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Analysing Adoption of Soil Conservation Measures by Farmers in Darjeeling District, India

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Abstract

The study attempts to assess the key determinants of the decision to adopt soil conservation. The study area is Teesta River Watershed, in Darjeeling District in the Eastern Himalayas. In this watershed, there have been soil conservation interventions both by the individual farmers on their own farm and by the government at the sub-watershed level. The data for this study was collected through a primary survey conducted during 2013. The distinguishing feature of our analysis is that it explicitly accounts for possible neighbourhood effects in influencing adoption. This is captured both by identifying adoption practices among farmers who are immediately upstream, and using spatial econometric techniques that incorporate the spatial distance between neighbouring farms. We use Bayesian formulation of a standard probit model in conjunction with Markov Chain Monte Carlo to estimate the model. The findings suggest strong and positive evidence of neighbourhood impact on farmers in making soil conservation decisions. We also examine if adoption decisions differ between farmers residing in treated and untreated sub-watershed and conclude that they do not. Knowledge about the magnitude and extent of spatial dependency can help the Government in designing better policies to promote the adoption of soil conservation practices at a lower cost.

Key words: Soil conservation measure, neighbourhood effect, spatial dependence, sub-watershed

JEL Codes: Q24, C21, C13, C11

1 Introduction

The problem with soil erosion is multifaceted. First and foremost, there can be on-site negative impact of soil erosion on agricultural yield (Mbaga-Semgalawe and Folmer, 2000). Viewed in a larger context, since agriculture is the major source of livelihood of people, particularly in developing countries, rapid soil erosion poses a threat to the food supplies and livelihoods of those involved in agriculture (Barbier, 1995). Moreover, beyond a certain threshold, soil erosion can make the process of regeneration of soil cover irreversible, and affect future food supplies and livelihoods. Therefore, the link between on-farm soil erosion and yield is both inter-generational and intra-generational. Degraded land affects other natural resources as well; for example, reduction in crop yields may force farmers to intensify deforestation (Lopez, 2002). Soil erosion also leads to significant negative externalities (Somanathan, 1991 and Mbaga-Semgalawe and Folmer, 2000). However, soil erosion can be limited, and the resulting top soil loss reduced, through proper on-site and off-site soil and water conservation measures.

Some of the common farm-level (on-site) measures used around the world are terracing, contour practices, revegetation, crop mixture, land-clearing, fallow practices, land drainage system, agro-forestry and crop residue management (Scherr, 1999). These on-farm soil conservation measures provide benefits ranging from local (increased crop yields to farmers), regional (various off-site benefits such as flood control) to global level (climate change mitigation benefits through carbon sequestration),[1] and can be both short-term and long-term in nature (Bouma et al., 2007). Given this context, this paper attempts to analyse the determinants of on-farm soil conservation practices in the mountainous Darjeeling district of West Bengal state, India. We model the primary drivers of farmers' decisions to adopt soil conservation.

A variety of factors influence a farmer's decision to adopt soil conservation measures. There is an incentive to adopt soil conservation if the discounted gain from the marginal increment of crop production is greater than the opportunity cost of forgone income (Moser and Barret, 2006). The random utility model provides the basis for consumer

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1 "Amount of carbon stored in soil and vegetation" (Guidi et. al,, 2014 from Foley et al., 2004)

choices between competing alternatives of soil conservation practices, and has been widely used in the vast empirical literature examining the determinants of soil conservation decision of farmers. These studies suggest that the predominant socioeconomic determinants of farmers' adoption of soil conservation practices are membership in farmers' organizations, number of years of school education of farmer (Sidibe, 2004), spouse's educational attainment, government assistance, household wealth, labour availability, market accessibility, extension service to the farmer (Teklewood et al., 2014), cash crop cultivation, perceived erosion level of the farm, farm size and a soil and water conservation programme (Mbaga-Semgalawa and Folmer, 2000) and existence of a formal credit market (Wossen et al., 2015). In addition, farm characteristics such as soil type, depth of soil, slope of the land and soil quality have a positive effect on the adoption of soil conservation practices (Teklewood et al., 2014).

A few studies introduced neighbourhood aspects into their analysis of the adoption of soil conservation practices 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 or soil conservation that attempt to incorporate the interdependence of decisions. The first strand explicitly accounts for interactions with neighbours through models of social learning and networks (Mbaga-Semgalawa and Folmer, 2000; Conley and Udry, 2003; Bandiera and Rasul, 2006; Moser and Barret, 2006 and Teklewood et al., 2014). 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 and 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 to model dependence either in the outcome variable (adoption) or in the error term, or both. The interaction is based on a measure of proximity that is typically geographical in nature. In the context of analysing the adoption of soil conservation practices, the use of 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 and Lapar, 2007).[2] The logic is rooted in Tobler's law: "Everything is related to everything else, but near things are more related than distant things" (Drukker, 2009). Factors such as inter-farm information flow, neighbourhood competition or cooperation, geographical clustering of innovators, etc., could induce similar adoption behaviour in farmers (Abdulai and Hoffman, 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 and Burty, 2005). These variables are often not measured, resulting in dependence in residuals, and thus spatial factors contribute indirectly to the observed adoption of soil conservation practices (Holloway and Lapar, 2007). Hence, it is important to model spatial dependence; otherwise, the estimated coefficients of the determinants of soil conservation practice can be biased. Generally, studies on technology adoption in agriculture like Pinkse and Slade, 1998; Colney, 1999; Holloway and Lapar 2007; Wang et al., 2013; Lapple and Kelly 2015 have used spatial dependence models, but it has not been used yet in studies on soil conservation. The present study adds to the literature of adoption of soil and water conservation practices by bringing the spatial aspect into the analysis of the adoption of soil conservation practices.

For the spatial correlation, we consider models of (a) spatial dependence in outcome, that is, adoption of soil conservation practice (the spatial lag model); (b) spatial dependence in the error terms of the decision equation (the spatial error model); and (c) a composite model that allows for both spatial dependences on outcome and errors following Anselin (2002), LeSage and Pace (2009) and others. We use the Bayesian formulation of a standard probit model in conjunction with the Markov Chain Monte Carlo (MCMC) method to estimate the parameters.

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2 "Such models deal with 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).

Besides the farm level soil conservation measure, many off-site measures exist; relevant for this study is the set of measures adopted for mountainous sub-watersheds to raise agricultural productivity. Watershed management can be effected at various scales, from the entire river basin to tiny upland watersheds. But most watershed development measures aim to manage smaller topographical units, like sub-watersheds as in our study area, rather than the entire river basin.[3] Farmers' decisions to adopt on-farm conservation practices can depend on the distribution of benefits of sub-watershed treatment, (Feder and Slade, 1985) making it necessary to consider sub-watershed treatment status as one of the determinants of soil conservation pratices. Hence, the present study also examines if farmers' adoption of soil conservation practices depends on whether the farmer resides in a treated sub-watershed or not, to understand if treatment at the sub-watershed level serves as a substitute of, or is complementary to, adoption.

We use primary data collected on the adoption of soil conservation practices during 2013. The findings suggest that there is neither substitution nor complementarity between sub-watershed treatment and adoption at the farmer level. This implies that sub-watershed treatment neither discourages farmers from adopting soil conservation practices at their farms nor encourages them to do so. The findings also suggest a strong and positive evidence of neighbourhood impact (both upstream and spatial) on farmers in making soil conservation decisions. A higher proportion of adopters in the immediate upstream neighbourhood increases the probability of adoption. Also, we find that, among several competing spatial models, it is the spatial lag probit model that best describes our data. In particular, it performs better than a non-spatial probit model. A comparison of the marginal effects for the two models suggests that failing to control the spatial dependency in outcomes leads to over-estimation of the impact of other variables in the adoption decision.

Capturing spatial dependency is, thus, important from the policy perspective. Knowledge of the magnitude and extent of spatial dependency can help the government and other

3 Food and Agriculture Organisation of the United Nation, ftp://ftp.fao.org/docrep/fao/010/a1295e/a1295e07.pdf, Aug 26/07/2015

organizations in designing better policies to promote the adoption of soil conservation practices at a lower cost.

The organisation of this study is as follows: Section 2 briefly discusses study area and soil conservation measures. Section 3 discusses the spatial dimension of soil conservation, which includes the conceptual framework, model specification and section 4 outlines method of estimation. Section 5 interprets the coefficients of different spatial models. Section 6 describes the data and the definition of variables. Section 7 discusses and compares the results of spatial and non-spatial analysis. Lastly, Section 8 concludes the discussion and describes the policy implications.

2 Study Area and Soil Conservation Measures

The study area is Darjeeling district in West Bengal state of India. Darjeeling district is located in the eastern part of the Himalayas, in the warm perhumid eco-region.[4] Its coordinates lie between 87^0 57" East and 88^0 53" East and between 26^0 27" North and 27^0 13" North. The altitude of the hills within the district varies between 300 feet and 10,000 feet. The soils in the steep hill slopes are shallow and excessively drained, and have severe erosion hazard. The soils of the foot hill slopes and valleys are moderately deep, well drained and loamy in texture and have moderate erosion hazard (West Bengal District Gazetteer Darjeeling, 2010).

Soil conservation measures, as noted earlier, may be categorised as on-site measures and off-site measures. The farm-level (on-site) soil conservation measures adopted by farmers are: contour bunding, plantation of woody perennials, i.e., afforestation, bamboo plantation, orchard plantation, terracing, tree belt (plantation of trees on the farm boundary), broom plantation; and grass stripping.[5] The list is exhaustive but not mutually exclusive. Among these measures, contour bunding and terracing are the measures that

4 "National Bureau of Soil Survey and Land Use Planning (NBSS & LUP) of the ICAR has delineated 20 agro-ecological regions (AERs) in the country using the FAO 1978 concept of superimposition of growing periods and bio-climate maps on soil physiographic map." (TNAU Agritech Portal, http://agridr.in/tnauEAgri/eagri50/AGRO101/lec07.pdf, July 26 2015). The Darjeeling district perhumid ecosystem is one of these.

5 "A strip planted with grass across the slope. It slows down water flowing down the slope and catches sediment that has been eroded uphill", Food and Agriculture Organisation of the United Nation http://www.fao.org/ag/ca/africa trainingmanualcd/pdf%20files/08WATER.PDF, October 23, 2015

reduce the velocity of rain water flow on the agricultural farm, thereby reducing top soil loss. The rest of the measures help maintain a permanent vegetative cover on the farm to protect top soil from erosion. However, these measures vary with respect to their effectiveness in soil conservation.

The off-site measures are undertaken mainly by the Teesta River Valley Programme for Soil Conservation. The Government of West Bengal (state government) started implementing the Teesta River Valley Programme to control soil erosion from 1977 onwards, with the help of Government of India (central government). The unit of treatment was the sub-watershed (National Land Use and Soil Conservation Board, 1992). The Teesta River Valley Programme was implemented by the State Forest Department. The department implemented several off-site measures, including: afforestation, broom/fodder cultivation, orchard plantation, belly benching and stream bank control, to avoid landslides (reducing the force of water through engineering construction and vegetation to minimize removal of soil particles of the site), construction of catch water drains (which divert the water flow and reduce soil erosion)[6], slip control/stabilization (technical measures to mitigate landslide) (National Land Use and Soil Conservation Board, 1992; Kurseong Soil Conservation Division, 2011; Kalimpong Soil Conservation Division, 2010).

3 Conceptual Framework: Accounting for the Spatial Nature of Adoption Decisions

We adapt the framework provided by Ballester et al. (2006) and Jackson (2008) to understand a household's decision to invest in soil conservation measures. We assume that farmers have full information about soil conservation practices adopted by their neighbours. Let there be n number of farmers, and let $e_i \in R_+$ represent the effort level of farmer i, where i=1, 2....n, expended to adopt soil conservation practices. We also assume that the payoff function of farmer i is a quadratic function of the effort:

$$U_i(e_i, e_{-i}) = a_i e_i - \frac{b_i}{2} e_i^2 + \sum_{j \neq i} w_{ij} e_i e_j \tag{1}$$

[6] Unabridged Dictionary, http://www.merriam-webster.com/dictionary/catchwater, October 23, 2015

The first two terms in the above equation is the standard utility of own effort e_i, where $a_i = a \geq 0$ and $b_i = b > 0$ for all i = 1, 2, 3,……., n are scalars. Too much effort is not warranted, since it diminishes the payoff at the margin, which is captured by the second term of equation (1). That is, equation (1) is concave in own effort, since $\frac{\partial^2 U_i}{\partial e_i^2} = -b < 0$. $e_{-i}$is the sum of the efforts of others, i.e., the combined effort of neighbours, and $w_{ij}$is the weight that farmer i puts on his neighbour j. The last term represents the network effect in the neighbourhood, i.e., it captures the utility from a bilateral interaction, $\frac{\partial^2 U_i}{\partial e_i e_j} = w_{ij}$, where $i \neq j$. If an increase in the effort level of j raises the effort level of i, then w_{ij}> 0 represents strategic complementarity. On the other hand, if an increase in the effort level of j diminishes the effort level of i, then w_{ij}< 0 and implies strategic substitution.

The best response of the farmer given the level of efforts by others is obtained by using the first order condition (i.e. differentiating with respect to own effort):

$$e_i = \frac{a}{b} + \sum \frac{w_{ij}}{b} e_j \tag{2}$$

The above expression suggests interdependence of efforts between farmers and their neighbours; this can arise from localized factors (like "neighbourhood effect, copy-catting, peer group effect, strategic interaction, etc." (Anselin, 2002)) and from diffusion of knowledge. Equation (2) can also be written in matrix form:

$$\begin{pmatrix} e_1 \\ \vdots \\ e_n \end{pmatrix} = \begin{pmatrix} a/b \\ \vdots \\ a/b \end{pmatrix} + \frac{1}{b}\begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}\begin{pmatrix} e_1 \\ \vdots \\ e_n \end{pmatrix} \tag{3}$$

or $e = \beta_0 + de$ (3a)

or $e = (I - d)^{-1}\beta_0$ (3b)

where I is the identity matrix, $\beta_0 = \left(\frac{a}{b}, \frac{a}{b}, \ldots\ldots\ldots, \frac{a}{b}\right)^{/}$ and $d = \frac{1}{b}\begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}$. A stable equilibrium exists if the matrix (I—d) is invertible. The matrix implies $(n^2 - n)$ possible relations between n observations, and since diagonal elements represent weights on the farmer i's own effort, they are all zero (LeSage and Pace, 2009).

3.1 Spatial Lag Model

We extend the above model (3a) by adding potential conditioning variables and distinguishing latent effort from observed effort. The empirical specification for the estimation of equation (3a) is as follows:

$$e^* = \rho W e^* + X\beta + u \tag{4}$$

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, as before, the unobserved effort of the neighbourhood firms e^*_{-i} influence e^*_i (Anselin, 2002). As mentioned in Section 1, the dependence in latent effort arises due to the flow of information among the farmers, and due to the competition or cooperation between them. We include X, which is a (n x k+1) matrix of other exogenous variables of household and farm characteristics (defined in Section 4), and $\rho = 1/b$ is the spatial autoregressive parameter (scalar), that is additional to any standard latent variable model. β is (k +1 x 1) vector of parameters and u is a random shock with $E(u) = 0, E(uu^{/}) = \sigma_u^2 I_n$.

If ρ=0, that is, there is no spatial dependence then equation (4) becomes:

$$e^* = X\beta + u \tag{5}$$

Equation (5) can be analysed using a standard (non-spatial) binary probit model. 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: for example, e is observed when $e^*>0$. Thus,

$$e_i = \begin{Bmatrix} 1\ if\ U_i(e^*) > 0 \\ 0\ if U_i(\ e^*) \leq 0 \end{Bmatrix} \tag{6}$$

where U_i (e^*) is the payoff from latent effort e^*.

From equation (6), we can get the conditional density function of effort given the exogenous variables:

$$\Pr(e_i = 1 |\ X) = \emptyset_i(X\beta) \tag{7}$$

where $\emptyset_i$ is the cumulative normal distribution function, given the assumption that u is normally distributed (Wang et al., 2013).

In case $\rho \neq 0$, the above equation (4) is known as spatial reaction function (Bruckner 2002), and is also called spatial lag model or spatial autocorrelation model. Through the above specification, this study models how the latent magnitude of effort of soil conservation at a farm (e*) is determined by the latent magnitude of effort of soil conservation in neighbourhood farm, $\rho W e^*$ (Anselin, 2002) and by various exogenous household and farm characteristics, $X\beta$. Assuming $(I - \rho W)$ is non-singular, equation (4) implies:

$$e^* = (I - \rho W)^{-1} X\beta + \varepsilon \tag{8}$$

where

$$\varepsilon = (I - \rho W)^{-1} u \tag{9}$$

As before, since e* is not observed, we use a discrete variable e_i to define if a given farmer adopts soil conservation measures or does not.

In this case, it can be shown that

$$\Pr(e_i = 1) = \Pr[\varepsilon_i < h_i(X, W, \beta, \rho)] \tag{10}$$

where h_i is the multivariate normal density function (Anselin, 2002), following the assumption of normality of u. The variance-covariance matrix of ε is as follows:

$$E(\varepsilon\varepsilon') = (I_n - \rho W)^{-1} (I_n - \rho W')^{-1} \sigma_u^2 \tag{11}$$

3.2 Spatial Error Model

Thus far, we have considered spatial dependence in soil conservation practices. There can also be dependency in unobserved factors. As mentioned in Section 1, this type of dependency arises due to many geographical and economic factors that remain unmeasured or unobserved, such as wind conditions, soil moisture content, soil quality, topography of land, local temperature, etc., that may influence the adoption of soil conservation practices and are correlated over space. Similar unobserved characteristics may lead to a similar level of effort in soil conservation; neighbouring farmers are more likely to face similar soil, topographic and climatic conditions than more distant farmers. In this case, we model only dependency of residuals, instead of dependence in the latent effort of soil conservation practice, and assume further that these unobserved factors are not correlated with the exogenous variables. Then, equation (4) can be modified as:

$$e^* = X\delta + v \tag{12}$$

where, $v = \gamma W v + z$
and, $E(z) = 0, E(zz^{/}) = \sigma_z^2 I_n$
or, $v = (I - \gamma W)^{-1} z$

Instead of exhibiting spatial dependency on outcome, the above equation (12) exhibits spatial dependency on the error term, and is termed spatial error model (LeSage and Pace, 2009). Analogous to equation (10), what is observed is a binary outcome, and the probability of adoption is given by:

$$\Pr(e_i = 1) = \Pr[v_i < h_i(X, W, \delta, \gamma)] \tag{13}$$

where h_i is the multivariate normal density function. The variance-covariance matrix of v is as follows:

$$E(vv^{/}) = \sigma_z^2 (I_n - \gamma W)^{-1} \left(I_n - \gamma W^{/}\right)^{-1} \tag{14}$$

3.3 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 and Pace, 2009) and can be written as follows:

$$e^* = (I - \rho W)^{-1} X\theta + \tau \tag{15}$$

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, as in equations (8) and (13), the probability of adoption can be explained as:

$$\Pr(e_i = 1) = \Pr[\tau_i < h_i(X, W, \theta, \rho, \gamma)] \tag{16}$$

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

$$E(\tau\tau^{\prime}) = (I_n - \rho W)^{-1}(I_n - \rho W^{\prime})^{-1}(I_n - \gamma W)^{-1}(I_n - \gamma W^{\prime})^{-1}\sigma_{\varphi}^2 \tag{17}$$

4 Method of Estimation

The method of estimation of the spatial lag model must account for the fact that the covariance structure (11) makes the marginal distribution of ε_i heteroscedastic (Anselin, 2002). As a result, the estimators of standard probit model are inefficient. In addition, ε_i are not independent and identically distributed due to spatial correlation. As a result, the likelihood function involves multidimensional integration, which is computationally intensive (Wang et al., 2013). Researchers have adopted several methods to tackle the dependency in space, heteroscedasticity in covariance matrix and computational burden. These include using methods like generalized methods of moments (Pinkse and Slade, 1998; Colney, 1999), MCMC (LeSage and Pace, 2009; Holloway and Laper, 2005; Lapple and Kelly, 2015), partial maximum likelihood estimator (Wang et al. 2013), etc. This study uses the Bayesian method in conjunction with the MCMC method to estimate the spatial probit model, following LeSage and Pace (2009). Section 4.1 discusses the fundamental framework of the MCMC method. Then, Section 4.2 applies it in the context of adoption of soil conservation practices.

4.1 Essentials of the Bayesian MCMC Estimation Approach

The posterior probability of $P(C \mid \omega)$ from Bayes' Rule is given by:

$$P(C \mid \omega) = \frac{P(\omega \mid C)P(C)}{P(\omega)} \tag{18}$$

where C is the model parameter, $P(\omega \mid C)$ is the likelihood, $P(C)$ is prior distribution and $P(\omega)$ is the data distribution. Since $P(\omega)$ does not contain any parameters, expression (18) can be rewritten as:

$$P(\complement \mid \omega) \propto P(\omega \mid \complement)P(\complement) \tag{19}$$

In the MCMC, the posterior distribution of equation (19) is decomposed into a sequence of conditional distribution of parameters instead of operating with posterior distribution. This methodology sequentially samples each parameter from their conditional distribution. It is based on the proposition that a large sample from these sets of conditional distributions for all parameters can approximate the form of the probability density function by deploying Kernel density estimators or histograms. Therefore, the exact analytical form of the distribution is not required under the MCMC method. More categorically, we can use kernel density estimation method to construct the entire posterior distribution of parameters as well as to compute mean and standard deviation (LeSage and Pace, 2009). As a result, the MCMC approach does not rely on the asymptotic properties to determine valid standard errors (Lapple and Kelley, 2015).

Let us consider spatial lag model i.e. equation (8). The parameters in $\complement$ are of two types:

1. parameters such as β and σ_u, where the form of conditional distributions are known; and
2. parameter such as ρ, where the form of conditional distributions are unknown.

For instance, in the case of $\beta,$ the conditional distribution takes the form of multivariate normal. We can draw the sample by following the Gibbs sampling approach to get the Bayesian parameter estimate of β. On the other hand, to get the Bayesian parameter estimates of ρ, the MCMC method counts on the Metropolis-Hastings algorithm. The essential feature of this algorithm is that it systematically creates its own Markov chain that converges to a distribution that we are interested in.

The estimation of expression (19) also involves the unobserved latent variable U(e^*) (see equation (6) for details) related with observed discrete choices. Following Albert and Chib (1993), LeSage and Pace (2009) replaced the unobserved latent variable with the estimated latent parameter. The underlying idea is that once the latent U(e^*) is recognized as an additional estimable set of parameters, then $P(\complement \mid U(e^*)) = P(\complement \mid U(e^*), e)$. $U(e^*)$, the continuous variable, has replaced the binary variable e. As a result of this equality, the joint posterior distribution of $\complement$ can be regarded as a

Bayesian regression problem with a continuous variable instead of a discrete one. Following LeSage and Pace (2009), we utilize this particular approach in the spatial lag model.

Again, following LeSage and Pace (2009), we assume that the conditional distribution of $U(e^*)$ takes the form of truncated multivariate normal distribution (TMVN) due to dependency in $u_i(e^*)$.

Following LeSage and Pace (2009), we also compute the conditional distribution of the spatial lag model based on normal prior for β, uniform prior for the spatial parameter for ρ and TMVN prior to $U(e^*)$. Further, we also assume $\sigma_u^2 = 1$, which is required for identification. To approximate the posterior distribution (19), we need to sequentially sample from the following three conditional distributions: $P(\beta \mid \rho, U(e^*))$, $P(\rho \mid \beta, U(e^*))$ and $P(U(e^*) \mid \beta, \rho)$. The MCMC sampling scheme for the conditional posterior distribution is as follows:

Step 1

For a normal prior $\beta \sim N(m, K)$, with mean m and variance-covariance K, sample $P(\beta \mid \rho, U(e^*))$ from a multivariate normal prior as

$P(\beta \mid \rho, U(e^*)) \propto N(m^*, K^*)$ where $m^* = (X^/X + K^{-1})(X^/Se^* + K^{-1}m), K^* = (X^/X + K^{-1})$ and $S = (I_n - \rho W)$, m= mean of normal prior and k can be identity matrix (LeSage and Pace, 2009).

Given $\sigma_u^2 = 1$ and known ρ and $U(e^*)$, we can set an arbitrary initial value $\beta = \beta_{(0)}$. From the initial value and given ρ and $U(e^*)$, we can calculate mean m^* and variance-covariance K^* from the above multivariate normal density of β. Given the algorithm in Gibbs sampling, we can get the vector of multivariate normal random value with mean m^* and variance-covariance K^*. Now, the initial $\beta_{(0)}$ can be replaced with the sampled β, denoted as $\beta_{(1)}$. The process of sampling the conditional distribution of β is to be continued until a large number of draws of β is done.[7]

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[7] See LeSage and Pace (2009) for details.

Step 2

Sample $P(\rho \mid \beta, U(e^*))$ by using uniform prior

For the parameter ρ, a sample can be drawn from $P(\rho \mid \beta, U(e^*)) \propto |I_n - \rho W| \exp\left(-\frac{1}{2}[SU(e^*) - X\beta]^{/}\,[SU(e^*) - X\beta]\right)$ (LeSage and Pace, 2009). This conditional distribution is not a known form of distribution, as in the case of parameter β and $U(e^*)$. The sampling of parameter ρ can be done by the Metropolis-Hastings algorithm, following Hastings (1970). The advantage of using this algorithm is that one need not worry about whether the actual process is following the Markov chain or not.[8]

Step 3

Sample $P(U(e^*) \mid \beta, \rho)$ by carrying out Gibbs sampling algorithm from Truncated Multivariate Normal Distribution

Sample needs to be drawn from a Truncated Multivariate Normal Distribution $U(e^*) \sim TMVN(\theta, \vartheta)$ subject to $O_1 \leq U(e^*) \leq O_2$,

where $\theta = (I_n - \rho W)^{-1} X\beta$ is the mean and $\vartheta = \left[(I_n - \rho W)^{/}(I_n - \rho W)\right]^{-1}$ is the variance-covariance matrix and O_1 and O_2 are the truncation bound (LeSage and Pace, 2009). These truncation bounds are contingent upon the observed discrete value of e.[9]

To construct MCMC estimates for the spatial lag model, in sum, we incorporate Gibbs sampling for multivariate normal and TMVN for the parameter β and $U(e^*)$ respectively and Metropolis-Hastings sampling for the spatial parameter ρ. A single sequence of samples from the above-mentioned distribution of parameters comprises a solitary pass through the MCMC sampler. We have to produce a substantial number of passes to construct a large sample of draws from the joint posterior distribution of β, ρ and $U(e^*)$ (LeSage and Pace, 2009).

[8] ibid.
[9] ibid.

4.2 Application of Spatial Lag Model in Adoption of Soil Conservation

We estimate these models for the 432 farmers of our sample, using software packages Stata and Matlab. In our application, $\omega = \{e, X, W\}$. Specifically, $e = 1$ for 211 adopters of soil conservation and e=0 for 221 non-adopters of soil conservation (see Section 6.2 for details), X consists of a constant term and other explanatory variables, such as socioeconomics variables, market access variables, farm characteristics and soil conservation practice in the immediate upstream neighbourhood (see Section 6.3 for details), and W = inverse distance decay or contiguity matrix (see Section 6.1 for details). $U(e^*)$ is the unobserved latent effort associated with the observed adoption or non-adoption of soil conservation measure. The spatial analysis is built on 1,000 MCMC draws and 100 passes. We separately conduct another run with 2000 MCMC draws and 200 passes, and find that both runs produce almost identical results.

5 Interpretation of Coefficients of Spatial Models

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 ith 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, x_{ki}, will affect the expected probability of adoption of his own and others' soil conservation practices. The marginal effect of the non-spatial probit model is given by:

$$\frac{\partial E[e \mid x_k]}{\partial x_k} = \emptyset(x_k \beta_k)\beta_k \tag{20}$$

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

$$\frac{\partial E[e \mid x_k]}{\partial x_k^{/}} = \emptyset(H^{-1} I_n \overline{x_k} \beta_k) \odot H^{-1} I_n \beta_k \tag{21}$$

Where $\odot$ is the Kronecker product,

$$H = (I_n - \rho W) \tag{22}$$

The diagonal element of expression (21) 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 x_{ki} also influences e_j which, in turn, affects e_i. Also, there is a cumulative effect of changes in x_{kj} where $i \neq j$ on e_i. 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 kth 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.

In our case, the direct effect is the change in the probability of soil conservation practices of the i^{th} farmer, because of a minute change in an explanatory variable of the same farmer, that is, x_{ki}i. On the other hand, the indirect effect is the change in the probability of adoption of soil conservation practice of farmer i due to the feedback effects from farmer j in the neighbourhood, i.e., the cumulative effect. The effect of the soil conservation practices of the neighbouring farm depends on physical proximity, which is captured by the spatial weight matrix and the spatial autocorrelation parameter.

The spatial error model does not contain the spatial lag explanatory variables or the outcome variable. Therefore, the interpretation of marginal effect is similar to that in the non-spatial probit model. In the general SAC model, the marginal effect takes a similar form as in expression (21), since the spatial lag error does not come into play when considering the $\frac{\partial E[e \mid x_k]}{\partial x_k^{/}}$. Therefore, the interpretation of marginal effects is similar to that in the spatial lag model (LeSage and Pace, 2009).

6 Data and Variable Definitions

The details of the primary survey conducted during June-August 2013 in Darjeeling district of Teesta River Valley in West Bengal state of India have been discussed in Singha (2016).

6.1 Spatial Weight Matrix

All the farms in the survey were geo-coded, and the software package Matlab was used to calculate the Euclidean distance between all the farms. We use this information to generate the different types of spatial weight matrix suitable for our analysis.

Given the context of adoption, we specify the spatial weight matrix W using neighbouring farmers who live within a specified distance. 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. We try various specifications, varying the distance within which spatial dependency is assumed to play a role. In all specifications, W_{ii}=0 and the matrix is symmetric and row-standardized, i.e., the row sum is bounded uniformly to 1. We implemented row-standardization as $W_{ij} = \frac{1/d_{ij}}{\sum_{j=1}^{n} d_{ij}}$, where d_{ij}= Euclidean distance between two farmers.

In another variant, the spatial weight matrix WC is specified as a contiguity matrix (Anselin, 2002), which assumes all the farmers within a village can be deemed to be neighbours and affect each others' decision. That is, WC_{ij}=1 within a village but WC_{ij}=0 outside the village. We implement row-standardization by dividing all the elements of a row i by number of non-zero entry of the row. Since our sample consists of 12 farmers from each village, this means that each farmer in our sample has 11 neighbours within a village. If we allow spatial dependency to prevail within a village as well as within the nearest village in our sample, the weight matrix consists of 23 neighbours in WC1. In similar fashion, the spatial dependency confined to the nearest two and three villages in our sample allows the weight matrix to pick 35 neighbours in WC2 and 47 neighbours in WC3 respectively.

6.2 Dependent Variable: Determining Adoption

The different types of soil conservation measures used by farmers include contour wall/contour bunding, afforestation/plantation of woody perennials, bamboo plantation, orchard plantation, tree belt, terracing, broom cultivation and grass stripping. This list is exhaustive but not mutually exclusive[10]. We specify adopters as those who have adopted at least two measures from contour bunding, afforestation and bamboo plantation. Table 1 suggests that 49 percent of the farmers have adopted at least two measures. We define these farmers as adopters. As a robustness check, we include a different measure of adoption, as noted later.

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

Farmers Adopting at least	Cumulative Percentage
None of the measures	25
One measure	51
Two measures	83
Three 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.
Note: The different adoption measures are: contour bunding, afforestation/ plantation of woody perennial and bamboo plantation.

6.3 Explanatory Variables

Adoption of soil conservation practices depends on a number of factors, such as the socioeconomic characteristics of the farmer/farming households, farm characteristics and measures of market access.

6.3.1 Socioeconomic Characteristics

In the literature, the socioeconomic characteristics of households that have been found relevant for adoption of soil conservation practices include age of the household head, years of education of household head, proportion of members active in labour market in a household, household size and proportion of household members who have at least 10 years of schooling.

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10 During the pilot survey, we also asked the respondents to rank each soil conservation measure by its effectiveness in tackling soil erosion on a scale of 1 to 10. By calculating the average, we worked out that the soil conservation practices considered most effective are contour terracing, contour/contour bunding, plantation of woody perennial, bamboo plantation and terracing. Only a few used contour terracing; therefore, we exclude this soil conservation practice. Moreover, 90 percent of the farmer reported to adopt terracing as soil conservation measure. We consider terracing as “no conservation measure”.

Table 2: Summary Statistics & Two Sample t-test with Survey Data

1	2	3	4	5
Variable	**Full Sample**	**Adopters**	**Non-adopters**	**Mean Difference = Adopters - Non-adopters**
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 studied at least 10 years	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 Colour	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**
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: 1) Primary survey carried out in Darjeeling District, West Bengal, India carried out 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 at least two soil conservation practices from contour bunding, afforestation and bamboo plantation, Non-adopter => farmers who adopted at most one soil conservation practice contour bunding, afforestation and bamboo plantation, 4) In Treated sub-watersheds state forest department of West Bengal has taken soil conservation measures. 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 Colour 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 oil Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness-2, Low Stoniness-Scale 3, Non stony- 4

The summary statistics for socioeconomic characteristics are presented in Table 2. The average age of the household head in our sample is 53. The average years of education of household head is only four years, with adopters having one more year of education than non-adopters. Adoption decisions may be made jointly by several household members (Teklewood et al., 2014 quoted from Zepeda and Castillo, 1997). Therefore, we include the proportion of household members who have at least 10 years of schooling as one of the explanatory variables; in our sample, approximately 22 percent of the household members of a family have studied more than 10 years.[11]

6.3.2 Market Access

Since higher transaction costs deter farmers from adopting soil conservation practices, these are expected to negatively influence adoption (Teklewood, 2014). In our study, we measure transaction cost by considering market access and by using two variables: distance to the nearest all-weather road and local market as reported by the respondents. The summary statistics of these variables are presented in Table 2. The distance to the nearest local market and all-weather road is lower for adopters than for non-adopters.

6.3.3 Farm Characteristics

We treat the total Farm area of the farmer as exogenous and as a household endowment, since most respondents reported that they inherited the land they were cultivating and did not purchase it.

Farmers' perceptions of the fertility and stoniness of the soil of their operational holdings are important determinants of the adoption of new technology; less fertile farms are more likely to see adoption. Topographical features can also influence adoption: altitude, soil colour, soil texture and soil stoniness help capture this. Farmers who own farms that have better topographical characteristics may be less likely to adopt soil conservation technology (Teklewood et al., 2014). We asked the farmers to report their perception of these farm characteristics on a hedonic scale (see the footnote below Table 2). The total

[11] There are other household characteristics that affect adoption of soil conservation practices, like risk attitude (Shiveley, 2001), discount rate, (Stocking & Murnaghan, 2001, pp. 27-30), etc. We assume that risk is correlated with landholding size, but do not include it separately as an explanatory variable.

farm area of the adopters seems more than non-adopters. However, the altitude of the farm of non-adopters is more as compare to adopters.

We conduct a two-sample test of difference of these qualitative farm characteristics (Table 2). Adopters and non-adopters are statistically different in soil colour and soil stoniness. Adopters are reported to have more black soil and less stoniness on their farms. Both of these are considered better farm characteristics, so it would appear that adopters have soil that is more (and not less) fertile.

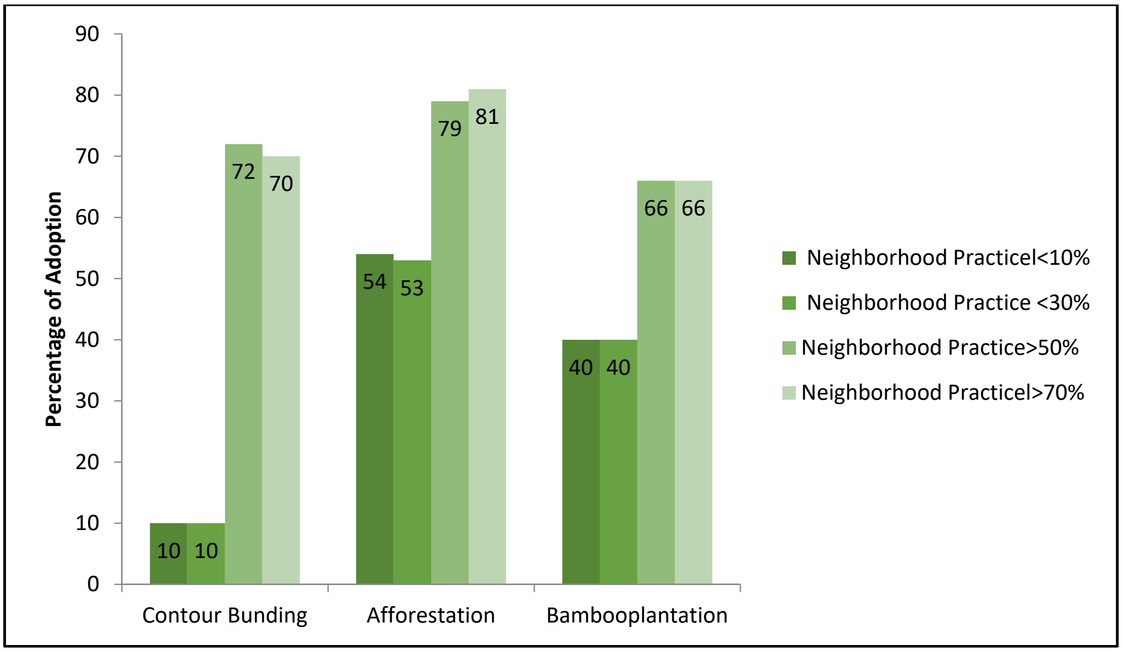
6.3.4 Sub-watershed and Village Characteristics

The study uses three dummy variables to capture sub-watershed characteristics that may impact the soil conservation decision. The first dummy captures whether 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. In the study, many villages are situated in or near the frontier of forest areas (forest village). Residents of these villages lack exclusive property rights over land; this lack may, therefore, act as a disincentive from investing in soil conservation. We use a third dummy variable for forest villages.

6.3.5 Soil Conservation in Immediate Upstream Neighbourhood

For each respondent farmer, this study elicited information on the soil conservation practices adopted on the nine nearest upstream farms. The existence of intensive soil conservation activity in the neighbourhood may have significant complementary or substitution effects on the conservation decision (Battaglini et al., 2012). Graph 1 presents the rate of adoption of the respondent farmer, conditional on information on proportion of adoption in immediate upstream neighbourhood. We find that when less than 10 percent of neighbours adopt contour bunding, then adoption of contour bunding as soil conservation technique on own farm is 10 percent. Similarly, when the rate of adoption of contour bunding in the neighbourhood is over 70 percent, then 72 percent of the respondents also use a contour bunding. This suggests that there may be significant complementarities between upstream adoption and sample farmer adoption. Similarly, when the proportion of adoption of afforestation lies between 10–30 percent in the immediate upstream neighbourhood, then 54–55 percent of the respondent farmers adopt afforestation. If the proportion of immediate upstream neighbourhood adoption of afforestation is over 50 percent, then the adoption rate among respondent farmers is around 80 percent. Therefore, a particular adoption measure is lower when its adoption measure is lower in the immediate upstream neighbourhood; the converse is also true.

Graph 1: Percentage of Adoption of Intensive Soil Conservation Measures in Immediate Upstream Neighbourhood Farms and Sample Percentage Distribution of Soil Conservation Measures at Farm



Source: Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013
Note: Immediate upstream neighbourhood farms represent the most immediate nine upstream surrounding farms from the farm of the respondent.

7 Results from Different Models

7.1 Estimated Coefficients from Non-spatial Analysis

We first estimate a probit model of adoption that does not incorporate any spatial dimensions, using household characteristics, input-output market access, farm characteristics, the proportion of neighbours upstream adopting soil conservation practices and village and sub-watershed characteristics, as discussed in Section 6.3 above. This serves as a benchmark for the results of the various spatial probit models. We also include the interactions between soil conservation practices in the neighbourhoods upstream.[12]

The estimated marginal effects (using equation 20 in Section 4.1 above) are presented in Table 3, along with heteroscedastic-consistent robust standard errors. They suggest that information on proportion of immediate upstream neighbours practising contour, afforestation and bamboo plantation are significant. We conduct a Wald Test (Cameron and Trivedi, 2005, pp. 452-456) to check if the coefficients of the interaction terms of information on soil conservation practices in the immediate upstream neighbourhood are jointly and significantly different from zero. We find that they are, which suggests that the interaction between soil conservation practices in neighbourhoods immediately upstream affects a farm's adoption of soil conservation practices.

Other significant variables include distance to the nearest local market, farm size, household size, soil stoniness and altitude of the farm in meters and dummies for very high soil erosion prone sub-watershed and for sub-watershed treatment.

The direction of relationship between probability of adoption and household and farm characteristics are as expected. *Ceteris paribus*, an increase of an acre in cultivated area increases the probability of adoption by 0.06; and the increase in household size by a member increases it by 0.03. Similarly, the coefficients of variables like distance to market and to all-weather roads are negative and statistically significant, but have a small marginal impact on adoption. Among the variables that capture farm characteristics, soil stoniness and farm altitude have a negative marginal impact. It indicates that farmers with land that is stonier are less likely to adopt. More specifically, as the perceived degree of farm stoniness increases, the probability of adoption decreases by 0.06. Again, the marginal impact of altitude on the probability of adoption is negative and significant, but economically small.

The marginal effect of sub-watershed dummies like dummy for very high and high soil erosion prone sub-watershed treatment status is relatively large. As the treatment status

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12 We have three specifications for the non-spatial probit model: Models 1, 2 and 3. We conduct a likelihood ratio test to find out which of the three alternative models best suit the data, and find Model 1 best suited. The marginal effects of Models 2 and 3 are given in Appendix Table 3.1

of sub-watershed changes from "untreated" to "treated", the probability of adoption in farm reduces by 0.2. It suggests complementarity between sub-watershed treatment and on-farm soil conservation. The existing literature, like Feder and Slade (1985), allows both complementarity and substitution between on-farm soil conservation and sub-watershed treatment under different circumstances.[13] On the other hand, with the change in the category of sub-watershed type, i.e., from medium and high soil erosion prone category to very high soil erosion prone category, the probability of adoption increases by 0.21. Very high soil erosion prone sub-watersheds are likely to experience higher soil erosion than sub-watersheds in the high and medium soil erosion prone category. Therefore, it is apparent to have positive marginal probability of adoption for the farmer who resides in very high soil erosion prone sub-watershed.

The information on proportion of immediate neighbours upstream practising contour and afforestation has the largest marginal effects on adoption: an increase of 1 percentage point in the proportion of upstream neighbours practising, respectively, contour and afforestation raises the probability of on-farm adoption by 0.31 and 0.43. This implies that upstream adoption has positive externalities downstream. The only significant interaction term is the interaction of the proportions of contour and afforestation adopters in the upstream neighbourhood. An increase of 1 percentage point in the proportion of simultaneous adoption of contour and afforestation decreases the probability of adoption by 0.05. The above findings indicate that assuming that adoption outcomes are independent from adoption in the neighbourhood immediately upstream is not plausible.

However, the analysis above has a limitation: as the discussion so far limits the neighbourhood to only the nine farm farms immediately upstream, the non-spatial probit model may provide only limited information on the interaction in adoption behaviour. The strategic interaction may prevail even outside the immediate upstream neighbourhood, and within the village or outside it. Importantly, 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.

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[13] See Feder and Slade (1985) for details.

Table 3: Non-Spatial (Ordinary) Probit Analysis Results (Marginal Effects) of Factors Influencing Adoption of Soil Conservation Practices

Variables	Model 1
Socio Economic Variables	
Age of the Household Head (Years)	0.002 (0.003)
Years of Education of Household Head (Years)	0.014 (0.009)
Household Member between age 14-65 (%)	-0.121 (0.141)
Household size	0.032* (0.017)
Proportion of household members studied at least 10 years	-0.023 (0.151)
Experience of household head in agriculture (Years)	0.003 (0.003)
Market Access Variables	
Distance to Nearest Local Market From farm (In Meters)	-7.62e-06** (3.11e-06)
Distance to all-weather Road (In Meters)	-1.88e-05* (1.07e-05)
Farm Characteristics	
Farm Size in Acres	0.061* (0.033)
Altitude of the farm in Meters	-0.000** (6.45e-05)
Soil Texture	0.003 (0.038)
Soil Colour	0.043 (0.031)
Soil Stoniness	-0.068* (0.042)
Villages and sub-watershed characteristics	
Forest Village Dummy†	0.089 (0.070)
Very high soil erosion prone sub-watershed Dummy†††	0.209** (0.094)
Sub-watershed treatment Dummy†††	-0.200** (0.095)
Information on Soil Conservation Practice in Immediate Upstream Neighbourhood	
Contour Bunding (%)	0.313** (0.134)
Afforestation (%)	0.431*** (0.116)
Bamboo Plantation (%)	0.239** (0.114)
Contour Bunding (%) X Afforestation (%)	-0.053** (0.023)
Contour Bunding (%) X Bamboo Plantation (%)	0.115 (0.110)
Afforestation (%) X Bamboo Plantation (%)	-0.209 (0.147)
Number of Observations	432

Sources: 1) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013, 2) †, †† and ††† from Kalimpong Soil Conservation Division (2010) and Kurseong Soil Conservation Division (2011)

Notes: 1) Standard error in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 3) Number of adopters: 211, number of non-adopters:221, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness-Scale 3, Non stony- 4, 4) In very high soil erosion prone sub-watersheds 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), 5) In Treated sub-watersheds state forest department of West Bengal has taken soil conservation measures, 7) Marginal Effect is based on equation (20).

7.2 Spatial Analysis

We estimate three sets of spatial models—spatial lag model (equation 8), spatial error model (equation 12) and general spatial autocorrelation model (equation 15)—and present the resulting estimates of spatial correlation parameters ρ (outcome) and λ (error) in Table 4 for a range of specifications of the spatial weighting matrix, including the inverse distance spatial weight matrix (W) and the contiguity matrix (WC).

Table 4: 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: 1) 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) In inverse-distance matrix W, $w_{ij}= 1/d_{ij}$, where d_{ij} represents arial distance between point i and j in kilimeters, 3) In Contiguity Matrix WC, $wc_{ij} = \begin{cases} 1 \; if\ i\ and\ j\ are\ neighbours \\ 0 \; otherwise \end{cases}$ 4) NA = Not Applicable.

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 λ 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 λ is not significant.

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 (equation 19) of five different weight matrices of the spatial lag model (Table 5). 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.

Table 5: 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: 1) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013.
Notes: 1) In inverse-distance matrix W, $w_{ij}= 1/d_{ij}$, where d_{ij} represents arial distance between point i and j in kilometres, 2) In Contiguity Matrix WC, $wc_{ij} = \begin{cases} 1 & if\ i\ and\ j\ are\ neighbours \\ 0 & otherwise \end{cases}$ 4) NA = Not Applicable, 4) Posterior Probability is calculated from the expression (19)..

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. Since the posterior probability of the spatial lag model for within village contiguity matrix is 0.26, which is not much smaller than 0.27, we also estimate the spatial lag model with for within village contiguity matrix. The spatial lag probit estimates with spatial weights, an inverse distance matrix up to three kilometres and within village contiguity matrix have been presented in Appendix Table 2.

7.3 Results of Spatial Lag Probit

Using the same set of covariates as used in Model 1 of non-spatial analysis of the adoption decision, estimates from a spatial lag model using a neighbourhood defined as extending up to three kilometres radius (inverse distance matrix) are reported in Table 6.[14] The table presents direct, indirect and total effects, as explained in equation 21, along with 95 percent confidence intervals. As mentioned in Section 4.1, the direct effects are the diagonal element of equation (21), which captures the change in the probability of adoption of the ith farmer due to a small change in the explanatory variable of the same farmer, and has a similar interpretation as the marginal effect in a non-spatial probit model.

All the coefficients of household characteristics have 90 percent confidence intervals that include zero (apart from the coefficient for the household size). The direct effect of the household size is 0.02, that is, an increase of 1 member of famer i's household increases farmer *i*'s probability of adoption by 0.02. The indirect effect of the same variable is 0.03, that is, the probability of adoption by farmer *i* due to an increase in 1 household member in the family of the neighbourhood of farmer *i* increases by 0.03. However, the 90 percent confidence interval of this variable includes zero. It implies that spatial spill over effect of family size on adoption is not credible. The total impact of the variable, therefore is 0.05; this variable was significant in the non-spatial analysis too. This finding is in line with previous studies such as Teklewood et al., 2014. However, proportion of household members between ages 14 to 65 is neither significant in spatial model nor in non-spatial model. This positive relationship between the household size and probability of adoption intuitively may be due to adoption measures are labour intensive. Larger household can devote more labour for soil conservation irrespective of the age composition within a household.

[14] In this inverse distance weight matrix, the absolute log likelihood value is highest in Model 1, and justifies its selection over Models 2 and 3 even in spatial analysis.

Table 6: 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) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013, 2) †, †† and ††† from Kalimpong Soil Conservation Division (2010) and Kurseong Soil Conservation Division (2011).
Notes: 1) Standard error in parentheses, 2) Number of adopters: 211, number of non-adopters:221, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness- 3, Non stony- 4, 4) In very high soil erosion prone sub-watersheds 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), 5) In Treated sub-watersheds state forest department of West Bengal has taken soil conservation measures, 6) Direct, indirect and total effect is based on equation (21)..

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. More specifically, with the increase of every additional acre in the farm area of farmer *i*, the probability of farmer *i*'s adoption of soil conservation practices increases by 0.04. Intuitively, it implies household with larger farm area are more likely to devote resource or take away land out of cultivation for adoption. The adoption measure such as afforestation and bamboo plantation can be seen as diversification of farm production activity. The study such as Pope and Prescott (1980) suggests positive association between farm production diversification and farm size. The indirect effect of the farm area is 0.07, and its total effect is 0.11. The 90 percent confidence interval of indirect effect of farm area does not include zero, implying a significant cumulative effect of neighbours' farm size on probability of adoption. Farm size in the neighbourhood is also associated with asset holding in the neighbourhood. Therefore, larger farm size in the neighbourhood can help the farmer to access informal credit, remittance and/or participate as agricultural labour. These factors can have cumulative positive effect on probability of adoption of soil conservation. None of the other farm characteristics has a significant impact in the spatial lag model. This is contrary to the findings of Bekele and Drake (2003) and of Wossen et al. (2015). This is also in contradiction to the finding of the non-spatial probit model of this study, where soil stoniness negatively affects adoption.

In non-spatial probit analysis, market access variables (such as distance to the nearest market and all-weather road) have a negative marginal effect (though small). Similar results are found in the study of Teklewood et al. (2014), though its marginal effects are larger than in this study. Our hypothesis about the transaction cost was negative impact on probability of adoption. Since distance to the market is supposed to impose added transaction cost on farmer to hire/purchase inputs (such as stone, sapling, labour etc.) and sell output (such as wood, fodder, bamboo etc.) of adoption measure. However, in the spatial lag probit model, these variables have no effects on adoption. Since significant mass of 90 percent interval straddling the origin. The explanation for non-significant effect may relate to the fact that farmers have access of inputs through local network. At the same time they use wood, fodder bamboo etc. for self-consumption and/or selling in or around nearby neighbourhood.

Information on upstream neighbours' adoption of soil conservation measures positively affects the probability of on-farm adoption. This is similar to the results from the non-spatial probit model. The proportion of neighbours immediately upstream that practise contour bunding, afforestation and bamboo plantation significantly and positively impact adoption. The indirect effect is, 0.28, while the direct effect is 0.17. This suggests that for every percentage point increase in the information of adoption of contour by immediate upstream neighbours of farmer *j* (farmer *i*'s neighbour), farmer *i*'s probability of adoption increases by 0.28 points. The significant indirect effect of this explanatory variable indicates that farmer *i*'s adoption decision is influenced by the information on adoption decision of not only his own immediate upstream neighbours but also by that of the immediate upstream neighbours of any other farmer *j*, in the radius of three kilometres. The total effect of proportion of immediate neighbour in upstream practising contour is, thus, 0.45. The direct, indirect and total effects of the information of proportion of immediate upstream neighbour adopting afforestation are 0.23, 0.41 and 0.64 respectively. Again, the direct, indirect and total effect of information on proportion of immediate upstream neighbour practising of practising bamboo plantation together are 0.16, 0.27 and 0.43, respectively. The significance of the direct effect on suggests that neighbourhood effects are important and positively impact adoption. Also important is the positive indirect effect, as it provides empirical evidence that adoption of soil conservation practice is not limited only to the immediate upstream but is diffused over the entire specified neighbourhood (radius up to three kilometres), and that farmers communicate with each other (Lapple and Kelly, 2015). The information on joint adoption of afforestation and bamboo plantation affects adoption negatively in terms of direct, indirect and total effect. The same variable had an insignificant marginal impact in non-spatial probit. On the contrary, the joint adoption of contour and afforestation has a negative marginal impact on adoption in the non-spatial probit model, but an insignificant impact in the spatial lag probit model.

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 treatment status of sub-watershed have positive and negative marginal impact under non-spatial probit, respectively. However, both these variables have insignificant effects in spatial analysis.

A comparison of the coefficients representing the direct effect of the spatial probit model and the marginal effect of the non-spatial probit model suggests major differences. The effect of farm area on the probability of adoption experiences a decline by 33 percent in the spatial model compared to the non-spatial model. Similarly, the effect of information proportion of upstream neighbours practising contour bunding, afforestation and bamboo plantation on probability of adoption is reduced by 48 percent, 46 percent and 4 percent, respectively, in the spatial model. The differences in the magnitudes of the marginal effects suggests that considering only a probit model that does not account for spatial dependence in outcomes likely results in biased estimates.

To assess if these coefficients differ if one uses the spatial contiguity matrix instead, the corresponding direct, indirect and total effects estimated from the spatial lag probit using a within-village contiguity matrix are presented in Table 7. In this case, the variables, like household size, soil stoniness have significant direct, indirect and total effects. Soil stoniness has insignificant effects in Table 6. Moreover, farm size has significant effects in Table 6. In Table 7, these variables have insignificant effects. Like in the spatial lag probit model with neighbours up to three kilometres, in this model the information on the proportion of adoption of measures like contour bunding, afforestation, bamboo plantation and interaction of afforestation and bamboo plantation has significant effects on probability of adoption.

So far, in our discussion, we have defined as adopters those farmers who adopted at least two practices of contour bunding, afforestation and bamboo plantation. Now, we change the definition of adopters to those farmers who adopted bamboo plantation and afforestation, and of non-adopters to those farmers who adopted only bamboo plantation. In this categorisation, we are left with 315 observations. However, the posterior mean of spatial lag parameter (ρ) for spatial lag model is still significant, and it is 0.46 for spatial lag probit with neighbourhood cut-off up to three kilometres. The significance of posterior mean of spatial lag parameter suggests that the spatial dependence of soil conservation measure is robust. The direct, indirect and total effects of this spatial lag model are presented in Table 8.

Table 7: Spatial Lag Probit Model Estimates of Factors Influencing Adoption of Soil Conservation Practices with Neighbourhood defined as being within Village (spatial contiguity matrix)

Variable	Direct Effect	Indirect Effect	Total Effect
Socio Economic Variables			
Age of the Household Head (Years)	0.001 (-0.002 to 0.004)	0.001 (-0.001 to 0.002)	0.002 (-0.003 to 0.006)
Years of Education of Household Head (Years)	0.010(-0.000 to 0.020)	0.005 (-0.000 to 0.012)	0.014 (-0.001 to 0.030)
Household size	0.021 (0.002 to 0.039)	0.010 (0.000 to 0.024)	0.031 (0.003 to 0.060)
Household Member between age 14-65 (%)	-0.103 (-0.263 to 0.61)	-0.049 (-0.148 to 0.029)	-0.153 (-0.38 to -0.092)
Proportion of household members studied at least 10 years	-0.030 (-0.187 to 0.129)	-0.014 (-0.103 to 0.065)	-0.045 (-0.282 to 0.189)
Experience of household head in agriculture (Years)	0.002 (-0.001 to 0.006)	0.001 (-0.005 to 0.003)	0.003 (-0.001 to 0.008)
Market Access Variables			
Distance to Market From Farm (Meters)	-0.000(-0.000 to -0.000)	-0.000 (-0.000 to -0.000)	-0.00(-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 Area (Acre)	0.037 (-0.007 to 0.066)	0.018 (0.001 to 0.044)	0.055 (-0.010 to 0.104)
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[$]	0.001(-0.041 to 0.042)	-0.000 (-0.022 to 0.020)	-0.002 (-0.062 to 0.059)
Soil Colour[$$]	0.026 (-0.011 to 0.062)	0.012 (-0.004 to 0.034)	0.038 (-0.016 to 0.091)
Soil Stoniness[$$$]	-0.052 (-0.097 to -0.009)	-0.024 (-0.058 to -0.002)	-0.077 (-0.148 to -0.012)
Villages and sub-watershed characteristics			
Forest Village Dummy[†]	0.052 (-0.037 to 0.137)	0.025 (-0.017 to 0.080)	0.077(-0.051 to 0.213)
Very high erosion prone sub-watershed Dummy[††]	-0.030 (0.107 to 0.52)	-0.013 (-0.055 to 0.027)	-0.043 (-0.161 to 0.80)
Sub-watershed treatment Dummy[†††]	-0.0134(-0.093 to 0.064)	-0.007 (-0.055 to 0.035)	-0.021 (-0.146 to 0.096)
Information on Soil Conservation Practice in Immediate Upstream Neighbourhood			
Contour Bunding (%)	0.168 (0.029 to 0.291)	0.079 (0.011 to 0.177)	0.248 (0.047 to 0.438)
Afforestation (%)	0.229 (0.118 to 0.347)	0.110 (0.026 to 0.220)	0.340 (0.170 to 0.525)
Bamboo Plantation (%)	0.158 (0.034 to 0.283)	0.077 (0.007 to 0.170)	0.236 (0.046 to 0.425)
Contour Bunding X Afforestation (%)	-0.004 (-0.043 to 0.045)	-0.002 (-0.025 to 0.021)	-0.006 (-0.067 to 0.063)
Contour Bunding X Bamboo Plantation (%)	0.065 (-0.039 to 0.187)	0.032 (-0.019 to 0.105)	0.98 (-0.058 to 0.282)
Afforestation X Bamboo Plantation (%)	-0.146 (-0.257 to -0.018)	-0.065 (-0.156 to -0.005)	-0.201 (-0.402 to -0.026)

Sources: 1) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013, 2) †, †† and ††† from Kalimpong Soil Conservation Division (2010) and Kurseong Soil Conservation Division (2011).
Notes: 1) Standard error in parentheses, 2) Number of adopters: 211, number of non-adopters:221, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness- 3, Non stony- 4, , 3) In very high soil erosion prone sub-watersheds 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), 4) In Treated sub-watersheds state forest department of West Bengal has taken soil conservation measures, 5) Direct, indirect and total effect is based on equation (21).

Table 8: Spatial Lag Probit Model Estimates of Factors Influencing Adoption of Soil Conservation Practices with Neighbourhood up to Three Kilometres (alternative adoption definition)

Variable	Direct Effect	Indirect Effect	Total Effect
Socio Economic Variables			
Age of the Household Head (Years)	-0.001(-0.005 to 0.003)	-0.001(-0.008 to 0.003)	-0.002(-0.012 to 0.006)
Years of Education of Household Head (Years)	0.008(-0.004 to 0.020)	0.008(-0.005 to 0.031)	0.015(-0.010 to 0.046)
Household size	0.024(-0.001 to 0.052)	0.026(-0.001 to 0.093)	0.051(-0.002 to 0.135)
Household Member between age 14-65 (%)	-0.255(-0.480 to -0.045)	-0.282(-1.042 to -0.012)	-0.537(-1.442 to -0.083)
Proportion of household members studied at least 10 years	0.165(-0.061 to 0.386)	0.171(-0.058 to 0.712)	0.336(-0.111 to 0.991)
Experience of household head in agriculture (Years)	0.003(-0.001 to 0.008)	0.004(-0.001 to 0.013)	0.007(-0.001 to 0.018)
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 Area (Acre)	0.018(-0.016 to 0.055)	0.017(-0.017 to 0.073)	0.035(-0.034 to 0.119)
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$	-0.031(-0.088 to 0.025)	-0.035(-0.158 to 0.021)	-0.066(-0.231 to 0.045)
Soil Colour$$	0.031(-0.017 to 0.077)	0.033(-0.016 to 0.137)	0.065(-0.032 to 0.200)
Soil Stoniness$$$	-0.004(-0.065 to 0.052)	-0.001(-0.076 to 0.076)	-0.005(-0.130 to 0.122)
Village Characteristics			
Forest Village Dummy†	0.074(-0.035 to 0.177)	0.077(-0.033 to 0.317)	0.151(-0.066 to 0.445)
Very high & high soil erosion prone sub-watershed Dummy††	-0.094(-0.240 to 0.040)	-0.097(-0.374 to 0.040)	-0.192(-0.552 to 0.080)
Sub-watershed treatment Dummy†††	-0.119(-0.247 to 0.002)	-0.120(-0.415 to 0.004)	-0.238(-0.586 to 0.005)
Information on Soil Conservation Practice in Immediate Upstream Neighbourhood			
Contour Bunding (%)	-0.029(-0.273 to 0.182)	-0.031(-0.379 to 0.230)	-0.060(-0.594 to 0.379)
Afforestation (%)	0.326(0.127 to 0.530)	0.336(0.030 to 0.957)	0.663(0.234 to 1.350)
Bamboo Plantation (%)	0.218(0.022 to 0.429)	0.230(0.006 to 0.831)	0.448(0.034 to 1.168)
Contour Bunding (%) X Afforestation (%)	0.006(-0.055 to 0.094)	0.005(-0.085 to 0.117)	0.010(-0.130 to 0.195)
Contour Bunding (%) X Bamboo Plantation (%)	0.031(-0.218 to 0.289)	0.027(-0.269 to 0.370)	0.058(-0.468 to 0.656)
Afforestation (%) X Bamboo Plantation (%)	-0.078(-0.407 to 0.233)	-0.079(-0.598 to 0.273)	-0.157(-0.898 to 0.511)

Sources: 1) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013, 2) †, †† and ††† from Kalimpong Soil Conservation Division (2010) and Kurseong Soil Conservation Division (2011).
Notes: 1) Standard error in parentheses, 2) Number of adopters: 169, Number of non-adopters: 146, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness- 3, Non stony- 4, , 3) In very high soil erosion prone sub-watersheds 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), 4) In Treated sub-watersheds state forest department of West Bengal has taken soil conservation measures, 5) Direct, indirect and total effect is based on equation (21)

The variables such as household members between age 14-65, the information on proportion of adoption of measures like afforestation and bamboo plantation in the immediate upstream neighbourhood have significant effects on the simultaneous adoption of afforestation and bamboo plantation. All these variables on information on soil conservation measures in the immediate upstream neighbourhood have credible 90 percent confidence interval in Tables 6 and 7. Unlike in Tables 6 and 7, the information on the proportion of contour bunding in the immediate upstream neighbourhood does not have any significant effect on the simultaneous adoption of afforestation and bamboo plantation. It demonstrates that information on the proportion of neighbours that adopts contour bunding as a soil conservation measure does not amount to a change in the probability of simultaneous adoption of afforestation and bamboo plantation. However, Tables 6, 7 and 8 differ in terms of farm size and interaction term of information on the proportion of afforestation and bamboo plantation in the immediate upstream neighbourhood. Both these variables have significant effects in Table 6 and 7 but insignificant effects in Table 8.

8 Conclusion, Policy Implication and Implications for Future Research

This paper analysed the determinants of on-farm soil conservation practices in a watershed in the Eastern Himalayas in India. To do so, it considered neighbourhood effects to be 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 for two reasons. First, soil conservation in one farm can assist or constrain it in adjacent farms, due to strategic interaction. Second, many unobserved factors, like local amenities, contribute to adoption. The presence of the first factor results in spatial dependency in conservation practices, and of the second factor in spatial dependency in error. We applied a model of spatial lag probit model (following Anselin (2002); LeSage and Pace (2009); and others) that allows us to capture neighbours' influence on outcome (i.e., the adoption decision). The model choice was motivated by the fact that—once we allow for spatial dependence in outcome—the spatial dependence in error is no longer significant. We defined neighbours as geographic neighbours, both within the village and up to a distance of three kilometres. We used the Bayesian formulation of a standard probit model in conjunction with the MCMC to estimate the parameters. We also compared the estimators of spatial and non-spatial probit.

The findings from the spatial lag probit suggest that sub-watershed treatment neither encourages farmers to adopt soil conservation practices nor discourages them from adopting these. The main finding, however, is that farmers located in close proximity (neighbours immediately upstream and within the sub-watershed) exhibit similar adoption behaviour; and that adoption of soil conservation measures is spatially interdependent. Spatial dependence in outcomes is important even after controlling for information on adoption behaviour in the immediate neighbourhood. Thus, models based on the non-spatial probit model are likely to yield biased estimates of the influence of key covariates in increasing adoption of on-farm soil conservation measures.

Another important aspect of the spatial autocorrelation model is the explanation of marginal effects. The marginal effect of this model assesses both direct and indirect effects. It implies how changes in the value of an independent variable of farmer *i* influence his own soil conservation practices (direct effect), and how a small change in an independent variable of farmer *j* in the neighbourhood influences farmer *i*'s decision to adopt soil conservation practices (indirect effect).

The study finds that household and farm characteristics are less important in adoption of soil conservation practices. Moreover, sub-watershed neither complements nor substitutes soil conservation practice adopted at the farm level. It suggests that government investment in sub-watershed does not have any impact on private adoption at the farm. At the same time, the significance of the spatial parameter provides new avenues to influence adoption of soil conservation among farmers. Despite the change in spatial weight matrix, and the categorisation of adopters and non-adopters of soil conservation measures, these two broad findings remain significant.

The findings of the study may have relevance for policy makers. Given that the Himalayan mountains are one of the 34 biodiversity hotspots worldwide, and that agriculture is one of the major drivers of deforestation in the Himalayas, 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. For example, agricultural extension workers can target small group farmers in a village to provide relevant assistance (like technical knowhow, training and financial support) for suitable soil conservation (suitable for a particular agro climatic condition) which will then get diffused taking advantage of strategic interaction. In our survey the respondents reported that agricultural extension service is absent in the region. Therefore, the findings of this study can lead to an alternative incentive mechanism rather than relying on the existing centralised top-down approach to encourage farm level investment in soil conservation.

There are several directions in which the research conducted in this study can be extended. The first is to track these farmers over time, and to construct a panel data set. This could help understand the timing of adoption decisions in general, of specific measures in particular; adoption decisions are undertaken gradually over time. Therefore, the non-adopter category of farmers in the present study includes both probable future adopters and never-adopters, and the adopter category includes recent adopters and long-time adopters. There could also be disadoption of soil conservation technologies in future. Understanding these dynamics and their implications is possible only through a panel study. Second, this study has used a narrow definition of neighbourhood, defined in term of physical proximity, that is, spatial distance. However, "neighbourhood" can also be defined in terms of socioeconomic, cultural and physical proximity and kinship ties. The role played by strategic interaction defined in these terms in determining adoption could be considered in further research.

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Appendix Table 1: Non-Spatial (Ordinary) Probit Analysis Result (Marginal Effects) of Factor Influencing Adoption of Soil Conservation Practices

Variables	Model 2	Model 3
Socio Economic Variables		
Age of the Household Head (Years)	0.003 (0.003)	0.002(0.002)
Years of Education of Household Head (Years)	0.014* (0.009)	0.012(0.008)
Household Member between age 14-65 (%)	-0.107 (0.137)	-0.048(0.135)
Household size	0.027 (0.017)	0.011(0.016)
Proportion of household members studied at least 10 years	-0.065 (0.154)	0.015(0.135)
Experience of household head in agriculture (Years)	0.003 (0.003)	0.004*(0.003)
Market Access Variables		
Distance to Market From farm (In Meters)	0***(0)	0***(0)
Distance to all-weather Road (In Meters)	0***(0)	0***(0)
Farm Characteristics		
Farm Size in Acres	0.066** (0.032)	0.065** (0.032)
Altitude of the farm in Meters	-0.000** (6.21e-05)	-0.000*** (6.02e-05)
Soil Texture	0.012 (0.037)	0.019 (0.034)
Soil Colour	0.039 (0.030)	0.069** (0.029)
Soil Stoniness	-0.072* (0.040)	-0.075** (0.037)
Village and sub-watershed Characteristics		
Forest Village Dummy†	0.058 (0.068)	-0.060 (0.065)
Very high soil erosion prone sub-watershed Dummy††	0.168* (0.096)	0.078 (0.095)
Sub-watershed treatment Dummy†††	-0.136 (0.096)	-0.003 (0.090)
Information on Soil Conservation Practice in Immediate Upstream Neighbourhood		
Contour Bunding (%)	0.329*** (0.091)	
Afforestation (%)	0.229* (0.127)	
Bamboo Plantation (%)	0.134 (0.085)	
Number of Observations	432	432

Sources: 1) Based on primary survey carried out in Darjeeling District, West Bengal, India carried out in the year 2013, 2) †, †† & ††† from Kalimpong Soil Conservation Division (2010) and Kurseong Soil Conservation Division (2011).

Notes: 1) Standard error in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 3) Number of adopters: 211, number of non-adopters:221, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness-Scale 3, Non stony- 4, 4) In very high soil erosion prone sub-watersheds 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), 5) In Treated sub-watersheds forest department of West Bengal has taken soil conservation measures, 7) Marginal effects are based on equation (20).

Appendix Table 2: Spatial Lag Probit Estimates of Factor Influencing Adoption of Soil Conservation Practices

Variables	Neighbours cut-off	
	Up to 3 Kilometers	Within Village
Socio Economic Variables		
Constant	-1.967***(0.741)	-1.583**(0.675)
Age of the Household Head (Years)	0.007(0.007)	0.006(0.007)
Years of Education of Household Head (Years)	0.032*(0.024)	0.036*(0.0237)
Household size (#)	0.09**(0.05)	0.086**(0.042)
Household Member between age 14-65 (%)	-0.305(0.371)	-0.304(0.369)
Proportion of household members studied at least 10 years (%)	-0.09(0.379)	-0.084(0.365)
Experience of household head in agriculture (Years)	0.008(0.007)	0.007(0.008)
Market Access Variables		
Distance to Market From farm (In Meters)	-0.000**(0.000)	-0.000**(0.000)
Distance to all-weather Road (In Meters)	-0.000*(0.000)	-0.000*(0.000)
Farm Characteristics		
Farm Size (unit)	0.128**(0.071)	0.122**(0.07)
Altitude in Meter (unit)	-0.000(0.000)	-0.000***(0.000)
Soil Texture$	-0.014(0.098)	-0.003*(0.095)
Soil Colour$$	0.117**(0.087)	0.104*(0.082)
Soil Stoniness$$$	-0.118*(0.098)	-0.168*(0.101)
Village and sub-watershed specific variables		
Forest Village Dummy†	0.214(0.177)	0.212(0.192)
Very high soil erosion prone sub-watershed Dummy††	0.545**(0.307)	0.58**(0.267)
Sub-watershed treatment Dummy†††	-0.455**(0.283)	-0.498**(0.278)
Information on Soil Conservation Practice in Immediate Upstream Neighborhood		
Contour Bunding (%)	0.514**(0.298)	0.593**(0.296)
Afforestation (%)	1.032***(0.279)	1.013***(0.271)
Bamboo Plantation (%)	0.674***(0.303)	0.598***(0.28)
Contour Bunding (%) X Afforestation (%)	0.074(0.176)	-0.101*(0.069)
Contour Bunding (%) X Bamboo Plantation (%)	0.246(0.271)	0.369**(0.239)
Afforestation (%) X Bamboo Plantation (%)	-0.613***(0.277)	-0.551**(0.273)
Rho (spatial parameter)	0.632***(0.137)	0.346***(0.106)
Number of observations	432	

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

Notes: 1) Standard error in parentheses, 2) ***, ** and * indicate significance at 1, 5 and 10 percent respectively, 3) Number of adopters: 211, number of non-adopters:221, 3) Soil Texture, Soil Colour 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 Colour: Gray- 1, Reddish- 2, Brown- 3, Black- 4, Scale of Soil Stoniness: High Stoniness- 1, Medium Stoniness- 2, Low Stoniness- 3, Non stony- 4, 4) In very high soil erosion prone sub-watersheds 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), 5) In Treated sub-watersheds forest department of West Bengal has taken soil conservation measures, 7) Spatial lag probit is based on equation (8) .

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