainy season and non-rainy seasons. Though the farmers in the study area cultivated redgram and vegetables also, due to paucity of data on these crops the study focused on paddy, maize, and cotton crops for the analysis. Further, the analysis is restricted only to *Kharif* (rainy) season due to a thin sample data representation in *Rabi* (non-rainy) season. As can be seen from Table 1, the mean value of profit significantly differs among adopters and non-adopters of SWC measures during the *Kharif* season for all principal crops.

5.1. Explanatory Variables

The explanatory variables used to generate the propensity score (i.e., the probability of SWC adoption) include, (a) plot-level characteristics such as area of the plot, soil type, level of erosion, irrigation, crop intensity (*i.e., the ratio of gross cropped area to net cropped area)*, and crop diversity (Herfindahl index)[7], connectivity factors including distance of the plot to the dwelling, road connectivity, and distance between the plot and the market;

[7] The Herfindahl index (HHI) represents "crop diversification and is estimated as the summation of all squared area shares occupied by crop/s in total cropped area. The value of this index varies from zero to one. It takes the value of one when there is full specialization and approaches to zero when there is full diversification". The detailed description of the index provided in Datta (2015).

Table 1: Summary Statistics of Crops Yield and Profits across Adaptors and Non-Adaptors

Crop season	Variable	Full sample	Adopters	Non-adopters	Mean difference (Adopters-Non-adopters per acre)
	Number of observations				
	All crops	403	206	197	
Rainy season	Paddy	263	135	128	
	Maize	236	136	100	
	Cotton	115	56	59	
	Per acre profit (in INR)				
	All crops	24412	27147	21552	5594***
	Paddy	17611	18783	16375	2408**
	Maize	10422	12135	8091	4044 ***
	Cotton	15691	16160	14566	914*
Non-rainy season	**Number of observations**				
	Paddy	141	48	93	
	Maize	16	11	5	
	Soybeans	16	12	4	
	Per acre profit (in rupees)				
	Paddy	20871	25182	18645	6537***
	Maize	20275	23381	13440	9941
	Soybeans	18668	20308	13750	6558

Source: Author's own calculations based on field study data; ***, **, *Significant at 1%, 5%, and 10% probability level, respectively

b) socioeconomic characteristics including experience of household head, sex of household head, formal years of education of the household head, household size and social status; and (c) village level characteristics such as community level SWC measures implemented through IWMP programme, extent of barren land, pastures, and current fallow land in the village where the plot is located.

Table 2: Summary of Explanatory Variables of Adopters and Non-Adopters

Variable	Definition of the variable	Adopters N=204		Non-Adopters N=199		Total Sample N=403	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Plot level characteristics							
Area of the plot	Cultivated area (in acres)	3.83	2.76	2.91	2.08	3.37	2.48
Crop intensity	Crop intensity index	6.47	1.95	6.64	2.12	6.55	2.03
Crop diversity	Crop diversity index	0.55	0.18	0.43	0.25	0.49	0.23
Socio economic variables							
Sex	Gender of the household (1=Male; 2=female)	1.09	0.29	1.14	0.34	1.11	0.32
Education	Years of education of household head (in years)	4.92	5.39	5.67	5.75	5.29	5.57
Years of experience	Years of farming experience (in years)	32.28	15.6	31.61	14.11	31.95	14.87
Household size	Size of the household (in numbers)	4.62	1.98	4.42	1.87	4.52	1.93
Market access variables							
Distance	Distance to dwell (in km)	2.24	0.46	2.21	0.48	2.22	0.47
Market distance	Distance to market (in km)	8.33	9.09	7.99	9.85	8.16	9.46
Village level characteristics							
Intervention	Watershed intervention (1=Yes; 0=No)	0.73	0.45	0.29	0.46	0.51	0.50
Barren	Barren uncultivable land at the village level (in %)	3.71	3.41	3.20	2.44	3.46	2.98
Pastures	Permanent pasture lands at the village level (in %)	0.77	1.30	0.56	0.84	0.67	1.10
Current	Current fallow lands at the village level (in %)	7.58	6.13	6.79	6.09	7.19	6.12
Other	Other fallow lands at the village level (in %)	10.79	5.92	8.88	5.22	9.84	5.66

Source: Author's own calculations based on field study data

Table 2 provides a summary of explanatory variables described above among the 'adopters' and 'non-adopters'. More than 80% of household heads are male among both adopters and non-adopters. Overall, farmers who adopt SWC measures are less educated (with mean of 4.9 years) compared to non-adopters (with mean of 5.67 years). The average years of farming experience of adopters is slightly higher (32.28 years) than non-adopters (31.61 years). The average family size is similar across the adopters and non-adopters. The average area of the plot is 3.83 acres for adopters and 2.91acres for non-adopters. Farmers who adopt SWC measures perceive greater soil erosion of their plots than the non-adopters. The average crop intensity on SWC adopting farms is lower (6.47) than non-adopting farms (6.64). The farmers implementing SWC measures have on average greater crop diversity on their farms compared to those who have not implemented SWC measures. The average distance of the plot to farmer's dwelling is more than 2 km among households in the study area. The mean distance of the farms to the market is nearly 8 km. The percentage of barren, pasture, current fallow and other fallow is 2.9%, 1%, 6.12% and 5.66%, respectively across the villages in the study area.

5.2. Neighborhood Data

The adoption of on-site SWC measures by the neighboring farmers could influence a farmer's decision to implement SWC measures and hence her agricultural outcome. The detailed information about the SWC activities in all the adjacent neighboring plots (for each of the farmer/plot surveyed) has been collected through primary survey. The adjacent neighbors of a farmer are defined as those whose plots share boundary with the plot of the surveyed farmer. The neighborhood variable was generated in two levels - first, if more than 50% of neighboring plots adopt a specific SWC measure, then the neighbors of the respondent are considered to have adopted that specific SWC measure (and coded as 1), and otherwise not adopted (and coded as 0). Second, if neighbors adopt more than one specific SWC measure then neighbors are considered to have undertaken SWC measures, otherwise not[8]. The neighborhood data is used to analyze scope for complementarity between SWC measures adopted by farmers and those adopted by his/her neighbors.

5.3. Outcome Variables

Two outcome variables, namely profit and yield per acre during the monsoon season are considered as relevant outcome variables in this study. Profit is estimated at aggregate level (i.e., over the crops paddy, maize, and cotton) and at individual crop level. Aggregate level profit equals the revenue from the three major crops cultivated in the study area minus crop wise input cost and annualized implementation cost of SWC measures[9]. The implementation costs of SWC measures have not been accounted for in the crop-wise profit calculations, due to difficulty in attribution of SWC measure to individual crops. Though data for the non-rainy season has also been collected, as already mentioned, the analysis is restricted to monsoon season only due to data limitations.

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[8] We have collected the data on neighbor's SWC activities from surveyed farmers based on their observation about neighbors on-site SWC adoption activities. The detailed description of neighborhood data is provided Dayakar and Kavi Kumar (2021) which utilized the same data set.

[9] Aggregate agricultural profit = [{{(total revnue$_{paddy}$-input cost$_{paddy}$) + (total revnue$_{maize}$-input cost$_{maize}$) + (total revnue$_{cotton}$-input cost$_{cotton}$)} – annualized SWC implementation cost}/total cultivated area]. The annualized implementation costs of SWC measures have been assessed based on the methodology suggested by Das (2015).

6. Results and Discussion

6.1. Neighborhood Influence on Crops Yield – Preliminary Results

Table 3 highlights the unadjusted impact of neighborhood influence on maize and paddy crops yields. A simple specification (Model 1) is followed wherein the outcome variable (paddy/maize yield) is explained through various combinations of SWC adoption among the farmers and their neighbors. Two additional variants (Model 2 and Model 3) are also specified with the inclusion of community level intervention, and control variables (e.g., soil type) as explanatory variables.

Table 3: Neighborhood Influence on Maize and Paddy Yields

Outcome variables	**Maize yield**			**Paddy yield**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	(1)	(2)	(3)	(4)	(5)	(6)
Farmer and Neighbor both adopt SWC	7.127*** (0.005)	5.456** (0.035)	5.305** (0.049)	0.756 (0.771)	-0.793 (0.773)	-0.735 (0.789)
Farmer adopts SWC, but neighbor does not adopt SWC	2.665** (0.020)	1.355 (0.247)	1.088 (0.362)	0.381 (0.724)	-0.735 (0.548)	-0.669 (0.581)
Farmer does not adopt SWC, but neighbor adopts SWC	-0.473 (0.863)	-0.971 (0.700)	-1.656 (0.491)	5.090* (0.063)	4.799 (0.117)	4.662 (0.137)
Community level intervention	-	2.933*** (0.002)	3.025*** (0.002)	-	2.518** (0.016)	2.525** (0.019)
Control Variables included	-	-	Yes	-	-	Yes
Constant	13.87*** (0.000)	12.61*** (0.000)	10.33*** (0.000)	19.24*** (0.000)	18.28*** (0.000)	16.00*** (0.000)
Observations	238	238	238	260	260	260

Note: *p*-values in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; irrigation and soil type covariates are controlled in Model 3.

The results suggest that adoption of SWC measures by both farmer and her neighbors significantly increase the maize yields in the study area. Column 1 in Table 3 shows that compared to the base category of both the farmer and her neighbors not adopting SWC measures, maize yields increase by 7.1 quintals if both undertake SWC measures, and the yield increases by 2.7 quintals if only farmer adopts SWC measures, and her neighbors does not undertake such measures. This highlights the complementarity in SWC measures between farmers and their neighbors, in case of rainfed crops such as maize. Models 2 and 3 results suggest that the influence of neighborhood effect becomes weak as other covariates partial out net effect, but the complementarity in SWC measures is still evident. On the other hand, in the case of paddy crop neighborhood influence is negligible at the farm level. This discrepancy can be attributed to the fact that maize crops in the study area are typically rainfed and rely on natural water sources, making SWC adoption more prevalent and impactful for these crops than paddy cultivation. Further, it is important to note that these adoptions of SWC measures and their resulting impact are closely tied to the specific location and the topography of the soil. As a result, we observe complementary neighborhood effects that are more pronounced for maize than paddy cultivation. Overall, the unadjusted estimates reported in Table 3 suggest that the adoption of SWC measures by the farmers and their neighbors' influences rainfed crops like maize and cotton is more due to its nature of cultivation compared to irrigated crops like paddy. The next section explores these results further to rigorously estimate the causal effects.

6.2 IPWRA Model Results

As mentioned above, IPWRA approach is employed to analyze the causal impact of on-site SWC measures on agricultural outcomes, viz., aggregate profit, crop-wise profit, and crop-wise yield per acre[10]. The probability of adopting SWC practice (i.e., the treatment model) is estimated using simple *logit* regression model. The predicted probabilities are utilized in estimating the inverse-probability weights. Plot level, socioeconomic, market access and village level characteristics are used to estimate matching score.

To check the robustness of treatment effect on treated (ATT) models, the conditional independence and covariate balance are tested (using '*tebalanceoverid*' and '*teffects overlap*' user written commands in *Stata*). The results suggest that the assumption of conditional independence is not violated (see Table A.1).

[10] Inverse-Probability-Weighted Regression Adjustment (IPWRA) and Endogenous Switching Regression (ESR) models are common approaches to correct selection bias problem while analyzing causal inferences. IPWRA model estimates based on observable parameters and do not account for unobservable heterogeneity. The ESR model corrects selection bias and the problem of unobservable heterogeneity as well. We employed IPWRA models for causal inference analysis and offered the discussion on estimated results. However, we also estimated ESR model for robustness check and found both IPWRA and ESR models estimated ATT values are reasonably close. This is taken to suggest that the influence of unobserved factors is negligible in the present study. The estimates based on ESR model are reported in Table A.3.

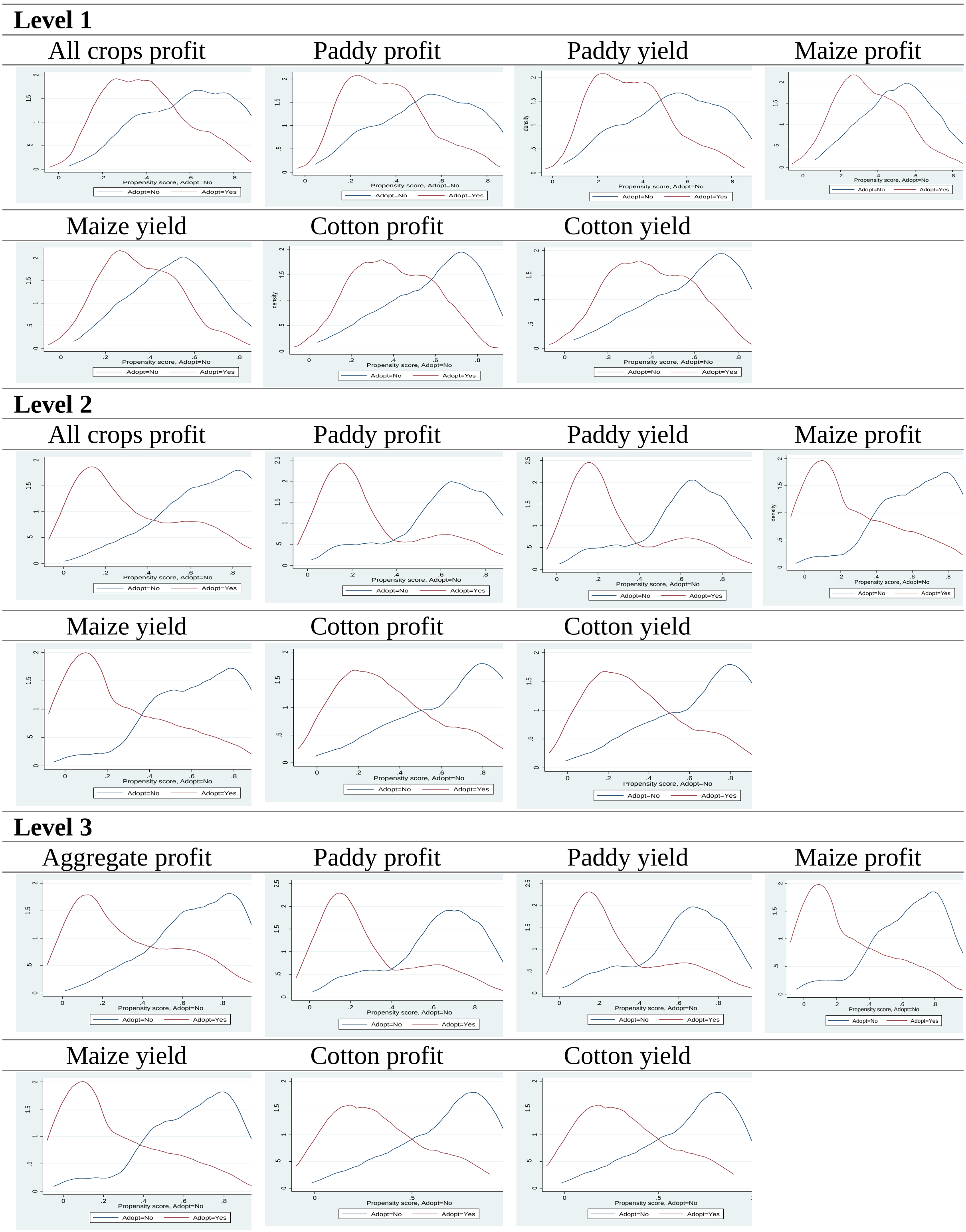

Figure 1: Kernel Density Distribution Showing Overlap between Adopters and Non-Adopters of SWC Measures at Different Levels of SWC Adoption

Note: Kernel Density Distribution is a propensity score distribution and common support region for propensity score estimation. The graph displays the estimated density of the predicted probabilities that an adapter is a nonadopter, and the estimated density of the predicted probabilities that a non-adopter is an adopter. **Level 1** indicates the impact of the adoption of SWC measures on agricultural output without accounting for community intervention and neighborhood effects; **Level 2** accounts for community intervention; **Level 3** accounts for both community intervention and neighborhood adoption of SWC measures.

The results from '*teffects overlap*' tests presented in Figure 2 show the overlap in distribution of propensity scores and satisfy the common support condition. Kernel matching approach is used while testing common support condition assumption. After ensuring matching of the covariates between the adopters and non-adopters, causal impact of SWC measures on aggregate profit, crop-wise profit and crop-wise yields has been estimated[11]. The results suggest that there is a significant difference in total profit, crop-wise profit and crop-wise yields between the adopters and non-adopters during the monsoon season in the study area.

Columns 1&2 in Table 4 report the estimated results for impact of SWC measures on agricultural outcomes. The findings show that the difference between the adopters and non-adopters in total profit attributable to SWC measures is about INR 2110 (at the 5% level of significance) in the study area. Crop wise effect of SWC measures for paddy, maize and cotton are estimated as INR 3500, INR 2910 and INR 5000, respectively, which are 23%, 34% and 39%, respectively of the corresponding baseline profit reported by the non-adopters of SWC measures. The model results show significant crop-wise ATT for yields as 3.26, 2.86 and 1.06 quintals of paddy, maize and cotton, respectively. These ATT are respectively, 19%, 22%, and 20% of the mean value of crop-wise yield of non-adopters' group (see Table 4 & column 2). Further, the results show that model estimated ATT of profit values are more sensitive than those estimated for yields. Maize and cotton crops are more sensitive than paddy according to the estimated ATT values, mostly due to possible extended irrigation facility to crops.

The community level intervention dummy is introduced to check complementarity between community level and individual level SWC measures and its causal impact on agricultural outcome. These results are reported in Columns 3&4 in Table 4. The difference between the adopters and non-adopters in total profit attributable to SWC measures is about INR 2150 (at

[11] As suggested in the literature, the ATT of multiple SWC interventions has also been estimated, however, discussion on the same is not provided here. Low, moderate and high levels of adoption of SWC measures are defined as such interventions when farmer implements at least one measure, 2 to 3 measures, and more than 3 measures, respectively. In case of multiple SWC interventions, comparison is made between adoption of low *vs.* moderate, low *vs.* high, and moderate *vs.* high SWC measures. The results pertaining to multiple SWC interventions are reported in Table A.2 and the overlap test results are reported in Figure A.1.

the 10% level of significance) in the study area, which is around 17% of the baseline profit of the non-adopter group. Crop wise effect of SWC measures for paddy, maize and cotton are estimated as INR 2280, INR 4730 and INR 4400, respectively. These treatment effects on the treated are 14%, 69% and 33% respectively of the mean value of crop-wise profit of the non-adopters group. The estimated results significantly attribute the crop wise ATT for yields at 3.10, 3.63 and 1.24 quintals of paddy, maize and cotton, respectively. These ATT are 18%, 29%, and 25% respectively of the mean value of crop-wise yield of non-adopters' group (Table 4). The overall impact of SWC measures is high in the presence of community level interventions through watershed management programme. The estimated ATT results suggest that the benefits of community level soil conservation measures are greater in maize and cotton farming. However, the results suggest community level interventions are negative on paddy yield and profits, driven perhaps by the irrigated nature of paddy cultivation in the study area.

Further, there is a possibility of positive/negative effect of adjacent farmers' SWC activities on agricultural outcome. Therefore, a neighborhood dummy was introduced to control the neighbors' on-site SWC measures along with the community level intervention dummy. The results are reported in Columns 5&6 in Table 4. The estimated ATT results suggest that neighborhood impact is significant and positive in overall agricultural profit. However, the impact of neighbors' adoption activities differs from crop to crop in the study area. The difference between the 'adopters' and 'non-adopters' in total profit attributable to SWC measures is about INR 2080 (at the 10% level of significance). Crop wise effect of SWC measures for paddy, maize and cotton are estimated at INR 2490, INR 4590 and INR 4900, respectively. The treatment effects on the treated are 16%, 15% and 66% percent, respectively of the mean value of crop-wise profit of the non-adopters group. It is also important to note that the above estimates may be overestimated due to the attribution of benefits from SWC measures exclusively to land degradation remediation. The estimated results show significant crop wise ATT for yields as 3.38, 3.48 and 1.35 quintals of paddy, maize and cotton, respectively. These ATT are 20%, 28%, and 27% percent respectively of the mean value of crop-wise yield of non-adopters' group. Further, estimated results suggests that the impact of adoption of SWC measures on rainfed crops is more due to its nature cultivation compared to irrigated crops like paddy.

It may be noted that owing to the changing base, percentage improvement in profit/yield across different 'Levels' of SWC adoption reported in Table 4 are not strictly comparable. For instance, in case of maize crop, the results reported in Table 4 indicate that compared to non-adopters, the profits are 35 percent higher for the adopters. This further increases to 69 and 66 percent, respectively when community level intervention and neighbor's adoption of SWC measures are also accounted for in the impact estimation. Since the non-adopters group changes based on different levels at which SWC measures are undertaken, the percentage improvements reported are not directly comparable. The direction of improvement, however, remains same even when a static baseline profit is considered. Using the baseline maize profits among the non-adopters reported in Table 1, the comparable improvements in maize profits under different levels at which SWC measure implementation is considered works out as 35, 58 and 56 percent, respectively.

Table 4 Impact of Adoption of SWC Measures on Profit and Yield

Outcome	**Level 1**		**Level 2**		**Level 3**	
	ATT (in ₹)	**Profit (in%)**	**ATT (in ₹)**	**Profit (in%)**	**ATT (in ₹)**	**Profit (in%)**
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate Level Profit	2110** (0.03)	16	2150* (0.08)	17	2080* (0.08)	16
Paddy (Profit)	3500** (0.04)	23	2280 (0.32)	14	2490 (0.27)	15
Paddy (Yield)	3.26*** (0.01)	19	3.10** (0.05)	18	3.38** (0.03)	20
Maize (Profit)	2910** (0.03)	34	4730*** (0.00)	69	4590*** (0.00)	66
Maize (Yield)	2.86*** (0.00)	22	3.63*** (0.00)	29	3.48*** (0.00)	28
Cotton (Profit)	5000* (0.06)	39	4400 (0.28)	33	4900 (0.22)	38
Cotton (Yield)	1.06* (0.08)	20	1.24 (0.19)	25	1.35 (0.15)	27

Note: *p*-values are in parenthesis; ***, **, * are significant at 1%, 5%, and 10% probability levels, respectively: **Level 1** indicates the impact of the adoption of SWC measures on agricultural output without accounting for community intervention and neighborhood effects; **Level 2** accounts for community intervention; **Level 3** accounts for both community intervention and neighborhood adoption.

The on-site SWC measures can serve multiple benefits including prevention of soil erosion, rainwater harvesting, and ground water improvement through infiltration. The empirical literature tends to accredit the benefits of on-site conservation measures to soil erosion prevention only (Kerr et al., 2002; Singha C, 2019). Due to the nature of practice, it is difficult to differentiate the benefits of SWC measures accruing separately to soil health and water levels.

Therefore, there could be an overlap between measures aimed at soil conservation alone and measures focusing on SWC. Thus, the results presented in this study may overestimate the benefits of soil conservation measures. On the other hand, the estimates may also provide an underestimate by considering the implementation of conservation measures to result in improvement of provisioning services only, ignoring regulating, supporting and cultural services from the land ecosystem. The net effect of these biases on the model estimates necessitates further study and provides scope for future research.

7. Conclusions

This study estimated the impact of the adoption of soil conservation measures using a survey of farmers in sub-watershed areas of Telangana. To estimate the causal impact of the adoption of SWC measures, a counterfactual comparison group using matching techniques was created, assuming that it is possible to capture the factors that influence the farmers' decision to adopt SWC measures on their farms. Following this, propensity scores were generated using a logit model to balance the observed covariates. The underlying assumption is that it is possible to capture the factors which influence the farmers' decisions to adopt different category of SWC measures on their own. The matching of both the groups were carried out using the IPWRA method. In addition to assessing the causal impact of farmer's own adoption of SWC measures on agricultural outcomes, the study also estimated the additional benefits emanating from community level conservation measures, and SWC measures implemented by the neighbors of the farmers.

Results suggest that adoption of SWC measures leads to significant improvements in the outcomes at aggregate level as well as across crops. The percentage improvement of outcome (between the adopters over the non-adopters) is higher in case of profit compared to the yield for all crops. There is complementarity between farmer's own conservation measures and community level interventions (such as those undertaken through programs such as IWMP), as well as conservation measures implemented by neighboring farmers. The influence of community level conservation activities and neighborhood SWC practices is more pronounced in the case of rainfed crops (such as maize) compared to the irrigated crops (such as paddy).

Long-lasting technological intervention including contour bunding, afforestation and slope-leveling are necessary to arrest and prevent future erosion. Especially, Peer learning can be crucial in incentivizing SWC adoption by adjacent farms. Policymakers should tailor their approach and support the location specific SWC needs to improve agricultural outcomes. In sum, the adoption of multiple SWC measures may be essential for farming in rainfed ecosystems. The government investment in developing infrastructure to neutralize soil erosion through watershed programme complements the farmers' adoption of conservation measures. Implementing multiple farm level SWC measures through sustainable agricultural practices not only improves farmer's income but also helps in sustaining the agricultural ecosystem.

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Appendix

Table A.1: Over Identification Test for Covariate Balance

Outcome	Level 1		Level 2		Level 3	
	Chi-square value	**P-Value**	**Chi-square value**	**P-Value**	**Chi-square value**	**P-Value**
Aggregate Level Profit	11.7946	0.9230	9.95639	0.9867	11.0034	0.9832
Paddy (Profit)	10.049	0.9303	16.5657	0.6193	12.4623	0.8992
Paddy (Yield)	10.1663	0.9263	17.1309	0.5810	12.8582	0.8834
Maize (Profit)	5.21656	0.9992	14.4772	0.8055	13.2823	0.8984
Maize (Yield)	6.28662	0.9985	13.9169	0.8731	13.4586	0.9196
Cotton (Profit)	8.1164	0.7760	10.1402	0.7519	7.84516	0.8972
Cotton (Yield)	8.1164	0.7760	10.1403	0.7519	7.84516	0.8972

Note: Null Hypothesis - Covariates are balanced: **Level 1** indicates the impact of the adoption of SWC measures on agricultural output without accounting for community intervention and neighborhood effects; **Level 2** accounts for community intervention; **Level 3** accounts for both community intervention and neighborhood adoption.

Table A.2: Impact of Adoption of Soil Conservation Practices on Profit and Yield

Outcome	Moderate vs Low		High vs Low		High vs Moderate	
	ATT (in ₹)	Profit (in%)	ATT (in ₹)	Profit (in%)	ATT (in ₹)	Profit (in%)
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate Level Profit	1570 (0.18)	12	4370* (0.08)	34	2800 (0.22)	19
Paddy (Profit)	3560* (0.09)	05	860 (0.80)	22	-2690 (0.39)	-13
Paddy (Yield)	2.23* (0.10)	12	3.27 * (0.06)	18	1.03 (0.52)	05
Maize (Profit)	2570 (0.12)	26	6770* (0.09)	74	4180 (0.20)	38
Maize (Yield)	2.1* (0.10)	15	07*** (0.00)	52	05** (0.02)	32

***, **,*Significant at 1%, 5%, and 10% probability level, respectively**. Note:** we did not estimate for the cotton crop due to the insufficient covariates. These estimations also did not include watershed intervention and neighborhood dummies due to the same reason

Table A.3: Endogenous Switching Regression Model Estimated Parameters

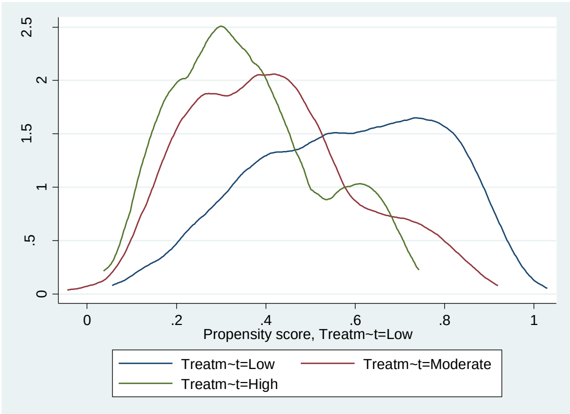
	Endogenous switching regression model					
	First stage		Second stage (Net revenue/Per acre)			
	SWC Adoption (1/0)		SWC Adopters		SWC Non-Adopters	
Variable	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Plot level characteristics						
Area of the plot	.018	0.440	-.026	0.284	.033	0.191
Soil type of the plot	-.101	0.154	.124*	0.072	.089*	0.062
Soil stoniness	.150**	0.021	-.125*	0.093	-.041	0.398
Slope of the plot	.220**	0.022	-.102	0.284	-.035	0.692
Soil erosion level	.198	0.011	-.092	0.188	.109	0.144
Access to irrigation	.147***	0.009	-.032	0.586	.010	0.831
Crop diversification	1.500***	0.000	-1.324***	0.002	-.291	0.277
Crop intensity	-.047	0.173	.092***	0.009	.126***	0.000
Socio economic characteristics						
Sex of the household head	-.126	0.576	.367	0.197	.035	0.789
Caste of household	-.030	0.776	-.017	0.857	.164*	0.084
Household head education	-.002	0.827	.001	0.937	.007	0.491
Years of experience	.000	0.823	-.001	0.795	.005	0.154
Household size	.046	0.160	-.043	0.177	-.081***	0.008
Market access variables						
Distance from the dwell	-.051	0.688	-.112	0.338	.000	0.999
Access to road	.022	0.800	-.017	0.833	-.004	0.953
Village level characteristics'						
Forest	.020***	0.015				
Barren land	.007*	0.091				
Permanent pasture	.107**	0.039				
Model statistics						
Constant	-2.256***	0.003	11.265***	0.000	7.812***	0.000
$\boldsymbol{\sigma_i}$			.693*	.056	.693*	.056
$\boldsymbol{\rho_i}$			-.975***	.015	-.053	.339
Number of observations	373		373		373	
SWC Impact						
			SWC Adopters	SWC Non-Adopters	ATT-value	P-value
			13641	10694	2948***	0.00

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

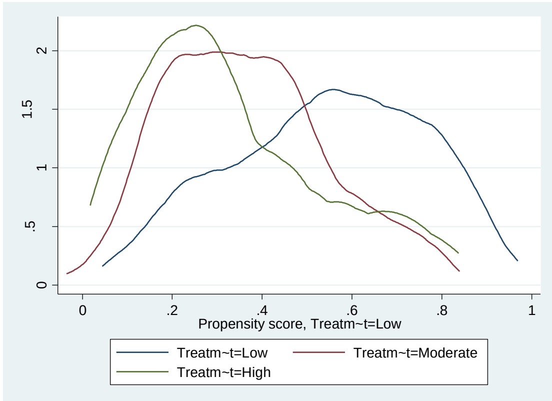
Figure A.1: Kernel Density Distribution Showing Overlap between Adopters and Non-Adopters of SWC Measure

Impact of SWC Adoption Measures on Farm Profit

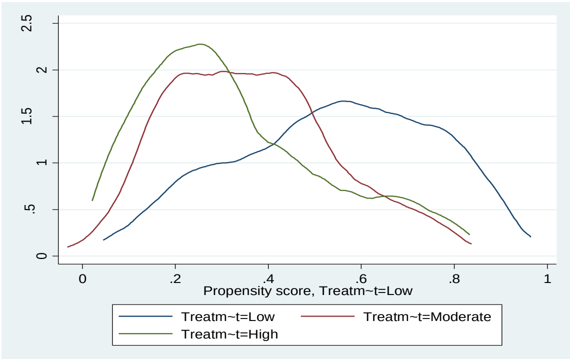
All crops profit
(Low vs moderate and high)



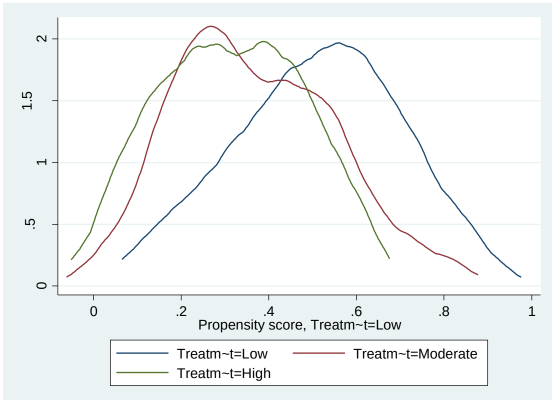
Paddy profit
(Moderate vs moderate and high)



Paddy yield
(low vs moderate and high)



Maizeprofit
(low vs moderate and high)



Maize yield
(low vs moderate and high)