CAUSAL IMPACT OF THE ADOPTION OF SOIL CONSERVATION MEASURES ON FARM PROFIT, REVENUE AND VARIABLE COST IN DARJEELING DISTRICT, INDIA

Abstract

This study attempts to evaluate the effects of on-farm soil conservation practices on farm profit and its components, revenue, and variable cost. Since farmers self-select themselves as adopters of conservation measure, there could be a problem of selection bias in evaluating their soil conservation practices. We address the selection bias by using propensity score matching. We also check if there exists spatial spill over in adoption of soil conservation measure and how it affects matching. We use primary survey data from the Darjeeling district of the Eastern Himalayan region for the year 2013. Our results suggest strong spatial correlation. The propensity score estimated from spatial model is able to provide better matches than non-spatial model. We find that the soil conservation can lead to a significant gain in revenues though they also increase costs. Thus, there is in no difference in profits.

JEL Classification: Q24, C21, C11

Key Words: Soil Conservation, Propensity Score Matching, Spatial dependence

1 Context and Objectives

A great deal of farming the world over takes place in mountainous areas that are ecologically fragile. It is also in these areas that the question of the availability of arable land is the most serious and the problem of soil erosion the most acute because of the instability of slopes which do not allow for the soil cover to evolve. The problem with soil erosion is multifaceted. First and foremost, there can be the negative impact of on-site soil erosion on agricultural yield. Soil is the most essential input in agriculture; eroded land suffers from depletion of nutrients such as nitrogen, phosphorus and potassium, organic and moisture content of the soil and reduction in cultivable soil depth. All these lead to a decline in soil fertility (Mbaga-Semgalawe & Folmer, 2000). In addition, soil erosion also result in significant negative externalities such as sedimentation in the river bed, water pollution, and a reduction in the water-carrying capacity of the soil. These, in turn, could cause silting in dams and water channels and affect local flora and fauna. Soil erosion can affect the hydrological cycle as well. It would increase the quantity of water runoff in the rainy season and reduce it during the dry season (Somanathan, 1991; Mbaga-Semgalawe & Folmer, 2000). Degraded land would affect other natural resources as well; for example, reduction in crop yields may force farmers to intensify their contribution to deforestation (Lopez, 2002).

However, the adoption of proper soil and water conservation measures can limit soil erosion and reduce the resulting top soil loss. Some farm-level measures widely adopted worldwide include terracing, contour bunding, revegetation, agro-forestry, crop mixture, fallow practices, land drainage systems and crop residue management (Stocking & Murnaghan, 2001). Viewed in a larger context, soil conservation is a part of sustainable agricultural practice, as soil disturbance is minimised (Teklewood et al., 2014). However, among the key barriers to the adoption of these measures are poverty, the risk associated with agriculture production, the high discount rate, government policy, the low benefit-cost ratio of soil conservation, and credit constraints in agriculture (Antle & Diagna, 2003; Stocking & Murnaghan, 2001; Bouma et al., 2007).

Nevertheless, if adopted, conservation measures would offer many regulating services such as carbon sequestration (Lal, 2004), preservation of the nutrient cycle (Adimassu et al., 2014), contributions to the maintenance of the hydrological cycle (Hueso-González et al., 2014), provisioning of services such as food (Thierfelder et al., 2015), wood (Kuntashula & Mungatana, 2013), and water (Pattanayak 2004), etc. for inhabitants as well as supporting services to dwellers such as improvement in soil fertility (Mwango et al., 2016) and biodiversity conservation (Chirwa et al., 2008).

However, quantifying the regulating and supporting services provided by soil conservation measures are either methodically challenging and/or potentially expensive. For instance, carbon sequestration, flood protection services and biodiversity conservation are public goods for which a market is absent.[1] At the same time, it is costly to measure soil fertility and soil nutrients across randomly selected plots. Nevertheless, provisioning services such as farm products, for e.g. crops and wood, have a market and can be valued using market prices, which makes farm products relatively easy to compare between adopters and non-adopters (Ma & Swinton, 2011). In the present study, we link soil conservation measures only with crop production and ignore the other benefits of soil conservation.

The present study seeks to estimate the extent to which farm-level adoption of soil conservation measures impacts farm profit and its constituents, revenue and cost.[2] Our attempt here is to provide the causal estimates of the impact, in particular, the average impact of farm-level soil

[1] Nevertheless, policy makers can design a special property right for these services (for e.g., climate change mitigation through carbon sequestration) in order to create value (Ma & Swinton, 2011).

[2] Soil conservation prevents soil loss and preserve nutrients of soil, organic and moisture content. All these lead to an improvement in soil fertility. To the extent that the conservation measures improve soil quality, should be reflected in higher output (vis-à-vis revenue), and it is conditional on other inputs and their efficient use (vis-à-vis cost). These measures may result in greater agricultural profit (Pattanayak, 2004).

conservation measures on adopters, i.e., the average treatment effect on the treated (ATT).[3] The study therefore assesses the on-site impacts of soil conservation. Although some conservation measures coproduce wood, fodder, etc., we assess the on-site impacts of soil conservation only on agricultural outcomes. We choose to ignore these by-products as an outcome variable in order to maintain uniformity in the comparison of outcomes between the adopters and non-adopters of soil conservation.

A large body of literature has tried to estimate the benefits of soil conservation vis-à-vis crop production. Among the methods they have adopted are the cost-benefit method (Lutz et al., 1994; Bizoza & Graff, 2012); estimation of the damage function (Walker, 1982; Walker & Young, 1984; Shiferaw & Holden, 2001); hedonic price of the land (Gardner & Barrow, 1984; King & Sinden, 1988), and the production function approach (Pattanayak & Mercer, 1998; Bekele, 2005; Bravo-Ureta et al., 2006). All the studies cited above have been able to provide the welfare measure of soil conservation to the farmer though, barring one (Pattanayak & Mercer, 1998), all have failed to consider the problem of the missing counterfactual. One major challenge in evaluating the impact of technology adoption, on soil conservation in the present instance, is finding the appropriate counterfactual to compare outcomes.

The ideal evaluation of soil conservation measures is only possible when the assignment of soil conservation involves an ex-ante experimental design. The random assignment is able to create a control group which is equal in all attributes (counterfactuals). However, it is quite costly to carry out a randomized control experiment to evaluate outcomes emanating from soil conservation. Many studies on the performance of natural resource conservation have therefore resorted to quasi-experiments (namely, *propensity score matching (PSM), difference in difference* and the *instrumental variable method)*, which is based on real-life data obtained from

[3] The average impact of the adoption of soil conservation measures on farmers who adopt them is the average treatment effect on the treated (Heckman & Vytlacil, 2007).

a field survey. In this kind of experiment, the random assignment of soil conservation measures is not possible since farmers self-select themselves into the categories of adopter and non-adopter. Consequently, there would be confounding factors that would affect both the adoption decision of farmers and agricultural outcome. The quasi-experimental methods control these confounding factors in the impact evaluation of soil conservation. There are only a handful of studies that segregate the socio-economic factors which simultaneously determine adoption decisions and agricultural outcomes. However, failure to do this would provide a biased estimate of the adoption of soil conservation measures (Godtland et al., 2004; Caliendo & Kopeinig, 2008; Kuntashula & Mungtana, 2014).

The study by Pattanayak & Mercer (1998) is a good example. The study evaluated the benefit of on-farm soil conservation measures (agroforestry, in the case of their study) on farm profit by using data from a household survey in the Philippines. Their results suggested that improved soil quality positively influences profit. But confounding factors may affect both adoption of agroforestry as well as profit as a result of which there could be self-selection bias (which we discuss below). The authors addressed this problem by using the Heckman two-step model. However, the Heckman two-step method is not a quasi-experimental method. Moreover, this method cannot accurately estimate impacts as compared to experimental methods (Lalonde, 1986). In contrast, credible evaluation can be done using quasi-experimental techniques (Dehija & Wahba, 1999).

We encountered a few studies that used the quasi-experimental method to evaluate the impact of on-farm soil conservation on farm outcome. A study by Faltermeier & Abdulai (2009) estimated the impact of the adoption and intensification of water conservation practices on farm output, demand for input, and net returns in Ghana. They found that while the adoption of bund technology increased input demand, it did not affect the household's output or net returns. The authors used the quasi-experimental method PSM to overcome the problem of selection bias.

Reddy et al. (2004) assessed the impact of soil and water conservation measures such as horticulture and forestry under a watershed development programme on crop productivity and net returns in India. Their findings suggested improved productivity of the land while the beneficiaries also experienced an increase in net returns. In the case under reference, the conservation measures were promoted by the watershed development agency through direct funding. The authors addressed the problem of self-selection through the “difference in difference method”. A study by Kuntashula & Mungtana (2014) established a linkage between soil conservation measures and fuel wood consumption.[4] They evaluated the impact of on-farm adoption of agroforestry on the consumption of fuel wood from public land in Ghana. They found that the adoption of the agroforestry measure significantly reduced fuel-wood collection from public land. Their results suggest that agroforestry significantly improved the availability of fuel wood on private farm land. The authors used the PSM method to control the confounding characteristics in impact evaluation.

In this study we too use the PSM methodology to measure the impact of adoption of various conservation practices on farmer profit, revenue and variable cost. In identifying the causal impact, the maintained assumption is that the decision on farm-level adoption is based on observable household, farm-level, and village characteristics. Once these covariates are accounted for, the assumption is that the adoption decision is independent of potential outcomes—in this case, farmer profit, revenue and cost. The PSM accounts for the observed covariates that might simultaneously determine the adoption and the farm outcomes. However, it does not account for the non-observed characteristics that might also simultaneously govern the on-farm adoption, farmer profit, revenue, and cost. This is one of the major limitations of PSM.

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[4] A soil conservation measure such as agroforestry co-produces fuel-wood along with providing its main service in the form of soil conservation (Kuntashula & Mungtana, 2014).

The PSM methodology matches adopters with non-adopters based on their propensity score. We define adopters and non-adopters in terms of the presence or absence of a certain set of soil conservation measures (see Section 3.2.1 for details). The propensity score is defined as the probability of adoption conditional on observed covariates (Hahn, 2010). Therefore, to estimate the propensity score we need to identify key determinants of the decision to adopt soil conservation. A variety of socio-economic factors of the farm household and farm characteristics influence a farmer's decision to adopt soil conservation measures.[5]

A few studies have introduced neighbourhood aspects in the literature of agricultural technology adoption. Battaglini et al. (2012) showed that there can be strategic substitutability (free-riding) or strategic complementarity with neighbours in investment in public goods like soil conservation. There are two main strands of the literature on technology adoption that attempt to incorporate the interdependence of decisions. The first strand explicitly accounts for interactions with neighbours through models of social learning and networks. [6] These studies follow Manski's (1993) observation that the "propensity of an individual to behave in a certain way changes with the behaviour of the individual's social group" (cited in Lapple & Kelley, 2015). The second strand attempts to capture the role of interaction on the decisions to adopt a given technology, by using techniques of spatial econometrics. In this technique, the interaction is based on a measure of proximity that is typically geographical in nature. [7]

In the context of analysing the adoption of soil conservation practices, the use of the spatial dependence framework is logical for many reasons. First, soil conservation in one farm can assist or constrain it in adjacent farms. The assumption is that households located near each other exhibit similar behaviour; closer the household, more similar the behaviour (Holloway & Lapar,

[5] See Wossen et al., (2015); Teklewood et al., (2014); Sidibe (2004) and Mbaga-Semgalawa & Folmer (2000) for details.

[6] See for instance Mbaga-Semgalawa & Folmer (2000); Conley & Udry (2003); Bandiera & Rasul (2006); Moser & Barret (2006) and Teklewood et al., (2014)

[7] Studies on technology adoption in agriculture such as Pinkse & Slade (1998); Colney (1999); Holloway & Lapar (2007); Wang et al., (2013); and Lapple & Kelly (2015) have used the spatial dependence models.

2007).[8] Factors such as inter-farm information flow, neighbourhood competition or cooperation, geographical clustering of innovators, etc., could induce similar adoption behaviour in farmers (Abdulai & Huffman, 2005). Second, soil conservation practices can be location-specific, with particular types of soil conservation practice more suitable for particular types of land. Agricultural productivity also depends on various localized factors, such as soil type and quality, ambient and soil moisture, ecosystem services, topography of land, and distance from the nearest stream (Colney, 1999). Similarity in all these factors may lead to similarity in farming and conservation practices (Pattanayak & Burty, 2005). These variables are often not measured, resulting in dependence in residuals. Thus, spatial factors contribute indirectly to the observed adoption of soil conservation practices (Holloway & Lapar, 2007).

Literature evaluating natural resource conservation mentioned above assume that the adoption of conservation measures by one farmer does not affect the outcome of another farmer. This assumption is known as Stable-Unit-Treatment-Value-Assumption (SUTVA). However, as noted above, soil conservation can potentially be an instance where this assumption is not feasible. Therefore, it is important to model the interdependence of the farmers' decisions as, otherwise, the estimated coefficients of the determinants of soil conservation practice can be biased. Consequently, the estimated propensity score would be wrong. One way to address it is to directly model the interdependence of farmers with regard to their adoption decisions (Imbens & Wooldridge, 2009). We model the interdependence in the adoption of soil conservation by using the technique of spatial econometrics. It would help us to identify the magnitude of the (spatial) interdependence as well as the optimum area of the (spatial) neighbourhood. The present

[8] "Such models deal with the question of how the interaction between economic agents can lead to emergent collective behaviour and aggregate patterns, and they assign a central role to location, space and spatial interaction" (Anselin, 2002).

study adds to the literature on evaluating natural resource conservation by highlighting potential biases in ATT that may result from ignoring spatial interdependence.

In addition to the farm-level soil conservation measures mentioned above, there are many off-site measures; of these, those of relevance to this study are the set of measures adopted for mountainous sub-watersheds by a government agency to prevent soil erosion. We call this set of measures "treatment". Under sub-watershed treatment, soil conservation measures are directly provided by the government. In our study area, the government agency develops infrastructure in the upstream forest areas of certain sub-watersheds (we discuss the details of the treatment in Section 2). Farmers' decisions to adopt on-farm conservation practices may depend on the distribution of benefits of sub-watershed treatment in the upstream, (Feder & Slade, 1985). In addition, the sub-watershed treatment can influence farm outcomes in the downstream of the same sub-watershed by providing soil conservation service (Pattanayak & Kramer, 2001). As a result, sub-watershed treatment status potentially serves as a confounding factor. Therefore, it is necessary to consider sub-watershed treatment status as one of the determinants of soil conservation practices.

We use first standard binary probit model to derive propensity scores. After matching, we compare the expected values of farm profit, revenue and cost between adopters and non-adopters to estimate the impact of adoption of plot-level soil conservation measures. In order to consider spatial correlation, we consider model of spatial dependence in outcome, that is, adoption of soil conservation practice (the spatial lag model) following Anselin (2002) and LeSage & Pace (2009). We use the Bayesian formulation of a standard probit model in conjunction with the Markov Chain Monte Carlo (MCMC) method to estimate the propensity score.

We use survey data from the Darjeeling district of the Teesta River Basin of the Eastern Himalayan Region. The findings suggest strong and positive evidence of the neighbourhood impact on farmers when it comes to making soil conservation decisions. Also, we find that, the spatial lag probit model best describes our data. In particular, it performs better than a non-spatial/ordinary probit model. Causal analysis indicates that some specific on-farm soil conservation measures do affect revenue and cost positively but do not affect farm profit. Especially, significant ATT is observed only in cases where there is simultaneous adoption of multiple soil conservation measures.

Our study uses cross-sectional data, which limits the ability to truly identify adoption. Given that adoption decisions are undertaken gradually over time, the present study includes, among the non-adopter category of farmers, both probable future adopters and never-adopters while the adopter category only includes long-time adopters. However, there could also be disadoption of soil conservation technologies in future. In addition, using a binary variable for adoption (adopter/non-adopter) might have serious limitations in better capturing the soil conservation. There can also be significant differences between a farmers who uses multiple soil conservation measures in a small share of the plot versus one who uses one soil conservation measure more intensively.

2 Study Area

2.1 Description of Study Area

The Eastern Himalayan region is the most vulnerable region in India in terms of soil erosion. This is due to the oscillatory nature of the topography, steep gradient, and heavy rainfall of the region. In addition, encroachment and deforestation of forest land, the ever-increasing demand for food, agricultural practices on sloping land, and indiscriminate shifting cultivation have also contributed to the exacerbation of the problem of soil erosion (Mandal & Sharda, 2013). The Teesta River Basin is located in the eastern part of the Himalayas. A rapid reconnaissance on 6.87 lakh hectares (out of a total catchment area of 12.65 lakh hectares in the Teesta River Valley), conducted by the All India Soil Land Use Survey Organisation of the Department of Agriculture at its Calcutta Centre in 1977 in order to understand the extent of soil erosion, led to the classification of 59 percent of the surveyed land as very highly prone or highly prone to soil erosion (National Land Use and Soil Conservation Board, 1992).[9] We are undertaking a case study of one of the most soil-erosion-affected districts in the Teesta River Basin in the Darjeeling District of the West Bengal State in India.

The district of Darjeeling comes under the warm perhumid eco-region.[10] The altitude of the hills within the district varies between 300 feet to 10,000 feet. The soils in the steep hill slopes are shallow and excessively drained, carrying a severe erosion hazard. The soils of the foot hill slopes and valleys, on the other hand, are moderately deep, well-drained, and loamy in texture carrying a moderate erosion hazard (West Bengal District Gazetteer Darjeeling, 2010). These translate into shallow soils that have little capacity for water storage. The average annual rainfall varies between 3,000 mm and 3,500 mm. The average number of rainy days in the area is 126[11] and these days are largely concentrated in the monsoon months, i.e., June to August. The Teesta is the major river of the district, its catchment affected by frequent landslides, slips, and erosion of river banks. As a result, the Teesta and its tributaries wash out an enormous amount of top soil every year (National Land Use and Soil Conservation Board, 1992).

Farmers in the region grow a multiplicity of crops including maize, squash, ginger, cardamom, chilies, peas, tomato, spinach, carrot, cabbage and beans as well as fruits like orange and pineapple. Land degradation due to water-induced soil erosion, along with other on-site and off-site impacts, poses a major threat to agricultural activity in the region. But the agricultural sector is also beginning to play a more important role in the region, in terms of

[9] To the best of our knowledge, no recent data is available in the public domain about the extent of soil erosion in the Teesta river basin.
[10] TNAU Agritech Portal, http://agridr.in/tnauEAgri/eagri50/AGRO101/lec07.pdf, July 26 2015
[11] Annual Admin Report, http://darjeeling.gov.in/admin_rpt/Annual_Admin_Report201112.pdf, December 14, 2014.

absorption of the work force, given the gradual decline in the tea industry in the region in the post-independence period (i.e., 1947). At the same time, during the past 50 years or so, the district has experienced a falling land-man ratio due to population growth and the ever-increasing demand on land for housing, road construction, agriculture, and grazing, which has resulted in deforestation. All these human interventions have produced large quantities of sediments in water bodies. Evidently, both geological and man-made causes have played a role in soil erosion in the region (Tirkey & Nepal, 2010).

2.2 Soil Conservation Measures in the Study Area

In this study, we consider a situation with two types of intervention. The first type of intervention details the soil conservation measures adopted by a farmer at his/her own farm. The second type of intervention refers to the soil conservation measures provided by the district forest department of the Government of West Bengal (i.e., the state government) with assistance from the Government of India (i.e., the central government), under Teesta River Valley Programme (TRVP). The sub-watershed has been the unit of interventions for the latter (National Land Use and Soil Conservation Board, 1992).

Among the farm-level (on-site) soil conservation measures adopted by farmers are stone terracing, stone wall, afforestation, bamboo plantation, orchard plantation, terracing, tree belt (plantation of trees on the farm boundary), broom plantation, and grass stripping. Though the list is exhaustive, activities on the list are not mutually exclusive. The measures vary, however, with respect to their effectiveness vis-a-vis soil conservation.

Integration of structural and vegetative measures have been established conservation practice by the farmer in the study area. The discussion with regional experts[12] and farmers during the pilot study reveals that the deliberate integration by these measures not only help to minimise

[12] Researchers of North Bengal University, Darjeeling, India

top soil loss on the preserved piece of land during wet season but also provide an array of diverse benefits (viz., better crop yield, fuel, timber and fodder) to the farm household. Among the measures adopted in the study area, stone terracing, stone wall, and terracing are very useful structural conservation measures. Stone terracing and terracing are measures that reduce the velocity of rain water flow on the agricultural farm, thereby reducing top soil loss. Terracing is made up of a sequence of successively receding flat or nearly flat platforms. However, if the ridge of the terrace is supported by stones (i.e., stone terracing), then it becomes more effective in reducing surface run-off as compared to terracing alone. The stone wall, which is another conservation measure, breaks the water flow during heavy rainfall which prevents the formation of splash and gully erosion (Van Oast et al., 2006) whereas the other measures (afforestation, bamboo plantation, orchard plantation, broom plantation, and grass stripping) help maintain a permanent vegetative cover on the farm to protect the top soil layer from erosion. However, experts and farmers both suggested that afforestation and bamboo plantations help to hold the soil layer firmly, thus reducing soil loss and increasing water penetration in the soil. As a result, afforestation and bamboo plantations are more effective as compared to the other vegetative measures (orchard plantation, tree belt, broom plantation and grass stripping) We report the average cost to implement (initial investment), type of maintenance, gestation period of these technologies and most commonly used measure in Online Appendix 1.

In addition to on-farm soil conservation, the district forest department under the state government (i.e., the Government of West Bengal) started building infrastructure to prevent soil erosion under TRVP from 1977 onwards (National Land Use and Soil Conservation Board, 1992). The placement of TRVP targeted the forest areas of sub-watersheds with a high sediment yield index, which is a measure of soil erosion.[13] However, not all sub-watersheds with a given level

[13]"Sediment yield per unit area is measured as sediment yield = erosivity × erodibility. Erosivity is an expression of rainfall (velocity, angle, frequency and duration), where erodibility indicates the soil detachment and transportation potential of the detached material. The erodibility factor is governed by the empirical equation as

of soil erosion were treated. The measures were both agronomic (afforestation and broom/fodder cultivation) and engineering (belly benching, stream bank, catch water drains, and slip control/stabilisation) in nature (National Land Use and Soil Conservation Board, 1992; Kurseong Soil Conservation Division, 2011; Kalimpong Soil Conservation Division, 2010). Since treatment in the up-stream forest area could affect soil-quality in the down-stream agricultural land of the same sub-watershed, treatment under TRVP can be seen as an off-site measure of soil conservation.

3. Sampling, Data and Description of Variables

3.1 Sampling

The sampling strategy was dictated by the treatment status of various sub-watersheds in the Teesta River Valley Programme. Of the 129 sub-watersheds delineated in the Teesta basin, 94 are located in the Darjeeling district while the remainder are located in Sikkim, the adjacent state. Of the 94 sub-watersheds in Darjeeling, 55 sub-watersheds belong to the very high, high or medium soil erosion prone category.[14] [15] Of the 55 sub-watersheds in the district, 23 sub-watersheds have already been treated while treatment is going on in 13 sub-watersheds. Furthermore, 19 sub-watersheds are likely to be treated in the near future. We decided to leave out the watersheds undergoing treatment because these have neither been treated completely nor left out. We adopted the classification of sub-watersheds defined in the TRVP reports (Kurseong Soil Conservation Division, 2011; Kalimpong Soil Conservation Division, 2010).

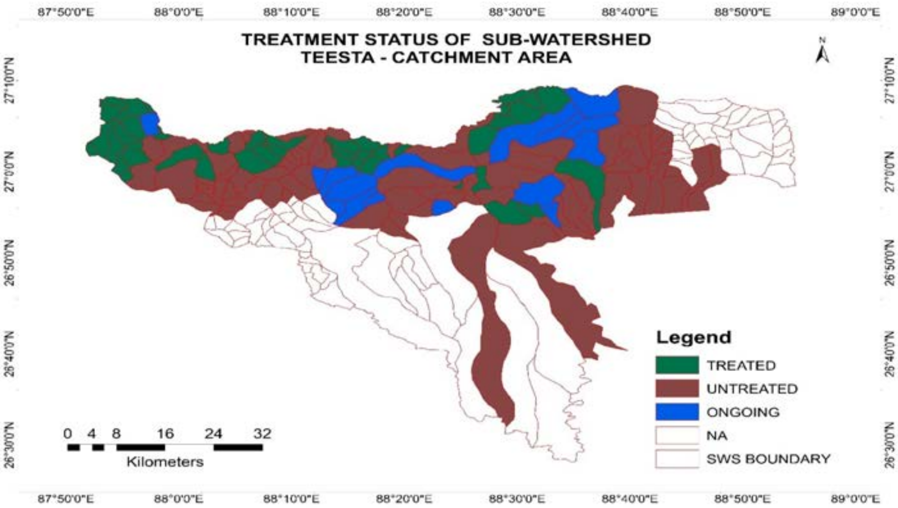
described below. R = P – F, where R stands for run-off, P is precipitation and F is infiltration capacity" (Soil and Land Use Survey of India, http://www.slusi.dacnet.nic.in/rrs.pdf, February 2, 2014).

[14] In very high soil-erosion-prone sub-watersheds, the Sediment Yield Index is 1450 and above; in high soil-erosion-prone sub-watersheds the Sediment Yield Index ranges between 1350 and 1449; and in medium soil-erosion-prone sub-watersheds the Sediment Yield Index lies between 1250 and 1349 (Kurseong Soil Conservation Division, 2011).

[15] The classification of sub-watersheds is according to the Sediment Yield Index of 1977. However, recent field conditions suggest that the medium erosion-prone sub-watersheds can be reclassified as high-erosion-prone sub-watersheds owing to the increase in the quantum of soil erosion (Kalimpong Soil Conservation Division, 2010).

We selected the 23 sub-watersheds listed as being treated and the 19 sub-watersheds classified as being likely to be treated soon as our controls or untreated watersheds. Of the 42 treated and untreated sub-watersheds, seven were located in extremely remote areas and, hence, inaccessible. Thus, the sample in this analysis includes 19 treated sub-watersheds and 16 untreated sub-watersheds. Figure 1 presents the sub-watersheds of the Teesta River Valley region delineated using the satellite image of the Landsat Operational Land Imager.

Figure 1: Delineated Sub-Watershed Boundary in Darjeeling



Source: Teesta Sub-Catchment Boundary, *Kurseong Soil Conservation Division and GIS and* Satellite Image Landsat, OLI

Having identified the treated and untreated watersheds, the next step was to select households from these areas. However, since the sub-watershed is a geophysical unit and not an administrative one, we super-imposed a map of village boundaries onto the sub-watershed boundaries using GIS (ArcView software). The total number of selected villages in the sample was 37, of which 18 villages were revenue villages (inhabitants have property right on land) and

9 forest villages (inhabitant does not have exclusive property right on land).[16] [17] We selected one village each from 33 sub-watersheds and 2 villages from 2 sub-watersheds.

We then selected a uniform number of households from each village. Since our budget could support approximately 450 sample households, we reallocated the 450 in equal proportion to all the 37 villages, which brought the total number of observations from each village to 12. Since no formal listings of the households were available, our enumerators compiled a list of household heads and determined the location of the household by approaching one or more village or hamlet elders. On average, a village consisted of 150 households. Therefore, once this list was compiled, we selected 12 households via random sampling with replacement from the prepared list when the necessity arose.

Our survey also showed virtually all the households to own, in addition to a homestead, a single plot of land which they cultivate. Given that the rental markets for land are relatively rare in this area, evidence of leased-out land was negligible. Where farmers had more than one plot (though negligible in number), we asked questions related to the largest plot.

Our survey, which was carried out in the calendar year of 2013, collected data on the post-monsoon crop (July to October) and the winter crop (November to March). Although we tried to revisit all the households of the first phase in the second phase of our survey, i.e., for the winter crop, we were unable to locate approximately 5 percent of the sample households during this round. In such instances, we visited the adjacent household. Enumerators interviewed an adult in the household, the interview being conducted in Nepali, which is the

[16] "Forest villages were set up in remote and inaccessible forest areas with a view to provide uninterrupted manpower for forestry operations. Of late, they have lost much of their significance owing to improved accessibility of such areas, expansion of human habitations and other similar reasons. Accordingly, some of the States converted forest villages to revenue villages well before 1980. Nevertheless, there still exist between 2500 and 3000 forest villages in the country". (Maharashtra Forest Department, http://mahaforest.gov.in/fckimagefile/Handbook-13.pdf, December 17, 2014).

[17] "Revenue village has a definite surveyed boundary and each village is a separate administrative unit with separate village accounts. It may have one or more hamlets. The entire revenue village is one unit" (Government of India, http://censusindia.gov.in/Data_Products/Library/Indian_perceptive_link/Census_Terms_link/censusterms.html, February 9, 2015).

native language of households in the study area. Approximately 65 percent of our respondents were male, the rest being female. Though we visited, in all, 444 households, we dropped 52 sample households from the post-monsoon season and 12 sample households from the winter season in the final data analysis because of doubts regarding the reliability of the information gathered.

3.2 Data and Descriptive Statistics

3.2.1 Adoption

In Section 2, we listed the different types of soil conservation measures used by farmers.[18] Our pilot study determined that the combination of one or more structural measure(s) along with vegetative measure(s) such as plantation of woody perennials or afforestation, and bamboo plantation are considered the most effective way to reduce top soil loss (see Section 2.2 for details). There was also not much variation in the adoption of some of the other measures (either all or none). As only a few used stone terracing (less than 4 percent), we excluded this soil conservation practice from our study. Moreover, since 94 percent of the farmers reported adopting terracing as a soil conservation measure, we considered terracing as a "no conservation measure" for the purposes of our study. The distribution of adoption measures of sample farmers is reported in Table 1.

Table 1: Distribution of Sample Farmers by Number of Adoption Measures

Farmers Adopting	Cumulative Percentage
No conservation measures	25
Stone wall	51
Stone wall and afforestation or bamboo plantation	83
All the measures	100
Total Sample Size	432

Source: Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013.

[18] During the pilot survey, the farmers and researchers also identified the other vegetative measures (i.e., orchard plantation, tree belt, broom plantation and grass stripping) as more means to complement farm income (fodder, horticulture) than those undertaken to protect top soil loss in the study area. We therefore left out these measures from our analysis.

The farmers have been practising these measures for more than ten years. This table suggests that 49 percent of the farmers have adopted stone wall along with afforestation and/or bamboo plantation. We define these farmers as adopters. As we expect that the synergistic impact of stone wall with afforestation, and/or bamboo plantation are likely to have higher yield effect than the individual impact of stone wall or no conservation measure.

3.2.2 Explanatory Variables

Adoption of soil conservation practices depends on a number of factors such as the socio-economic characteristics of the farmer/farming households, farm characteristics, measures of market access, and information on soil conservation in the immediate upstream neighbourhood. We present the description and summary statistics of the above in Table 2. Most of the variables we used were drawn from the studies of Mbaga-Semgalawa & Folmer (2000); Sidibe (2004); Teklewood et al. (2014); Wossen et al. (2015); and Lapple & Kelly (2015). We assume, all these explanatory variables as non-constant exogenous variables. They were used to study the factors that influence a farmer's decision to adopt soil erosion prevention measures. Some variables such as government support to farmers for soil conservation; extension services to farmers; membership in farmers' organizations; and accessibility of credit from the formal credit market could not be included due to similarity in answers (leading to lack of variability) among the respondents. For instance, all the respondents reported that extension services for farmers in the surveyed area were absent. They also reported that they never accessed credit from the formal credit market.

For each respondent farmer, we elicit information on the soil conservation practices adopted on the nine nearest upstream farms (Lapple & Kelly, 2015). The existence of soil conservation activity in the immediate upstream neighbourhood may have significant complementary or substitution effects on the conservation decision (Battaglini et al. 2012).

Table 2: Summary statistics & two sample t-test of the variables used in the analysis

1	2	3	4	5
Variable	**Full Sample**	**Adopters**	**Non-adopters**	**Mean Difference = Column 3 – Column 4**
Number of observations	432	211	221	
Proportion in sample (%)	100	49	51	
Number of observations in treated sub-watershed	220	90	130	
Number of observations in un-treated sub-watershed	212	121	91	
Number of observations in forest village	120	47	73	
Number of observations in Revenue village	312	164	148	
Number of observations in very high$ soil erosion prone sub-watershed	120	75	45	
Number of observations in high$$ and medium$$$ soil erosion prone sub-watershed	312	136	166	
Socio-economic variables				
Age of the household head (years)	53 (.70)	54 (1.03)	52 (.96)	1.15 (1.41)
Years of education of household head (years)	4 (.19)	4 (.29)	3 (.25)	1*(.4)
Household member between age 14-65 (%)	3.81 (.080)	3.88 (.11)	3.73 (.15)	0.15 (.16)
Household size	5 (.08)	5 (.1)	5 (.1)	0.23 (.16)
Proportion of household members who have at least 10 years of schooling	0.21 (.01)	0.22 (.016)	0.20 (.015)	0.025 (.022)
Experience of household head in agriculture (years)	27 (.62)	28 (.9)	26 (.87)	2* (1.25)
Market access variables				
Distance to nearest market from farm(in meters)	11323 (502)	8835 (618)	13743 (753)	-4908*** (977)
Distance to all-weather road (in meters)	2950 (185)	2377 (199)	3507 (306)	-1129*** (368)
Farm characteristics				
Farm area in acres	1.25 (.052)	1.52 (0.08)	1 (.05)	0.52*** (.10)
Altitude of the farm (in meters)	1281 (24)	1193 (31)	1366 (37)	-173** (49)
Soil texture	2.17 (0.04)	2.17 (0.06)	2.16 (0.05)	0.01
Soil color	2.89 (0.05)	3.03 (0.06)	2.75 (0.06)	0.28***
Soil stoniness	2.22 (0.04)	2.15 (0.05)	2.29 (0.05)	-0.14**
Information on soil conservation practice in immediate upstream neighborhood				
Contour bunding (%)	33 (8)	56 (8)	12 (2)	34***
Afforestation (%)	67 (4)	90 (7)	45 (3)	45***
Bamboo plantation (%)	53 (2)	69 (4)	38 (3)	31***

Sources: A primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013, 2) Kalimpong Soil Conservation Division (2010), Kurseong Soil Conservation Division, (2011).

Notes: 1) Standard deviation in parentheses; 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively; 3) Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted either stone wall or no conservation measure; 4) In treated sub-watersheds, the state forest department of West Bengal has taken soil conservation measures in forest area. In untreated sub-watersheds, no government initiative for soil conservation; 5) $ Sediment Yield Index is 1450 and above, $$ Sediment Yield Index 1350 -1449, $$$ Sediment Yield Index 1250-1349, "Sediment Yield Index" calculated as "weighted arithmetic mean of the products of the erosion intensity weightage value and delivery ratio over the entire area of the hydrologic unit by using suitable empirical equation" (Soil and Land Use Survey of India, slusi.dacnet.nic.in/rrs.pdf, February 2, 2014); 6) Soil texture, soil color and soil stoniness have been reported by the respondent according to a hedonic scale. Scale of soil texture: sandy/coarse--- 1, loamy/medium coarse—2, clay- 3, silt-4; Scale of soil color: grey - 1, reddish - 2, brown - 3, black – 4; Scale of soil stoniness: high stoniness- 1, medium stoniness- 2, low stoniness-scale 3, non-stony- 4; 7) "Information on soil conservation practice in immediate upstream neighborhood": elicited information on the soil conservation practices adopted on the nine nearest upstream farms.

In addition, we use three dummy variables to capture sub-watershed characteristics that may impact the soil conservation decision. The first dummy captures whether the upstream forest of the sub-watershed was treated under the TRVP or not, and the second captures whether the sub-watershed belongs to the very high erosion-prone category or not. The third dummy relates to whether a village is a forest village or not. Many villages are situated in or near the frontier of forest areas (i.e., forest village). Since residents of such villages lack exclusive property rights over land, it may act as a disincentive from investing in soil conservation. Like other explanatory variables we consider these sub-watershed characteristics as exogenous variables.

Table 2 suggests that there are significant differences between adopters and non-adopters in several covariates. Though we will not go into a detailed discussion, we wish to underline that these differences in covariates provide support for control of confounding factors in order to assess the causal impact of on-farm soil conservation measures.

3.2.3 Outcome Variables

Table 3 compares differences by season in the three outcome variables (profit, revenue, and variable cost per acre). We report the construction of these variables in Online Appendix 2. Table 3 shows that adopters bear a significantly higher cost than non-adopters in the winter season. However, we do not see any significant difference in other outcome variables for the winter crop. On the other hand, in the monsoon season, the mean difference is positively significant with regard to farm profit per acre (at the 10 percent level of significance), total revenue per acre (at the 10 percent level of significance), and variable cost (at the 5 percent level of significance). The t-statistic suggests that adopters tend to earn higher farm profits per acre and bear higher variable costs for farming. On the other hand, we do not observe any significant difference in any of the agricultural outcomes by combining winter and monsoon crop.

Table 3: Summary Statistics of outcome variables, Adopters and Non-adopters

Crop Season	Variable	Full sample	Adopters	Non-adopters	Mean difference (adopter-non-adopter)
Winter	Number of observations	432	211	221	
	Per acre profit (INR)	8230 (360)	8060 (651)	8394 (329)	-334
	Per acre total revenue (INR)	19855 (435)	20478 (693)	19256 (531)	1221
	Per acre variable cost (INR)	11624 (361)	12418 (605)	10862 (401)	1556**
Monsoon	Number of observations	392	230	162	NA
	Per acre profit (INR)	7037 (424)	7617 (578)	6214 (7334)	1403*
	Per acre total revenue (INR)	20570 (594)	21699 (794)	18967 (879)	2732**
	Per acre variable cost (INR)	13532 (404)	14081 (497)	12752 (676)	1328*
Aggregate of Winter and Monsoon	Number of observations	389	191	198	NA
	Per acre profit (INR)	15224 (592)	15871 (971)	14504 (687)	1466
	Per acre total revenue (INR)	40435 (785)	41319 (1181)	39582 (1040)	1736
	Per acre variable cost (INR)	25210 (554))	25347 (831)	25077 (749)	270

Source: Based on a primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013.
Notes: 1) Standard error in parentheses; 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively; 3) 3) Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted either stone wall or no conservation measure; 4) NA => Not applicable, 5) INR => Indian Rupee.

4 Conceptual Framework

A fundamental problem in causal inference is that it is impossible to observe the outcome and its counterfactuals on the same farmer (Holland, 1986). But a solution for this would be to use a randomized control trial, in which soil conservation measures are assigned randomly though this can rarely be implemented practically. For this reason, we relied on quasi-experimental techniques, such as the PSM methodology, to deal with the problem of the missing counterfactual. This section discusses the problem of selection bias in studying the causal impact of soil conservation measures and how PSM can be used to overcome it.

$D_i = 1$ if the farmer i is an adopter of soil conservation measures

$D_i = 0$ if the farmer i is a non-adopter of soil conservation measures

To estimate ATT, we need to determine the outcome of the counterfactual state, which is to observe the counterfactual outcome of the adopter of the soil conservation measure in a non-adoption state. Thus,

$$ATT = E[\pi(1)|D = 1] - E[\pi(0)|D = 1] \quad (1)$$

where π is the outcome variable, i.e., farm profit and its components, namely, revenue and variable cost. Although the outcome for the adopter in the non-adoption state, that is, $E[\pi(0)|D = 1]$ cannot be observed, it is possible to estimate the difference:

$$E[\pi(1)|D = 1] - E[\pi(0)|D = 0] \quad (2)$$

This is the difference in expected farm outcomes between adopters and non-adopters. However, this is a biased estimate of the impact of adoption since it is more than likely that the outcomes of adopters and non-adopters may have been different even in the absence of any soil conservation measure (Duflo et al., 2007). For instance, determinants of soil conservation measures and outcome variables share many factors (as mentioned in Section 3.2.2). In general, outcomes on farms with soil conservation measures do not represent the outcomes on farms without soil conservation measures due to the non-random or voluntary nature of adoption (Godtland et al., 2004; Caliendo & Kopeinig, 2008).

The matching approach is one possible way to overcome selection bias. It assumes that the adoption decision is based on observables and that once these are accounted for, it is possible to construct, for each adopter of soil conservation measures, a comparable group of non-adopters who have similar observable characteristics. The matching techniques impose three assumptions. The first is the assumption of unconfoundedness, or conditional independence. That is, given a set of observable Z, the farm outcomes are independent of the adoption of soil conservation measures.

We assume that these covariates are all exogenous. Specifically, the conditional independence can be written as follows:

Assumption 1. Conditional independence: $\pi(0), \pi(1) \coprod D \mid Z$ (Caliendo & Kopeinig, 2008).

The second assumption is common support which is written as follows:

Assumption 2. Common support: $0 < P(D = 1|Z) < 1$ (Caliendo & Kopeinig, 2008).

In other words, 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.

Assumption 3. SUTVA (already defined in Section 1): according to this, a farmer's adoption of soil conservation measures does not depend on another farmer's adoption (We consider interdependence of soil conservation measures within a specified neighbourhood in Section 5).

One implication of these assumptions is that no unobservable factors influence adoption and farm profit (and its components) simultaneously (Caliendo & Kopeinig, 2008). If these assumptions are met, the PSM technique can be used to match adopters and non-adopters and create counterfactuals. The ATT is given by:

$$ATT(PSM) = E[\prod(1)\big|D = 1, P(Z)] - E[\prod(0)\big|D = 0, P(Z)] \qquad (4)$$

where P(Z)=P(D=1 | Z) is the propensity score, i.e., the conditional probability for a farmer to adopt soil conservation measures given his observed covariates Z.[19] Therefore, $ATT\ (PSM)$ is the mean difference in farm outcomes (profit, revenue and variable cost) over common support between adopters and non-adopters.

5 Spatial Interaction Effect of Farmer in Adoption Decision

To show interdependence in the adoption decision of farmers, we adapt the empirical specification provided by Anselin (2002).

$$e^* = \rho W e^* + Z\beta + u \qquad (5)$$

[19] The PSM methodology also resolves the curse of dimensionality by using the propensity score, generated from all the covariates in vector Z, to create the counterfactual (Hahn, 2010).

where, e^* is a vector of latent effort. In this case, e^* is not observed but is present in the effort function of our representative farmer. In other words, the unobserved effort of the neighbourhood farmer e^*_{-i} influence e_i^* (Anselin, 2002). We include Z, which is a $(n\,X\,k+1)$ matrix of the other observed explanatory variables (defined in Section 3.2.2). β is $(k+1\ \ X\ \ 1)$ a vector of parameters and u is a random shock with $E(u)=0, E\left(uu^{/}\right)=\sigma_u^2 I_n$.

We try to capture interdependence of farmers through the spatial weight matrix W. For a sample of n farmers, we specify W to be an $(n\,X\,n)$ matrix defined as the inverse of the Euclidean distance between neighbours. This assigns higher weights to nearby farmers than to relatively distant farmers (Anselin, 2002). Finally, ρ is the spatial autoregressive parameter (scalar), which is additional to any standard latent variable model.

Assuming $(I-\rho W)$ is non-singular, equation (5) implies:

$$e^* = (I-\rho W)^{-1}X\beta + \varepsilon \tag{6}$$

where

$$\varepsilon = (I-\rho W)^{-1}u \tag{7}$$

The specification (5) is known as the spatial lag model or spatial autocorrelation model (Anselin, 2002). In a real world situation, we cannot observe the quantum of effort that farmers put into soil conservation. The standard way to model this is to assume that an action e is observed whenever the underlying latent variable e* meets a condition. Thus,

$$e_i = \begin{Bmatrix} 1\ if\ U_i(e^*) > 0 \\ 0\ if U_i(\,e^*) \leq 0 \end{Bmatrix} \tag{8}$$

where $U(e^*)$ is the payoff from the latent effort e^*. Here, we use a discrete variable e_i to define whether a farmer adopts soil conservation measures or not.

In this case, it can be shown that

$$\Pr(e_i = 1) = \Pr[\varepsilon_i < h_i(X, W, \beta, \rho)] \tag{9}$$

where h_i is the multivariate normal density function, following the assumption of normality of u. The non-zero values in the i th row of W govern the array of interaction with neighbourhood farmers. This interaction affects the probability of adoption of farmer *i* (Anselin, 2002). Thus the above specification (9) violates SUTVA. The variance-covariance matrix of ε is as follows:

$$E\left(\varepsilon\varepsilon^{/}\right) = (I_n - \rho W)^{-1}\left(I_n - \rho W^{/}\right)^{-1}\sigma_u^2 \tag{10}$$

The interpretation of marginal effects with spatial probit models is quite different from that of marginal effects under standard probit models. For instance, in a spatial lag model, a change in the explanatory variable of i^{th} farmer has an effect not only on the soil conservation practices of the ith farmer e_i but also on those of other farmers e_j, $i \neq j$. This means that a change in the k^{th} variable of i^{th} farmer,, z_{ki} will affect the expected probability of adoption of his own and others' soil conservation practices. The marginal effect of the non-spatial or ordinary probit model is given by

$$\frac{\partial E[e \mid z_k]}{\partial z_k} = \emptyset(z_k\beta_k)\beta_k \tag{11}$$

In contrast, the marginal effect of the spatial probit model is given by

$$\frac{\partial E[e \mid z_k]}{\partial z_k^{/}} = \emptyset(H^{-1}I_n\overline{z_k}\beta_k) \odot H^{-1}I_n\beta_k \tag{12}$$

Where $\odot$ is the Kronecker product,

$$H = (I_n - \rho W) \tag{13}$$

The diagonal element of expression (12) above represents the direct effect, which is like the marginal effect of the non-spatial probit model. But in this model, there are feedback effects as well as a change in e_i from a z_{ki} also influences e_j which, in turn, affects e_i. Also, there is a cumulative effect of changes in z_{kj} on e_i, where $i \neq j$. The off-diagonal elements represent indirect effects. It is common to refer to the row sums as the "total effect to an observation": it is the impact on e_i from changing the k^{th} explanatory variable in the specified neighbourhood. The average direct effect is taken over all diagonal elements while the average indirect effect is the difference between average total effect and average direct effect. By symmetry, the row sums and column sums are the same. The difference between the total effect and the direct effect represents the indirect effect (LeSage & Pace, 2009).

The violation of SUTVA due to spatial dependency on unobserved factors (Spatial Error Model) and spatial dependence in both outcome as well as errors (General Spatial Autocorrelation Model). We discuss these spatial models in Online Appendix 3.

6 Estimation method

For the binary adoption case, the study estimates the probability of adoption in relation to non-adoption by using the probit model. We estimate the propensity score using the socio-economic, market access, farm characteristics, market access, village characteristics and information on soil conservation practice in immediate upstream neighborhood variables that are mentioned in Table 2 of Section 4.3.

The method of estimation of the spatial lag model must account for the fact that the covariance structures (see specifications 10) make the marginal distribution of ε_i heteroscedastic (Anselin, 2002). As a result, the estimators of the standard probit model are inefficient. In addition, ε_i are not independent and identically distributed due to spatial correlation. Consequently, the likelihood function involves multidimensional integration, which is computationally intensive (Wang et al., 2013). This study uses the Bayesian method in conjunction with the MCMC method to estimate the spatial probit model, following LeSage & Pace (2009) for the binary adoption case.

The present study uses the Epanechnikov Kernel matching, as it uses information from all observations, thus providing for lower variance (Caliendo & Kopeinig, 2008).

7 Econometric Results

We present the estimates from the binary probit model of the propensity score of adoption in Online Appendix 4. However, the presence of any sort of spatial pattern in outcome, or error, or both outcome and error, may provide a biased marginal effect of the explanatory variables. Though we will not go into a detailed discussion, we wish to underline that the spatial lag model best fits our data compared to other spatial models (see the discussion in Online Appendix 5 for details). The value of the spatial paramer $\rho=0.6$ and it is statistically significant at the 1 percent level of significance (see Appendix Table 5a of the Online Appendix 5). This justifies the use of spatial probit models rather than the non-spatial probit model and suggests that farmers within the specified neighbourhood (three kilometres of radius) are spatially dependent.

7.1 Spatial Lag Probit Estimates

Table 4 presents direct, indirect and total effects, as explained in equation 12, along with 95 percent confidence intervals. All the coefficients of household characteristics have 95 percent confidence intervals that include zero (apart from the coefficient for the household size). The total area of the farm, which is part of the farmer's asset holding, has the expected positive sign in the spatial lag model. The 95 percent confidence interval of indirect effect of farm area does not include zero, implying a significant cumulative effect of neighbours' farm size on the probability of adoption. None of the other farm characteristics has a significant impact in the spatial lag model.[20]

[20] See Singha (2017) for detailed analysis of these estimates.

Table 4: Spatial Lag Probit Model Estimates of Factors Influencing Adoption of Soil Conservation Practices with Neighbourhood up to Three Kilometres (Spatial Distance Matrix)

Variable	Direct Effect	Indirect Effect	Total Effect
Socio Economic Variables			
Age of the Household Head (Years)	0.002 (-0.001 to 0.005)	0.002 (-0.002 to 0.010)	0.005 (-0.003 to 0.014)
Years of Education of Household Head (Years)	0.009(-0.001 to 0.019)	0.015 (-0.001 to 0.041)	0.025 (-0.002 to 0.057)
Household size	0.021 (0.002 to 0.039)	0.038 (-0.003 to 0.098)	0.059 (0.005 to 0.132)
Household Member between age 14-65 (%)	-0.105 (-0.267 to 0.058)	-0.187 (-0.587 to 0.094)	-0.292 (-0.784 to 0.163)
Proportion of household members studied at least 10 years	-0.037 (-0.198 to 0.119)	0.059 (-0.372 to 0.209)	-0.097 (-0.557 to 0.327)
Experience of household head in agriculture (Years)	0.002 (-0.001 to 0.005)	0.004 (-0.001 to 0.012)	0.006 (-0.002 to 0.017)
Market Access Variables			
Distance to Market From Farm (Meters)	0.000 (0.000 to 0.000)	-0.000 (0.000 to 0.000)	-0.000 (-0.000 to -0.000)
Distance to all weather Road (Meters)	0.000 (0.000 to 0.000)	-0.000 (0.000 to 0.000)	-0.000 (-0.000 to -0.000)
Farm Characteristics			
Farm Size (Acre)	0. 04 (0.009 to 0.07)	0.072 (0.011 to 0.165)	0.112 (0.021 to 0.236)
Altitude of the farm (Meters)	-0.000 (-0.000 to 0.000)	-0.000 (-0.000 to 0.000)	-0.000 (-0.000 to 0.000)
Soil Texture$	-0.005 (-0.048 to 0.035)	-0.011 (-0.102 to 0.064)	-0.017 (-0.141 to 0.094)
Soil Colour$$	0.03 (-0.01 to 0.065)	0.049 (-0.012 to0.145)	0.078 (-0.023 to 0.201)
Soil Stoniness$$$	-0.043 (-0.088 to 0.000)	-0.0745(-0.206 to 0.000)	-0.119 (-0.282 to 0.000)
Villages and sub-watershed characteristics			
Forest Village Dummy†	0.052 (-0.034 to 0.148)	0.088 (-0.056 to 0.292)	0.140 (-0.0911 to 0.407)
Very high soil erosion prone sub-watershed Dummy††	0.025 (-0.101 to 0.055)	0.039 (-0.192 to 0.099)	-0.064 (-0.285 to 0.162)
Sub-watershed treatment Dummy†††	-0.017 (-0.096 to 0.063)	-0.027(-0.200 to 0.124)	-0.043 (-0.288 to 0.182)
Information on Soil Conservation Practice in Immediate Upstream Neighbourhood			
Contour Bunding (%)	0.165 (0.032 to 0.285)	0.285 (0.042 to 0.670)	0.450 (0.086 to 0.920)
Afforestation (%)	0.231 (0.119 to 0.343)	0.406 (0.107 to 0.862)	0.638 (0.270 to 1.163)
Bamboo Plantation (%)	0.156 (0.025 to 0.293)	0.268 (0.031 to 0.634)	0.425 (0.063 to 0.875)
Contour Bunding X Afforestation (%)	0.021 (-0.038 to 0.084)	0.035 (-0.081 to 0.173)	0.056 (-0.112 to 0.253)
Contour Bunding X Bamboo Plantation %)	0.041 (-0.077 to 0.165)	0.073 (-0. 134 to 0.324)	0.114 (-0.199 to 0.476)
Afforestation X Bamboo Plantation (%)	-0.138 (-0.257 to -0.022)	-0.238 (-0.564 to -0.021)	-0.376 (-0.788 to -0.058)

Sources: 1) A primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013, *2)* Kalimpong Soil Conservation Division (2010), Kurseong Soil Conservation Division, (2011).

Notes: 1) Standard deviation in parentheses; 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively; 3) Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted either stone wall or no conservation measure; 4) Number of adopters: 211, number of non-adopters:221; 5) $, $$ and $$$ have been reported by the respondent according to a hedonic scale. Scale of soil texture: sandy/coarse--- 1, loamy/medium coarse—2, clay- 3, silt-4; Scale of soil color: grey - 1, reddish - 2, brown - 3, black – 4; Scale of soil stoniness: high stoniness- 1, medium stoniness- 2, low stoniness-scale 3, non-stony- 4; 6) † inhabitants does not have exclusive property right (Maharashtra Forest Department, http://mahaforest.gov.in/fckimagefile/Handbook-13.pdf, December 17, 2014); 7) ††Sediment Yield Index is 1450 and above, "Sediment Yield Index" calculated as "weighted arithmetic mean of the products of the erosion intensity weightage value and delivery ratio over the entire area of the hydrologic unit by using suitable empirical equation" (Soil and Land Use Survey of India, slusi.dacnet.nic.in/rrs.pdf, February 2, 2014); 8) ††† the state forest department of West Bengal has taken soil conservation measures in forest area. In untreated sub-watersheds, no government initiative for soil conservation, 9) Direct, indirect and total effect is based on equation (12).

As far as sub-watershed and village-level variables are concerned, the coefficients associated with the dummy for sub-watershed of very high soil-erosion-prone category and dummy for forest village are insignificant. However, what is noteworthy is that the sub-watershed treatment neither discourages farmers from adopting soil conservation practices at their farms nor encourages them to do so.

Nevertheless, information on upstream neighbours' adoption of soil conservation measures positively affects the probability of on-farm adoption. The significance of the direct effect suggests that neighbourhood effects are important and positively impact adoption. Also important is the positive indirect effect, as it provides empirical evidence that the adoption of soil conservation practice is limited not only to the immediate upstream but is diffused over the entire specified neighbourhood (within a radius of up to three kilometres in our study) and that farmers communicate with each other about adoption (Lapple & Kelly, 2015).[21]

7 Comparing Adopters with Non-adopters

We present the distribution of propensity scores estimated by ordinary probit model and spatial lag probit in Figure 2a and 2b respectively. These figures suggest that there is a substantial region of common support over which matching can be undertaken.

For the PSM estimates to be valid, the characteristics of adopters and non-adopters need to balance after matching. We use the two-sample t-test for difference in means to evaluate if this is indeed the case. Table 5 reports the post-matching two sample t-tests (the absolute p-value of mean difference) for all the variables (except for dummy and interaction variables). As evident from column 3 of Table 5, post-matching for the binary adoption case eliminates the differences for all socio-economic, market access and farm characteristics variables when the

[21] ibid

propensity score is estimated by spatial lag probit. However, there are still differences in some covariates when the propensity score is estimated by ordinary probit model.

We also compare the post-matching mean and median percentage bias for the binary and multiple adoption case between the two propensity score estimation methods (i.e., ordinary probit and spatial lag probit) in Table 6. The mean and median percentage bias is the average bias of all observed covariates. On these basis of these percentage bias, we can conclude that the kernel matching procedure based on the spatial lag probit is able to reduce the bias (or balance the covariates) between adopters and non-adopters, more than the ordinary probit.

Figure 2 Propensity Score Graph

Figure 2a: Propensity Score Graph based on Ordinary Probit

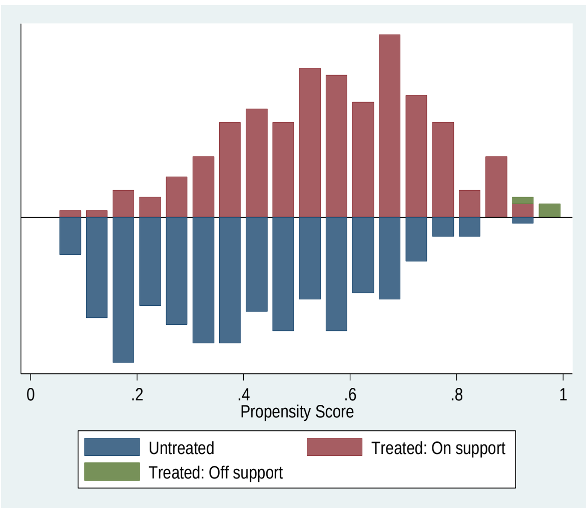
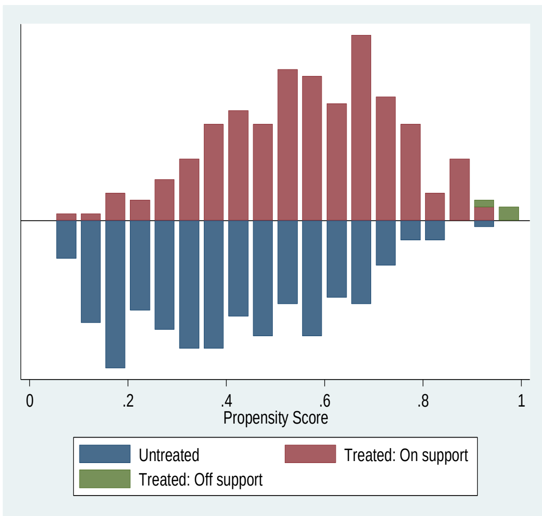


Figure 2b: Propensity Score Graph based on Spatial Lag Probit



Source: Based on the primary survey carried out in Darjeeling District, West Bengal, India in the year 2013.
Note: The Propensity Graph shows the distribution of the propensity score of adopters and non-adopters

Table 5: Post-Matching two sample t-test of mean difference

Variables	Absolute p-value of mean difference between Adopters with Non-Adopters after conditioning on propensity score based on Ordinary Probit	Absolute p-value of mean difference between Adopters with Non-Adopters after conditioning on propensity score based on Spatial Lag Probit
Socio Economic Variables		
Age of the Household Head (Years)	0.48	0.92
Years of Education of Household Head (Years)	0.42	0.8
Household Member between age 14-65 (%)	0.79	0.77
Household size (Numbers)	0.42	0.31
Proportion of household members studied at least 10 years	0.73	0.83
Experience of household head in agriculture (Years)	0.2	0.52
Market Access Variables		
Distance to Nearest Local Market From farm (IMeters)	0.0	0.3
Distance to all-weather Road (Meters)	0.14	0.88
Farm Characteristics		
Area of the farm in Acre (unit)	0.0	0.70
Altitude of the farm (Meter)	0.04	0.45
Soil Texture	0.96	0.19
Soil Colour	0.04	0.16
Soil Stoniness	0.15	0.37
Information Soil Conservation Practice Adopted in Immediate Upstream Neighbourhood		
Contour Bunding (%)		0.87
Afforestation (%)		0.19
Bamboo Plantation (%)		0.60
Number of Observations	432	

Source: Based on a primary survey carried out in the Darjeeling District, West Bengal, India, in the year 2013.
Notes: Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted either stone wall or no conservation measure.

Table 6: Post-matching mean and median percentage of bias

Method of Estimation of propensity score	Mean percentage bias	Median percentage bias
Ordinary Probit	13	11.5
Spatial lag probit	9	6.7

Source: Based on a primary survey carried out in the Darjeeling District, West Bengal, India, in the year 2013. Notes: Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted either stone wall or no conservation measure.

Table 7 reports the results of the causal effect of adoption on various outcomes. We report the ATT conditional on the binary probit as well as the binary spatial lag probit propensity score. A comparison between columns 3 and 6 indicates that in a couple of cases (i.e., per acre total revenue and cost in the winter season), the PSM based on ordinary probit tends to overestimate the ATT. However, the number of matched adopters and non-adopters is roughly the same. Despite that, a difference is observed in ATT. This is because the kernel matching method puts a higher weight on adopters who are close (in terms of the propensity score) to the non-adopters and a lower weight on distant adopter (Caliendo & Kopeinig, 2008). The same observation is likely to have a very different propensity score in two different methods of estimating the propensity score. This difference is driven by a spatial correlation and it has a huge implication for the identification of the impacts on agricultural outcomes. For instance, ATT on per acre total revenue based on the binary probit PSM is significant in the winter season. On the contrary, the same ATT is insignificant when we use the other method to estimate the propensity score. Nevertheless, ATT based on the spatial lag probit is reliable since the assumption of SUTVA is violated.

We find that ATT is statistically significant for per acre total revenue (with an estimated impact of INR 3,334 per acre) and per acre variable cost (with an estimated impact of INR 2,112 per acre) during the monsoon season at the 5 percent level of significance. During the winter season, on the other hand, the ATT is insignificant for all the outcome variables. The seasonal difference in the outcome variable may be due to the uneven distribution of rainfall (see Section 2.1 above). Furthermore, the seasonal aggregation reveals that neither of the ATTs is significant. This could be because, in the monsoon season, farmers face surplus water while they face dry conditions in the winter months, which means that the dry conditions of the winter season necessitate intensive soil and water conservation from the farmer (Bhutia, 2014). The results seem to indicate that the conservation measures lack in intensity.

Table 7: Impact of Adoption of Soil Conservation Practices on Farm Profit, Revenue and Variable Cost: Comparing Adopters with Non-Adopters

Outcome	Season	Propensity score based on binary probit			Propensity score based on spatial lag probit		
		ATT	Non-adopters (on support)	Adopters (on support)	ATT	Non-adopters (on support)	Adopters (on support)
Per acre profit (in INR)	Winter	-236 (333)	219	207	546 (891)	219	203
Per acre total revenue (in INR)		1598* (886)	219	207	1752 (1197)	219	203
Per acre total variable cost (in INR)		1834*** (740)	219	207	1140 (960)	219	204
Per acre profit (in INR)	Monsoon	1653 (882)	162	222	1224 (1070)	162	223
Per acre total revenue (in INR)		3740*** (1246)	162	222	3334** (1473)	162	223
Per acre total variable cost (in INR)		2087*** (890)	162	222	2112** (1094)	162	223
Per acre profit (in INR)	Aggregate of Winter and Monsoon	1501 (1226)	198	188	2243 (1617)	198	184
Per acre total revenue (in INR)		2651* (1633)	198	188	3248 (2286)	198	184
Per acre total variable cost (in INR)		1150 (1156)	198	188	998 (1650)	198	184

Source: 1) Based on a primary survey carried out in the Darjeeling District, West Bengal, India, in the year 2013.
Notes: 1) Standard errors in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 3) ATT is based on equation (4), 4) Adopter => observations who adopted at least two soil conservation practices from stone bunding, afforestation and bamboo plantation; Non-adopter => observations who adopted at most one soil conservation practice, 5) INR => Indian Rupee

The results suggest that soil conservation measures lead to a significant increase in yield for adopters. Although the higher yield comes with higher costs, the impact on farm revenues is positive in the rainy season. The variable cost component consists largely of labour costs (see

Online Appendix 2 for details). Hence, the positive and significant ATT of the total variable cost per acre during the monsoon season may be suggestive of complementarity between labour demand and on-farm soil conservation (Pattanayak & Burty, 2005).

Measuring soil conservation between adoption and non-adoption precludes the estimation of the causal impact of different types of soil conservation measures on the same set of outcome variables. Hence, we should turn to multiple adoption comparisons for a more nuanced analysis of the role of adoption, that is, one sensitive to the fact that adoption consists of multiple soil conservation measures. The Online Appendix 6 presents the comparisons in terms of impact on the three outcome variables (profits, revenues, and variable costs): a) farmers who adopt two measures (namely, stone wall and afforestation or bamboo plantation) compared to those who adopt none; b) farmers who adopt three measures (namely, stone wall, afforestation and bamboo plantation) compared to those who adopt none; c) farmers who adopt two measures (namely, stone wall and afforestation or bamboo plantation) compared to those who adopt only stone wall; and d) farmers who adopt three measures (namely, stone wall, afforestation and bamboo plantation) compared to those who adopt only stone wall. To conduct pair-wise comparisons of these four different and mutually exclusive[22] soil conservation measures or adoptions we follow a methodology proposed by Imbens (2001) and Lecher (2001 & 2002). [23]

Without going into detail discussion, we wish to underline some facts about Online Appendix 6. First, the spatial paramer ρ for all pair wise comparison is still statistically significant at the 1 percent level of significance for pair-wise comparisons of four soil conservation adoption

[22] This is in conformity with the literature on dose-response. For example, synergistically the combination of stone wall, afforestation and bamboo plantation could always be different from the combination of stone wall and afforestation. As a result these two categories of adoptions are mutually exclusive (Lechner, 2002).

[23] In the standard evaluation literature, the adoption variable takes a binary value. However, in many cases (as in ours) the adoption variable can take more than two values. Imbens (2001) and Lechner (2001 & 2002) proposed a methodology to estimate the causal impact of multi-valued treatment known as Generalised Propensity Score Matching where the generalised propensity score is the conditional probability of adopting a particular soil conservation measure.

groups.[24] Second, the Epanechnikov Kernel matching methods provide a quite different common support region between treatment and control group as is evident from the different number of matched observations in the two propensity score estimation methods (i.e., conditional probit and conditional spatial lag probit). It has significant implications on the causal impact of adoption measure(s). Third, we split the data into several sub-samples to compare adopters of multiple measures with those who adopt fewer measures. In the small sub-samples, we are left with fewer control observations. However, the Epanechnikov Kernel matching method uses the weighted average of almost all farm households in the control group to build the counterfactual outcome. As a result, it throws away the least number of observations from the control group as compared to other matching methods. Nevertheless, the possibility that the many observations used as controls are actually bad matches with the adopters cannot be ruled out (Caliendo & Kopeinig, 2008).

8. Conclusions and Policy Implications

This study attempted to estimate the causal impact of the adoption of soil conservation measures such as stone wall, afforestation and bamboo plantation on per acre farm profits, revenues and costs, using our survey of farmers in the Teesta Valley, where the problem of soil erosion is severe. To estimate the causal impact of the adoption of soil conservation measures, given that our maintained assumption is that it is possible to capture the factors that influence the farmers' decision to adopt different types of soil conservation measures on their farms, we created a counterfactual comparison group using matching techniques.

One of the crucial assumptions to identify the causal impact is "the absence of interaction among the farmers in adoption decisions", i.e., SUTVA. However, neighbourhood effects are crucial in the decision to adopt, given that soil conservation is location-specific, where "location" extends beyond an individual farm. Accounting for the role of spatial dependence is important because

[24] ibid.

soil conservation in one farm can assist or constrain it in adjacent farms due to strategic interaction. The presence of strategic interaction results in spatial dependency in conservation practices. We modelled this interaction with the spatial econometrics method and estimated the propensity score with the spatial lag probit model too. We also estimate the propensity score by the ordinary probit model.

We find that farmers located in close proximity exhibit similar adoption behaviour and that adoption of soil conservation measures is spatially interdependent. Therefore, the assumption of SUTVA is violated. As a result, the propensity score estimated by the spatial lag probit balances the observed covariates better than the propensity score estimated by the ordinary probit. In addition, PSM based on the spatial lag probit is also able to reduce bias in the estimated ATT. The results from the PSM methodology suggest no difference in per acre profits between the winter and monsoon seasons. Although revenues from adoption are higher, they also come with higher variable costs so that there is no difference in profits.

The adoption of multiple soil conservation measures such as stone wall, afforestation and/or bamboo plantation may be an essential precondition for farming in an ecologically fragile ecosystem like the Himalayas. However, it seems insufficient financial gain to farmers from adoption in Teesta river valley may halt their efforts of soil conservation. The insignificant profit can act as disincentive to spend on the maintenance of structural measures such as stone wall and terracing given the high expenses associated with it. Though the maintenance cost of afforestation is lower than that for structural measures, with a number of off-site and on-site environmental benefits, it takes a major portion of land out of farm production for years, thus incurring a huge opportunity cost for the farmer. The lower financial return from conservation may also discourage the farmer to devote optimal portion of land for afforestation.

With regard to government investment in sub-watersheds to reduce top soil loss, it does not have any impact on private adoption at the farm. Nevertheless, the significance of the spatial parameter in our study suggests new avenues to influence adoption of soil conservation among farmers by the government and other developing agency. Avenues like neighbourhood influence on the adoption of soil conservation practices may be usefully exploited to promote soil conservation measures. It may be useful to invest in geographically-intensive information programmes for sustainable agricultural practices. In addition, alternative incentive mechanisms to encourage afforestation, such as an incentive design, i.e., a contract between farmers and government (or a private agency), to sequester carbon through afforestation should be adopted to address this issue, particularly, if such contracts carry a monetary incentive which would encourage farmers to participate. Immediate benefits of such adoption are financial stability to the farmer, sustainable farm practices, and the mitigation of Green House Gas emissions through carbon sequestration.

This study is not without limitations. One major limitation is that the study is based on a partial equilibrium analysis of adoption decisions among farmers and has considered impacts only at the farm level. However, as noted above, the impacts of such action both by the government and the individual farmer are bound to extend beyond the river basin carrying general equilibrium implications for the supply of farm products and prices in the local economy. An analysis of these effects is merited in future work. The second limitation relates to the need to track these farmers over time and to construct a panel data set. It would assist in understanding the timing of adoption decisions in general and of specific measures in particular. Understanding these dynamics and their implications is possible only through a panel study. Thirdly, this study has used a narrow definition of neighbourhood, defined in terms of physical proximity, i.e., spatial distance. However, "neighbourhood" can also be defined in terms of socio-economic, cultural as well as kinship ties. The role played by strategic interactions, defined in these terms, in determining adoption could be considered in future research.

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Online Appendix 1

The discussions with several groups of farmers also revealed that monetary costs of soil conservation measures. These costs are the expected cost during the survey and not the actual cost borne by the farmer. The initial cost to implement stone terracing and terracing are INR 150,000-170,000 per acre and INR 20,000–30,000 per acre, respectively, while the average cost to build a stone wall is INR 50,000. Ideally, these measures need frequent (i.e., seasonal or annual) maintenance such as removal of sediment, weeds, monitoring, and maintaining of the height of terraces or walls, particularly after heavy rainfall. The gestation period of these measures is just one year. In contrast, the initial investment, in the case of vegetative afforestation and bamboo plantation, is INR 8000 per acre and INR 5000 per acre, respectively. However, the on-farm opportunity cost of these vegetative measures is quite high since a portion of farm land has to be taken off from farming for the purpose. But the maintenance cost (in terms of effort) of the measures, which involves removal of sediment, weeds and damage plants, is lower than that for structural measures. Nevertheless, the gestation period for the vegetative measures is higher and can vary between three to seven years. Hence, terracing is the most commonly used conservation measure due both to its effectiveness as well as lower initial cost and short gestation period in comparison with many of the other measures.

Online Appendix 2

Construction of Key Variables

There are three key variables: per acre profit, revenue and variable cost. The farmers in the sample use both sell their crops and also consume within the household. For produce, there are two prices: farm gate price[25] and market price. To generate the total revenue, first we calculate revenue from selling a crop by multiplying its farm gate price with the quantity sold. Next, we calculate the implied revenue from the consumption of a crop by multiplying its market price with the quantity consumed. By adding the revenues from selling and consumption, we get the total revenue from a crop. To get the total revenue, we calculate revenue from each crop, as outlined above and aggregate across all the crops to get total revenue.

By and large, there is no expenditure on fertilizers, pesticides, seeds, irrigation, etc. Of the respondents, 98 percent use cow dung and compost for fertilizer. Only 4 percent of the respondents reported purchasing pesticides from the market and 7 percent reported purchasing seeds. Therefore, the only major inputs for cultivation are land and labour. The calculation of a wage rate must account for the fact that there are three types of labour used in cultivation: household, hired and exchange. If the household reported the use of household labour and/or exchange labour as agricultural labour, we used a wage rate INR 100 per day roughly corresponding to the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) wage rate (for eight hours a day). [26] For hired labour, the wage rate per eight hours as reported by the farmer was used.[27] Labour cost is computed as the sum of all three categories

[25] "Price of the product available at the farm, excluding any separately billed transport or delivery charge" (OECD.Stats, https://stats.oecd.org/glossary/detail.asp?ID=940, April 10, 2014).

[26] The amount of wage fixed by nationwide MNREGA was Rs. 136 per day (eight hours' work) in 2013 in West Bengal. Sample survey suggests that villagers effectively earn Rs. 100 per day due to leakage. Therefore, it was the forgone wage that the household labour sacrifices to work on their farm.

[27] This likely underestimates the wage cost, as the cost of hired labour is generally much higher (so that the average wage across all categories is in the range of Rs 220 to Rs 260 per day).

of labour.

Since there are no rental markets for land in the study area, labour is the only variable cost incurred; using the method outlined above to aggregate across different kinds of labour. We subtract the total variable cost from the total revenue to get the farm profit. One concern in the calculation of revenues and costs is that there can be composition of commodity effect instead of adoption effect driving differences in outcome variables. But the sample data suggest that the crop composition between adopter and non-adopter is similar.

Farm profit is calculated as the difference between total revenue and total variable cost. The area under cultivation is taken across all crops. Finally, we divide profit, revenue and variable cost by area under cultivation to get these outcome variables in per acre term.

Online Appendix 3

1 Spatial Error Model

As mentioned in Section 5, there can also be dependency in unobserved factors. We further assume that these unobserved factors are not correlated with the exogenous variables. Then, equation (5) can be modified as:

$$e^* = X\delta + v \quad \text{(A1)}$$

where, $v = \gamma W v + z$

and, $E(z) = 0, E(zz^{/}) = \sigma_z^2 I_n$

or, $v = (I - \gamma W)^{-1} z$

The above equation (A1) exhibits spatial dependency on the error term, and is termed the spatial error model (LeSage & Pace, 2009). Analogous to equation (9), what is observed is a binary outcome and the probability of adoption is given by:

$$\Pr(e_i = 1) = \Pr[v_i < h_i(X, W, \delta, \gamma)] \quad \text{(A2)}$$

where h_i is the multivariate normal density function. The presence of W in specification (A2) bring range of unobserved spatial spill over. As a result, this specification also violates SUTVA. The variance-covariance matrix of v is as follows:

$$E(vv^{/}) = \sigma_z^2 (I_n - \gamma W)^{-1} \left(I_n - \gamma W^{/}\right)^{-1} \quad \text{(A3)}$$

The spatial error model does not contain the spatial lag explanatory variables or the outcome variable. Therefore, the interpretation of the marginal effect is similar to that in the non-spatial probit model.

2 General Spatial Autocorrelation Model

A model that incorporates spatial dependence in both outcome as well as errors is known as the general spatial autocorrelation model (SAC model) (LeSage & Pace, 2009) and can be written as follows:

$$e^{*} = (I - \rho W)^{-1} X\theta + \tau \tag{A4}$$

where, $\tau = (I - \rho W)^{-1}(I - \gamma W)^{-1}\varphi$

and, $E(\varphi) = 0, E(\varphi\varphi^{/}) = \sigma_{\varphi}^{2} I_n$

Similarly, like the spatial lag and spatial error models, in equations (9) and (A2), the probability of adoption can be explained as:

$$\Pr(e_i = 1) = \Pr[\tau_i < h_i(X, W, \theta, \rho, \gamma)] \tag{A5}$$

where h_i is the multivariate normal density function with the variance-covariance matrix of τ as follows:

$$E(\tau\tau^{/}) = (I_n - \rho W)^{-1}\left(I_n - \rho W^{/}\right)^{-1}(I_n - \gamma W)^{-1}\left(I_n - \gamma W^{/}\right)^{-1}\sigma_{\varphi}^{2} \tag{A6}$$

Again, like the previous two models, the presence of W in specification (A5) violates the assumption of SUTVA. In the general spatial auto correlation model, the marginal effect takes a similar form as in expression (12) since the spatial lag error does not come into play when considering the $\frac{\partial E[e \mid z_k]}{\partial z_k^{/}}$. Therefore, the interpretation of marginal effects is similar to that in the spatial lag model (LeSage and Pace, 2009).

Online Appendix 4

Table: Non-Spatial (Ordinary) Probit Analysis Results (Marginal Effects) of Factors Influencing Adoption of Soil Conservation Practices

Variables	**Marginal Effects**
Socio-economic variables	
Age of the household head (years)	0.002(0.002)
Years of education of household head (years)	0.012(0.008)
Household member between age 14-65 (%)	-0.048(0.135)
Household size	0.011(0.016)
Proportion of household members who have at least 10 years of schooling	0.015(0.135)
Experience of household head in agriculture (years)	0.004*(0.003)
Market access variables	
Distance to nearest local market from farm (in meters)	0***(0)
Distance to all-weather road (in meters)	0***(0)
Farm characteristics	
Farm area in acres	0.065** (0.032)
Altitude of the farm in meters	-0.000*** (6.02e-05)
Soil Texture$	0.019 (0.034)
Soil Colour$$	0.069** (0.029)
Soil Stoniness$$$	-0.075** (0.037)
Village and sub-watershed Characteristics	
Forest village dummy†	-0.060 (0.065)
Very high soil erosion prone sub-watershed dummy†††	0.078 (0.095)
Sub-watershed treatment dummy†††	-0.003 (0.090)

Sources: 1) A primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013, *2) Kalimpong Soil Conservation Division (2010), Kurseong Soil Conservation Division, (2011).*

Notes: 1) Standard deviation in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 3) Adopter => farmers who adopted stone wall, afforestation and/or bamboo plantation; Non-adopter => farmers who adopted only stone wall or no conservation practice,, 4) Number of adopters: 211, number of non-adopters:221, 5) $, $$ and $$$ have been reported by the respondent according to a hedonic scale. Scale of soil texture: sandy/coarse--- 1, loamy/medium coarse—2, clay- 3, silt-4; Scale of soil color: grey - 1, reddish - 2, brown - 3, black – 4; Scale of soil stoniness: high stoniness- 1, medium stoniness- 2, low stoniness-scale 3, non-stony- 4, 6) † inhabitants does not have exclusive property right (Maharashtra Forest Department, http://mahaforest.gov.in/fckimagefile/Handbook-13.pdf, December 17, 2014), 7) ††Sediment Yield Index is 1450 and above, "Sediment Yield Index" calculated as "weighted arithmetic mean of the products of the erosion intensity weightage value and delivery ratio over the entire area of the hydrologic unit by using suitable empirical equation" (Soil and Land Use Survey of India, slusi.dacnet.nic.in/rrs.pdf, February 2, 2014),. 8) ††† the state forest department of West Bengal has taken soil conservation measures in forest area. In untreated sub-watersheds, no government initiative for soil conservation,

Online Appendix 5

Spatial Analysis

We estimate three sets of spatial models—spatial lag model (equation 5), spatial error model (equation A1) and general spatial autocorrelation model (equation A4)—and present the resulting estimates of spatial correlation parameters ρ (outcome) and λ (error) in Appendix Table 5a for a range of specifications of the spatial weighting matrix, including the inverse distance spatial weight matrix (W) and the contiguity matrix (WC) (LeSage & Pace, 2009).

Appendix Table 5a: Spatial Parameter Estimate for Spatial Models by Neighbours Cut-off Distance and Weighting Matrix

Neighbours cut-off	Spatial parameter posterior mean of Spatial Lag Model (ρ)	Spatial parameter posterior mean of Spatial Error Model (γ)	Spatial parameter posterior mean of General Spatial Model ρ	γ
Inverse Distance Decay Matrix				
Up to 1 Kilometre	0.62***	0.63***	0.39**	0.20
Up to 3 Kilometres	0.60***	0.64***	0.44***	0.11
Up to 5 Kilometres	0.62***	0.69***	0.49**	0.04
Contiguity Matrix				
Within Village	0.37***	0.42***	0.26**	0.17
Nearest 1 Village in sample	0.35***	0.58***	0.21**	0.33

Source: Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013. Notes: 1) Standard error in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 2) Spatial lag model is based on equation 7, Spatial error model is based on equation A1 and general spatial autocorrelation model is based on equation A4, 3) In inverse-distance matrix W, $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} represents arial distance between point i and j in kilometres, 4) In Contiguity Matrix WC, $wc_{ij} = \begin{cases} 1 \; if \; i \; and \; j \; are \; neighbours \\ 0 \; otherwise \end{cases}$

Note that for all variants of spatial weight matrix, the estimated posterior mean of ρ of the spatial lag model and the estimated posterior mean of γ of the spatial error model are statistically significantly different from zero. This justifies the use of spatial probit models rather than of the non-spatial probit model, and suggests that farmers within the specified neighbourhood are spatially dependent. This spatial dependency is due to dependency in adoption and/or in unobserved factors. However, when spatial dependence in both outcome and error are modelled together through estimation of the general spatial autocorrelation model, then the estimated spatial correlation on outcome, that is posterior mean of ρ remains significant but estimated spatial correlation on error, which is posterior mean of γ is insignificant across all the distance decay spatial weight matrices. Similarly, when we use contiguity matrix as spatial weight matrix, the spatial lag estimator (ρ) of the general spatial autocorrelation model for neighbourhood within a village and nearest village is significant, but the estimated γ is not significant.[28]

Taken together, the results from three different spatial models suggest that the spatial lag model best describes our data, and is therefore used for further analysis. The significance of the spatial parameter suggests that a farmer's adoption of soil conservation practices positively influences neighbouring farmers' adoption decision. This still leaves the question of which of the various spatial weight matrices W to use. To select one, we compare the posterior probabilities of adoption of five different weight matrices of the spatial lag model (Appendix Table 5b). From the magnitudes, it appears that using an inverse weight matrix up to neighbourhood cut-off three kilometres is the best fit for spatial analysis, as it has the highest posterior probability.

Appendix Table 5b: Posterior Probability of adoption Spatial Lag Model by Neighbours Cut-off Distance and Weighting Matrix

Inverse Distance Decay Matrix		Contiguity Matrix	
Neighbours cut-off	**Posterior Probability**	**Neighbours cut-off**	**Posterior Probability**
Up to 1 Kilometre	0.04	Within Village	0.26
Up to 3 Kilometres	0.27	Nearest 1 Village in sample	0.05
Up to 5 Kilometres	0.04		

Source: Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013. Notes: 1) Spatial lag model is based on equation 7, Spatial error model is based on equation A1 and general spatial autocorrelation model is based on equation A4, 2) In inverse-distance matrix W, $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} represents arial distance between point i and j in kilometres, 3) In Contiguity Matrix WC, $wc_{ij} = \begin{cases} 1 \; if \; i \; and \; j \; are \; neighbours \\ 0 \; otherwise \end{cases}$, 4) Posterior Probabilities is calculated from the equation 11.

On the basis of these results, this study estimates and analyses a spatial lag model with an inverse distance matrix up to three kilometres as the spatial weight matrix.

[28] We tried spatial models on several distance decay and contiguity matrices but presented few to avoid repetition.

Online Appendix 6

Appendix Table 6a: Impact of Adoption of Soil Conservation Practices on Farm Profit, Revenue and Variable Cost (Winter Crop)

Outcome	Number of soil conservation measures Control	treatment	Propensity score based on binary probit ATT	On support Control	treatment	Propensity score based on spatial lag probit ATT	On support Control	treatment
Per acre profit (in INR)	None	stone wall & afforestation or bamboo plantation	481 (969)	126	109	646 (1059)	126	109
	None	stone wall, afforestation & bamboo plantation	-2198 (1949)	126	61	954 (2102)	126	47
	Stone wall	stone wall & afforestation or bamboo plantation	-993 (813)	131	95	338 (969)	113	113
	Stone wall	stone wall, afforestation & bamboo plantation	-2745* (1574)	86	95	535 (2140)	113	63
Per acre total revenue (in INR)	None	stone wall & afforestation or bamboo plantation	-25 (1438)	126	109	1389 (1581)	126	109
	None	stone wall, afforestation & bamboo plantation	2830 (2353)	126	61	5240* (2949)	126	47
	Stone wall	stone wall & afforestation or bamboo plantation	-2231** (1120)	131	95	-1005 (1330)	113	113
	Stone wall	stone wall, afforestation & bamboo plantation	1124 (1992)	95	86	2279 (2979)	113	63
Per acre total variable cost (in INR)	None	stone wall & afforestation or bamboo plantation	-507 (1046)	126	109	744 (1167)	126	109
	None	stone wall, afforestation & bamboo plantation	5029 (1988)	126	61	4285** (2121)	126	47
	Stone wall	stone wall & afforestation or bamboo plantation	-1238 (882)	131	95	-1344 (1052)	113	120
	Stone wall	stone wall, afforestation & bamboo plantation	3870 (1675)	95	86	1743 (2310)	113	63

Source: 1) Based on the primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013.
Notes: 1) Standard deviation in parentheses; 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively; 3) ATT is based on equation $ATT^{rs}(PSM) = E[\pi(r)|D = r, P^{r|rs}(Z)] - E[\pi(s)|D = s, P^{r|rs}(Z)]$; where $P^{r|rs}(Z)$ is the conditional probability on the sub-sample containing the adoption groups r and s (Imbens, 2001; Lecher, 2001 & 2002); 4) The value of spatial lag parameter for pair wise comparison between None Vs Stone wall & afforestation or bamboo plantation= 0.29*, None Vs Stone wall, afforestation & bamboo plantation= 0.44**, Stone wall Vs Stone wall & afforestation or bamboo plantation= 0.52***, Stone wall Vs Stone wall, afforestation & bamboo plantation=0.29*; 5) INR => Indian Rupee.

Appendix Table 6b: Impact of Adoption of Soil Conservation Practices on Farm Profit, Revenue and Variable Cost (monsoon crop)

1	2		Propensity score based on binary probit			Propensity score based on conditional spatial probit		
Outcome	Number of soil conservation measures		ATT	Om support		ATT	On support	
	Control	Treatment		Control	Treatment		Control	Treatment
Per acre profit (in INR)	None	stone wall & afforestation or bamboo plantation	915 (2217)	68	115	-993 (2328)	68	116
	None	stone wall, afforestation & bamboo plantation	876 (2197)	68	83	-557 (2189)	68	93
	Stone wall	stone wall & afforestation or bamboo plantation	1450 (1898)	97	135	1408 (1976)	97	122
	Stone wall	stone wall, afforestation & bamboo plantation	1262 (2124)	97	104	1174 (1847)	97	93
Per acre total revenue (in INR)	None	stone wall & afforestation or bamboo plantation	3567 (2966)	68	115	-838 (3250)	68	116
	None	stone wall, afforestation & bamboo plantation	3548 (2983)	68	83	-1539 3345)	68	93
	Stone wall	stone wall & afforestation or bamboo plantation	7108*** (1878)	97	135	7924*** (1949)	97	122
	Stone wall	stone wall, afforestation & bamboo plantation	5629** (2357)	97	104	5247** (2144)	97	93
Per acre total variable cost (in INR)	None	stone wall & afforestation or bamboo plantation	2651 (2423)	68	115	155 (2617)	68	135
	None	stone wall, afforestation & bamboo plantation	2671 (2079)	68	83	-996 (2282)	68	93
	Stone wall	stone wall & afforestation or bamboo plantation	5658*** (1664)	97	135	6515*** (1738)	97	122
	Stone wall	stone wall, afforestation & bamboo plantation	4367*** (1613)	97	104	4073*** (1453)	97	93

Source: 1) Based on the primary survey carried out in Darjeeling District, West Bengal, India, in the year 2013.
Notes: 1) Standard deviation in parentheses; 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively; 3) ATT is based on equation $ATT^{rs}(PSM) = E\left[\pi(r)\middle|D = r, P^{r|rs}(Z)\right] - E\left[\pi(s)\middle|D = s, P^{r|rs}(Z)\right]$; where $P^{r|rs}(Z)$ is the conditional probability on the sub-sample containing the adoption groups r and s (Imbens, 2001; Lecher, 2001 & 2002); 4) The value of spatial lag parameter for pair wise comparison between None Vs Stone wall & afforestation or bamboo plantation= 0.29* , None Vs Stone wall, afforestation & bamboo plantation= 0.44**, Stone wall Vs Stone wall & afforestation or bamboo plantation= 0.52***, Stone wall Vs Stone wall, afforestation & bamboo plantation=0.29*; 5) INR => Indian Rupee.