Impact of the adoption of vegetative soil conservation measures on farm profit, revenue and variable cost in Darjeeling district, India

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ONLINE APPENDIX

Appendix A. Average cost of different soil conservation measures

The discussions with several groups of farmers revealed the monetary costs of soil conservation measures. These costs are the expected cost during the survey and not the actual cost borne by the farmer. The initial cost to implement stone terracing and terracing are Indian Rupees (INR) 150,000–170,000 per acre and INR 20,000–30,000 per acre, respectively, while the average cost to build a stone wall is INR 50,000. Ideally, these measures need frequent (i.e., seasonal or annual) maintenance, such as removal of sediment and weeds, monitoring, and maintaining of the height of terraces or walls, particularly after heavy rainfall. The gestation period of these measures is just one year. In contrast, the initial investment, in the case of vegetative afforestation and bamboo planting, is INR 8,000 per acre and INR 5,000 per acre, respectively. However, the on-farm opportunity cost of these vegetative measures is quite high since a portion of farmland has to be taken off farming for the purpose. But the maintenance cost (in terms of effort) of the measures, which involves removal of sediment, weeds and damage plants, is lower than that for structural measures. Nevertheless, the gestation period for the vegetative measures is higher and can vary between three to seven years. Hence, terracing is the most commonly used conservation measure due both to its effectiveness as well as lower initial cost and short gestation period in comparison with many of the other measures.

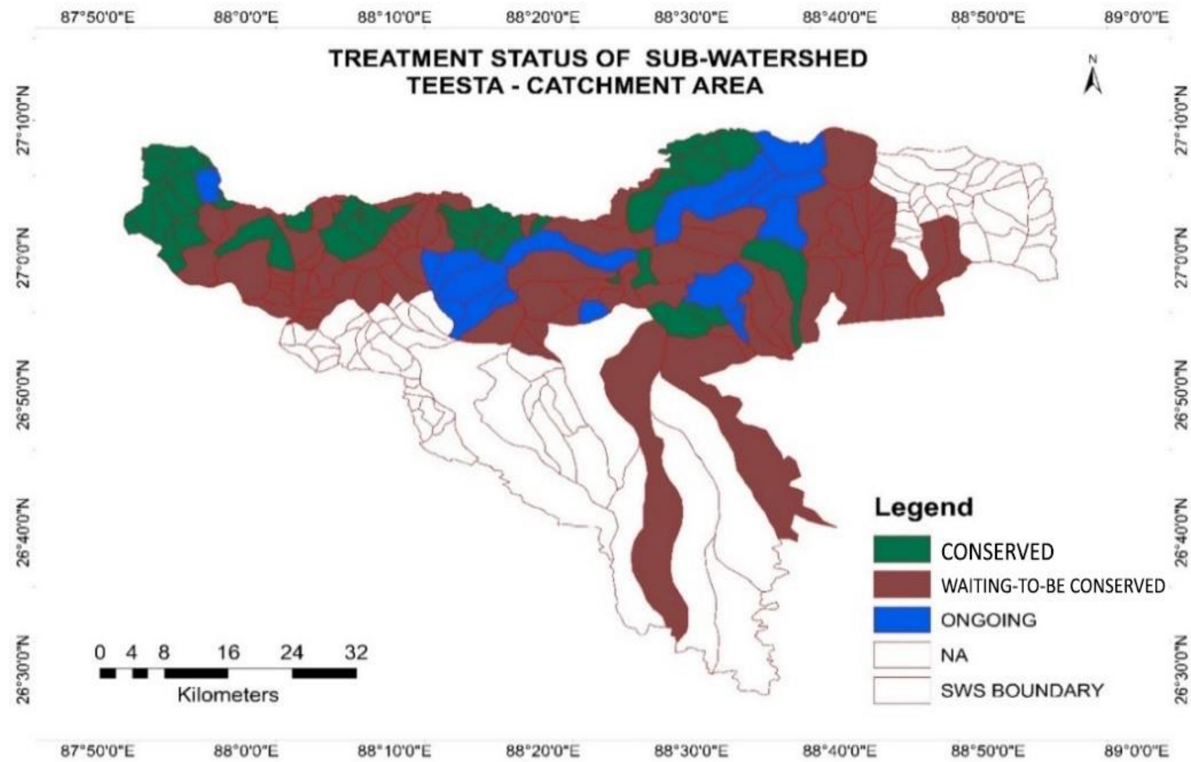


Figure A1. Delineated sub-watershed boundary in Darjeeling.

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

Table A1. Distribution of exhaustive combinations of soil conservation measures by sample farmers

Farmers adopting	**Number (percentage)**	**Category**
Stone terracing	1 (0.23)	*a*
Terracing	7 (1.62)	
Stone terracing + minor vegetative measures	4 (0.92)	
Terracing + minor vegetative measures	97 (22.45)	
Stone wall + terracing	4 (0.92)	*b*
Stone wall + terracing + minor vegetative measures	106 (24.53)	
Stone wall + afforestation + terracing	2 (0.46)	*c*
Stone wall + bamboo planting + terracing	3 (0.69)	
Stone terracing + stone wall + afforestation + minor vegetative measures	7 (1.62)	
Stone terracing + stone wall + bamboo planting + minor vegetative measures	2 (0.46)	
Stone wall + afforestation + terracing + minor vegetative measures	92 (21.29)	
Stone wall + bamboo planting + terracing + minor vegetative measures	10 (2.31)	
Stone wall + afforestation + bamboo planting + terracing	3 (0.69)	*d*
Stone wall + afforestation + bamboo planting + terracing + minor vegetative measures	94 (21.75)	

Note: Minor vegetative measures indicate a farmer who adopts at least one conservation measure from orchard planting, tree belt, broom planting and grass stripping.
Source: Based on a primary survey carried out in the Darjeeling district, West Bengal, India in the year 2013.

Appendix B. Construction of key variables

There are three key variables: per acre profit, revenue and variable cost. The farmers in the sample both sell their crops as well as consume some of it within the household. For produce, there are two prices: farm gate price[1] and market price. To generate the total revenue, first we calculate the revenue from selling a crop by multiplying its farm gate price by the quantity sold. Next, we calculate the implied revenue from the consumption of a crop by multiplying its market price by the quantity consumed. By adding the revenues from selling and consumption, we get the total revenue from a crop. To get the total revenue, we calculate revenue from each crop, as outlined above, and aggregate across all the crops to get the total revenue.

By and large, there is no expenditure on fertilizers, pesticides, seeds, irrigation and so forth. Of the respondents, 98 per cent use cow dung and compost for fertilizer. Only 4 per cent of the respondents reported purchasing pesticides from the market and 7 per cent reported purchasing seeds. Therefore, the only major inputs for cultivation are land and labor. The calculation of a wage rate must account for the fact that there are three types of labor used in cultivation: household, hired and exchange. If the household reported the use of household labor and/or exchange labor as agricultural labor, we used a wage rate of INR 100 per day which roughly corresponds to the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) wage rate (for eight hours a day).[2] For hired labor, the wage rate per eight hours, as reported by the farmer, was used.[3] Labor cost is computed as the sum of all three categories of labor.

Since there is no rental market for land in the study area, labor is the only variable cost

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

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

[3] This likely underestimates the wage cost, as the cost of hired labor is generally much higher (so that the average wage across all categories is in the range of INR 220-260 per day).

incurred using the method outlined above to aggregate across different kinds of labor. We subtract the total variable cost from the total revenue to get the farm profit. One concern in the calculation of revenues and costs is that there could be composition of commodity effect instead of adoption effect driving differences in outcome variables. But the sample data suggest that the crop composition between adopter and non-adopter is similar.

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

Appendix C. Marginal effect of spatial models

In the spatial lag model, a change in the explanatory variable of the i^{th} farmer has an effect not only on the soil conservation practices of the i^{th} 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 the i^{th} farmer,, z_{ki}, will affect the expected probability of adoption of his own and others' soil conservation practices. The marginal effect of the non-spatial or ordinary probit model is given by:

$$\frac{\partial E[e \mid z_k]}{\partial z_k} = \emptyset(z_k \beta_k)\beta_k. \qquad \text{(A1)}$$

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

$$\frac{\partial E[e \mid z_k]}{\partial z_k^{/}} = \emptyset(H^{-1} I_n \overline{z_k} \beta_k) \odot H^{-1} I_n \beta_k \ , \qquad \text{(A2)}$$

where $\odot$ is the Kronecker product,

$$H = (I_n - \rho W). \qquad \text{(A3)}$$

The diagonal element of expression (A2) represents the direct effect, which is like the marginal effect of the non-spatial probit model. But in this model, there are feedback effects as well as a change in e_i from a z_{ki} which also influences e_j which, in turn, affects e_i. Also, there is a cumulative effect of changes in z_{kj} on e_i, where $i \neq j$. The off-diagonal elements represent indirect effects. It is common to refer to the row sums as the "total effect to an observation": it is the impact on e_i from changing the k^{th} explanatory variable in the specified neighborhood. The average direct effect is taken over all diagonal elements while the average indirect effect is the difference between average total effect and average direct effect. By symmetry, the row sums and column sums are the same. The difference between the total effect and the direct effect represents the indirect effect (LeSage and Pace, 2009).

The spatial error model does not contain the spatial lag explanatory variables or the outcome variable. Therefore, the interpretation of the marginal effect is similar to that in the non-spatial probit model. In the general spatial auto correlation model, the marginal effect takes a similar form as in expression (A2) since the spatial lag error does not come into play when considering the $\frac{\partial E[e \mid z_k]}{\partial z_k^{/}}$. Therefore, the interpretation of marginal effects is similar to that in the spatial lag model (LeSage and Pace, 2009).

Appendix D. Spatial analysis

We estimate three sets of spatial models and present the resulting estimates of spatial correlation parameters ρ (outcome) and γ (error) for a range of specifications of the spatial weighting matrix, including the inverse distance spatial weight matrix (W) and the contiguity matrix (WC) (LeSage and Pace, 2009).

Table A2. Spatial parameter estimate for spatial models by neighbors' cut-off distance and weighting matrix

Neighbors' 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 kilometer	0.62***	0.63***	0.39**	0.20
Up to 3 kilometers	0.60***	0.64***	0.44***	0.11
Up to 5 kilometers	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

Notes:
In the inverse-distance matrix W, $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} represents aerial distance between point i and j in km.
In the contiguity matrix WC, $wc_{ij} = \begin{cases} 1 & if\ i\ and\ j\ are\ neighbors \\ 0 & otherwise \end{cases}$.
Source: Based on a primary survey carried out in the Darjeeling district, West Bengal, India carried out in the year 2013.

Note that for all variants of the 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 the non-spatial probit model, and suggests that farmers within the specified neighborhood 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 the posterior mean of ρ, remains significant but the estimated spatial correlation on error, which is the posterior mean of γ, is insignificant across all the distance decay spatial weight matrices. Similarly, when we use the contiguity matrix as spatial weight matrix, the spatial lag estimator (ρ) of the general spatial autocorrelation model for a neighborhood within a village and nearest village is significant, but the estimated γ is not significant.

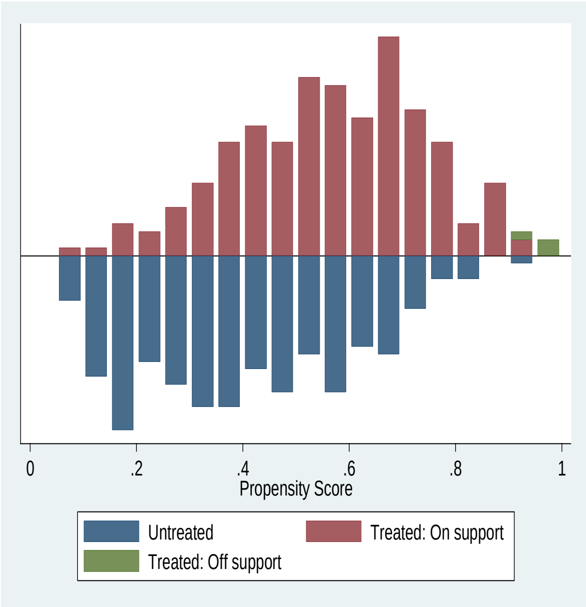
Taken together, the results from the three different spatial models suggest that the spatial lag model best describes our data. It is thus used for further analysis. The significance of the spatial parameter suggests that a farmer's adoption of soil conservation practices positively influences neighboring farmers' adoption decisions. This still leaves the question of which of the various spatial weight matrices W to use. To select one, we compare the posterior probabilities of adoption of five different weight matrices of the spatial lag model (table A3). From the magnitudes, it appears that using an inverse weight matrix up to neighborhood cut-off three kilometers is the best fit for spatial analysis, as it has the highest posterior probability.

Table A3. Posterior probability of adoption of spatial lag model by neighbors' cut-off distance and weighting matrix

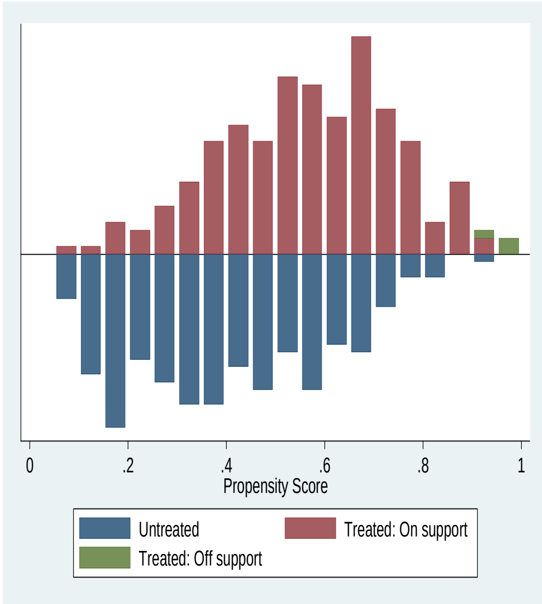
Inverse distance decay matrix		**Contiguity matrix**	
Neighbor cut-off	**Posterior probability**	**Neighbor cut-off**	**Posterior probability**
Up to 1 kilometer	0.04	Within village	0.26
Up to 3 kilometers	0.27	Nearest 1 village in sample	0.05
Up to 5 kilometers	0.04		

Notes: In the inverse-distance matrix W, $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} represents aerial distance between point i and j in km. In the contiguity matrix WC, $wc_{ij} = \begin{cases} 1 \text{ } if \text{ } i \text{ } and \text{ } j \text{ } are \text{ } neighbors \\ 0 \text{ } otherwise \end{cases}$.
Source: Based on a primary survey carried out in the Darjeeling district, West Bengal, India carried out in the year 2013.

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



(a) Propensity score graph based on ordinary probit



(b) Propensity score graph based on spatial lag probit

Figure A2. Propensity score graph.

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

Table A4. Post-matching two-sample t-test of mean difference

Variables	Mean difference in percentage between adopters and non-adopters after conditioning on propensity score based on ordinary probit in percentage (absolute p-value)	Mean difference in percentage between adopters and non-adopters after conditioning on propensity score based on spatial lag probit (absolute p-value)
Socioeconomic variables		
Age of the household head (years)	7 (0.48)	-5.7 (0.56)
Years of education of household head (years)	8 (0.42)	23 (0.02)
Household members between ages 14-65 (%)	-2.6 (0.79)	6 (0.54)
Household size (numbers)	7.9 (0.42)	19 (0.04)
Proportion of household members who have studied at least up to 10 years	3.4 (0.73)	-10 (0.31)
Experience of household head in agriculture (years)	12.6 (0.2)	-1 (0.92)
M**arket access variables**		
Distance to nearest local market from farm (meters)	-32.1 (0.0)	7 (0.41)
Distance to all-weather road (meters)	-13.3 (0.14)	9.5 (0.20)
Farm characteristics		
Area of the farm in acre (unit)	37.8 (0.0)	34 (0.01)
Altitude of the farm (meter)	-20.1 (0.04)	0 (0.99)
Soil texture	-0.5 (0.96)	9 (0.36)
Soil color	20 (0.04)	9(0.35
Soil stoniness	-14.2 (0.15)	-3.7 (0.73)
Information on soil conservation practices adopted in immediate upstream neighborhood		
Stone wall (%)		-3.5 (0.5).
Afforestation (%)		-8.2 (0.16)
Bamboo planting (%)		-5.5 (0.60)
Number of observations	432	

Notes: Adopters: Farmers who adopted terracing, stone wall, afforestation and/or bamboo planting; Non-adopters: Farmers who adopted terracing and stone wall.
Source: Based on a primary survey carried out in the Darjeeling district, West Bengal, India, in the year 2013.

Table A5. Pre- and post-matching mean percentage of bias

Pre-matching mean percentage bias	Method of estimation of propensity score	Post-matching mean percentage bias
16	Ordinary probit	13
47	Spatial lag probit	9

Note: The mean percentage bias is the average bias of all observed covariates.
Source: Based on a primary survey carried out in the Darjeeling district, West Bengal, India, in the year 2013.

References

LeSage JP and Pace RK (2009) *Introduction to Spatial Econometrics*. Boca Raton: CRC Press.