Tradeoffs between rural development policies and forest protection: spatially-explicit modeling in the Central Highlands of Vietnam

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Abstract

Alleviating rural poverty remains an important objective of development policy in many areas of the world. However, traditional means of increasing rural livelihoods such as increased investments in agricultural intensification measures can have disastrous impacts on natural resources such as forests by greatly increasing incentives for clearing. This paper contains a spatially-explicit model of land use in the Dak Lak province in the Central Highlands of Vietnam. Land use is modeled using a reduced-form multinomial logit model, and policy simulations are conducted. These simulations demonstrate that the adoption of yield-increasing inputs requires concomitant forest protection policies, both in terms of forest area and spatial configuration.

Keywords: land use; spatial modeling; GIS; policy simulations; rural development; landscape metrics; Vietnam

1 Introduction

Land use patterns are the collective result of the interaction among local geophysical and agro-climatic indicators, demographic variation, market forces, technical and institutional innovation, and related rural development policies. An increasingly important policy objective for many developing countries is to develop programs that improve the livelihood of the rural poor, but at the same time preserve natural resources, particularly forest cover and quality or biodiversity. So far little is known about the spatial consequences of land-use policy interventions as such an analysis necessitates spatially explicit data for both natural and socioeconomic indicators.

Our objective is to analyze the influence of policy, technology, socioeconomic, and geophysical conditions on land use using a reduced-form, spatially explicit multinomial logit model that combines data from a village-level survey with remotely sensed data derived from Landsat imagery. Specifically, we evaluate the impact of two policy tools often suggested to protect forest cover and to improve people's livelihoods in areas dependent on agricultural production: the creation of protected areas, and the adoption of yield-increasing technologies. Simulations are carried out to assess the effects of these policy scenarios of rural development on land-use patterns. We explore policy scenarios that could have potentially counteracting effects on the landscape. Restricting particular land uses within an area may increase the demand for land elsewhere, thereby stimulating the need to clear additional forest for agriculture. On the other hand, land-saving technologies such as fertilizer can reduce the pressure on the forest to provide agricultural land. Thus, careful consideration should be given to the likely impacts on forest cover when designing rural development programs.

In this paper, we qualitatively compare differences in predicted land use for each policy tool in isolation, as well as their combined impact. This approach allows for the analysis of potential changes in land use and provides a tool to evaluate the presence of potential hot-spots of land-use change following rural development interventions. An empirical application is presented for two districts of Dak Lak province in the Central Highlands of Vietnam (Figure 1). Dak Lak exhibits an interesting case in the study of land use dynamics with its abundant forest resources, ethnic diversity, high immigration rates and dynamic agricultural and socioeconomic development, particularly during the last decade, which is characterized by rapid, labor-and capital-intensive growth in the agricultural sector.

Figure 1: Location of research area

The next section contains a brief literature review of spatially explicit land-use models and the main drivers for land-use change. In particular, we examine selected studies which relate land-use change to (1) technological progress in agriculture; and (2) the protection of natural areas. Section three presents an analytical model of factors that influence the area of land under agricultural use including incentives to expand cultivation into forested areas. The methodological approach and the data sources are introduced in section four and the integration of spatially explicit data with socioeconomic indicators is presented in section five. Section six contains the results from the econometric estimation and the simulation of policy interventions, followed by conclusions and policy implications. We find that investments in agricultural intensification methods do result in more forest clearing in locations with adequate market access, which can be partially mitigated by expanding forest protection efforts.

2 Relevant Literature

A successful model of land use must be able to represent and explain the complex interactions among markets, institutions, policy, and land quality in shaping the landscape. Chomitz & Gray (1996) developed a model that motivated spatially explicit returns to land use as a function of two simple factors: geophysical suitability, related to Ricardian land rent, and von Thünen's notions of market accessibility. At equilibrium, each parcel of land will be managed according to its highest-valued use, given these factors. Other important factors to consider include policies, institutional variation, and changes in market conditions.

The Chomitz & Gray (1996) approach was expanded by Nelson et al. (2001) to consider variations in land tenure. Many studies have considered that land tenure security may be inversely related to the discount rate (Godoy and Contreras 2001) by suggesting that the more insecure the tenure, the less likely users will be to make long-term investments in their land, which may in turn accelerate deforestation. Nelson et al. (2001) found that, ceteris paribus, there was likely to be greater extent of forest in those areas set aside for certain indigenous groups in Panama, because land was more sustainably managed once the future of those areas was guaranteed. To adequately measure such effects, the interaction between protection and the underlying geophysical characteristics of the area must be considered. Cropper et al. (2001) find that investments that increase the probability of forest clearing such as road building do not increase the threat of clearing within protected areas, if those areas are not suitable for agricultural production in terms of topography and soil quality. They support the notion that protected areas are often designated as protected in the first place because of their low agricultural potential.

Technological progress in agriculture, such as higher yields from improved seed varieties or the adoption of labor-saving farming practices, increases farmer's profits as long as output prices remain constant (Angelsen and Kaimowitz 2000). For an individual farmer technological progress, therefore, will reduce pressures on forests only if it reduces the profitability of agriculture on currently forested lands. This would occur, e.g., if labor-intensive technological progress such as new fertilizer technologies that require more weeding, bind labor resources on currently cultivated land. Then, the effect of agricultural intensification could be a short-term increase in forest cover assuming labor constraints of frontier farmers. Conversely, the introduction of labor-saving technologies, e.g. herbicides, might release labor and provoke the clearing of forests as agriculture becomes more profitable due to increasing labor productivity. Particularly in the case of an export crop, agricultural improvements can greatly increase the potential profitability of agriculture on currently forested lands (Amsberg 1998). In this case, intensification could lead to increased deforestation, depending on the relative suitability of the landscape for the new crops. Carpentier et al. (2000) find substantial evidence in the Amazon of increased deforestation rates corresponding to increased intensification on previously cleared land. Serneels & Lambin (2001) discuss how agro-climatic conditions and market accessibility became more important for mechanized agriculture as opposed to subsistence agriculture. Technical investments can have spinoff effects on other inputs and often cost of access becomes more important after agricultural intensification measures are increased. One example are new crop varieties, which rely on access to chemical fertilizers as a yield-increasing external input.

Many researchers discuss the balancing act that national governments often face between providing much needed support to the rural poor but also protecting valuable natural resources.

Cropper et al. (2001) note that, if forest conservation is an important goal, consideration must also be given to identifying those areas most in need of conservation; i.e., areas where the benefits of conservation in terms of habitat or diversity of species are the highest. Deininger & Minten (2002) also underscore the need to obtain additional information on opportunity costs in terms of rural livelihoods as well as benefits of habitat protection. Their study controls for local wages by using rural poverty levels as a proxy variables. They find that high levels of poverty are statistically associated with higher probability of deforestation, indicating that an important policy goal would be to decrease poverty, and particularly supporting non-agricultural employment opportunities to reduce dependence on forests.

3 Methodology and Data

Land use is approximated by visual interpretation of a Landsat Enhanced Thematic Mapper (ETM) image from 2000. The resulting land-use map is categorized into three classes: (1) mixed agricultural land (cash and food crops) including cultivated upland plots; (2) paddy fields, both with one and two crops a year; (3) all non-agricultural land comprising forests of different quality and small areas of mixed grassland as well as fallowed upland plots. Results of earlier studies showed a modest increase in forest cover, mainly due to agricultural intensification, better market access and government policies on forest protection (Müller and Zeller 2002).

We explain land use as a function of four types of regressors. First, we use geophysical indicators such as two binary surfaces of soil suitability for mixed agriculture and paddy rice, and continuous surfaces for the altitude and the slope of land.[1] Second, we employ variables that describe socioeconomic characteristics of the villages several years before the satellite images

[1] Several of the meteorological stations from which we interpolated rainfall data are situated outside of our spatial sample. Therefore, we excluded the rainfall surfaces from the regressions.

were taken, to indicate driving factors of the demand for land that would yield the observed land-use patterns several years hence.[2] Here, we capture endogenous, and therefore lagged, population as a time-variant variable to indicate the state in 1990. Pfaff (1999) indicates that the impact of population on forest cover in the Amazon has not been straightforward; earlier settlers have a qualitatively greater impact than later ones. A continuous population surface was generated from village recall data cross-checked with official statistics for 1990 by interpolating the point coverages of village locations with inverse distance weighting (Bracken 1994). Tradition and cultural influences on land use are captured by a dummy for the ethnic composition of the villages. Political capital of the villages we proxy with a dummy awarded to villages with the status of hero villages. Villages, which assisted the Northern Vietnamese government in the fight against the South and the U.S. were awarded this title from the communist government after the War. Hero villages are expected to get a preferential treatment from local and national governments in terms of access to services and infrastructure. Third, exogenous policy variables to describe government investments and macro-level policies are included in the model. These consist of a quantification for the spatial placement of policy-induced investments in road and market infrastructures and the introduction of agricultural technologies, proxied by the area irrigated per village, and the year of introduction of a compound fertilizer containing nitrogen, phosphorus and potassium (NPK) as the most important yield-increasing input in the research area. To capture market access we used a road layer representing the part of the road network passable during the whole year and existing since the time of French colonial rule in the first part of the 19th century. Therefore, we assume the road layer to be exogenous to present-day land use.

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[2] The conceptual framework assumes that land use at the point of observation is more or less at equilibrium. Therefore, it is important to allow time between an initial state and hypothesized point of equilibrium. A 10 year lag period is somewhat arbitrary, but the year 1990 provided a suitable point of reference for the recall questions.

In addition, areas delineated as New Economic Zones (NEZ)[3] were incorporated as a measure of the length since the inauguration of government-controlled immigration and associated investments. The presence of an NEZ is hypothesized to yield a positive coefficient on the presence of intensive agricultural production such as paddy rice. As an additional policy variable we include the potentially endogenous placement of protected areas as a binary indicator (Cropper et al. 2001).[4]

Fourth, we incorporate a measure of the landscape structure using the Euclidean nearest-neighbor distance (ENN) statistic and an indicator for landscape fragmentation. The ENN distance is an indicator to quantify patch isolation and equals the distance to the closest patch of the same category (McGarigal et al. 2002). Landscape fragmentation is measured as shape complexity, which is equal to the ratio of perimeter to area of a particular landscape patch adjusted for the standard square size of the raster cells (McGarigal et al. 2002). Due to possible scale economies in a situation of agricultural intensification and increasing market orientation, pixels under agricultural production will tend to be more spatially concentrated (less isolated) and exhibit a more homogenous structure (less fragmented), in areas close to market centers and in favorable natural conditions (Geoghegan et al. 1997, Parker 2000). Agricultural land uses are, therefore, anticipated to show fairly homogeneous patterns. The location of the villages in the research area including topography and the road network are depicted in Figure 3 in the appendix. Detailed descriptive statistics of the employed variables are reported in Table 1.

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[3] A resettlement scheme undertaken by the government after the end of the war in 1975, where people from densely populated areas such as the Red River Delta and the Mekong Delta were moved to less-densely settled areas for agricultural production.

[4] To integrate the delineation of protected areas in unfavorable natural conditions we explored interaction variables, such as the combined effect of the protection dummy with soil suitability for maize cultivation and with slope. However, we had to drop the interaction terms due to multicollinearity issues.

Table 1: Descriptive statistics for independent variables

Label	Obs	Mean	Std.Dev	Min	Max
Spatial lag slope (degrees)	22,321	21.01	16.74	0	77.9
Elevation (100m)	22,321	5.88	1.67	4.2	13.19
Soil suitability for paddy	22,321	0.14	0.35	0	1
Soil suitability for mixed agriculture	22,321	0.04	0.19	0	1
Population, 1990	22,294	65.10	26.67	0.23	285.98
Ethnic minority village (0/1)	22,321	0.62	0.49	0	1
Hero village (0/1)	22,321	0.31	0.46	0	1
Km to all-year road	22,321	5.86	5.36	0	23.08
Years since establishment of NEZ	22,321	9.26	8.55	0	24
Years since introduction of NPK	22,321	4.26	3.70	0	20
Increase in irrigated area (ha), 2000	22,321	7.38	13.02	0	62.5
Protection dummy (0/1)	22,321	0.08	0.27	0	1
Distance to nearest neighboring patch (100m), 1992	22,304	1.20	1.13	1	25.1
Shape complexity, 1992	22,304	8.45	1.97	1	9.44

Source: authors

4 Spatial Data Integration

Ideally, to integrate spatially explicit data derived from geographical information systems (GIS) and remote sensing (RS) techniques with village survey data, the scale of the analysis should match the unit of decision-making. Yet, in Vietnam as in most developing countries, plot maps and village boundaries are not available (Nelson and Geoghegan 2002). This renders spatial modeling a time-consuming and costly task due to the necessary delineation of the spatial extent of plots or villages, e.g. using Global Positioning Systems (GPS), in order to link socioeconomic data, usually derived from surveys, with GIS layers.

Instead, we approximate village boundaries as the spatial base unit for the integration of socioeconomic with spatially explicit variables in order to delineate each village's sphere of influence on the landscape. Village centroids for all surveyed villages were recorded using GPS. A cost-distance algorithm was then applied to create 'accessibility catchments', generated around each village centroid and based on estimated transport costs (Bigman and Deichmann 2000).

Spatial accessibility is similar to Euclidean distance functions, but instead of calculating the actual distance from one point to another, the shortest cost distance (or accumulated transportation cost) from each cell to the nearest source cells is determined (Figure 2).[5] Hence, survey data, apart from population, takes the value of the interviewed village for each point that has lower transportation costs to the geographic location of that village than to any other village location.

The units of analysis are square pixels of 50 by 50 meters, i.e. 0.25 hectares.[6] To focus on changes at the forest margins influenced by human interventions, we restrict the analysis to those pixels that have a cost of access below the mean for the transportation cost surface (Figure 2). In that way, we include nearly all the agricultural area in 2000 and eliminate remote and high mountainous areas covered mostly with thick primary forest, which are outside measurable human influence.

At present, there are no models or test statistics available to account for substantive spatial interaction in a qualitative dependent variable framework (Anselin 2001). To compensate for potential spatial dependence in the dependent variables, Besag's coding scheme was used (Besag 1974), also employed by Nelson & Hellerstein (1997) and Munroe et al. (2002) in similar studies. The regular spatial sample was drawn by selecting every 5th cell in the X and Y directions so that no selected cells are physical neighbors and observations are spaced 200 meters apart. The sampling procedures allow us to apply standard estimation techniques (Anselin 2001a) and resulted in a dataset of 22,300 observations used for subsequent econometric modeling. In addition, we include slope as a spatially lagged variable (Munroe et al. 2002; Nelson et al. 2001; Nelson and Hellerstein 1997), which captures the influence of surrounding geophysical conditions

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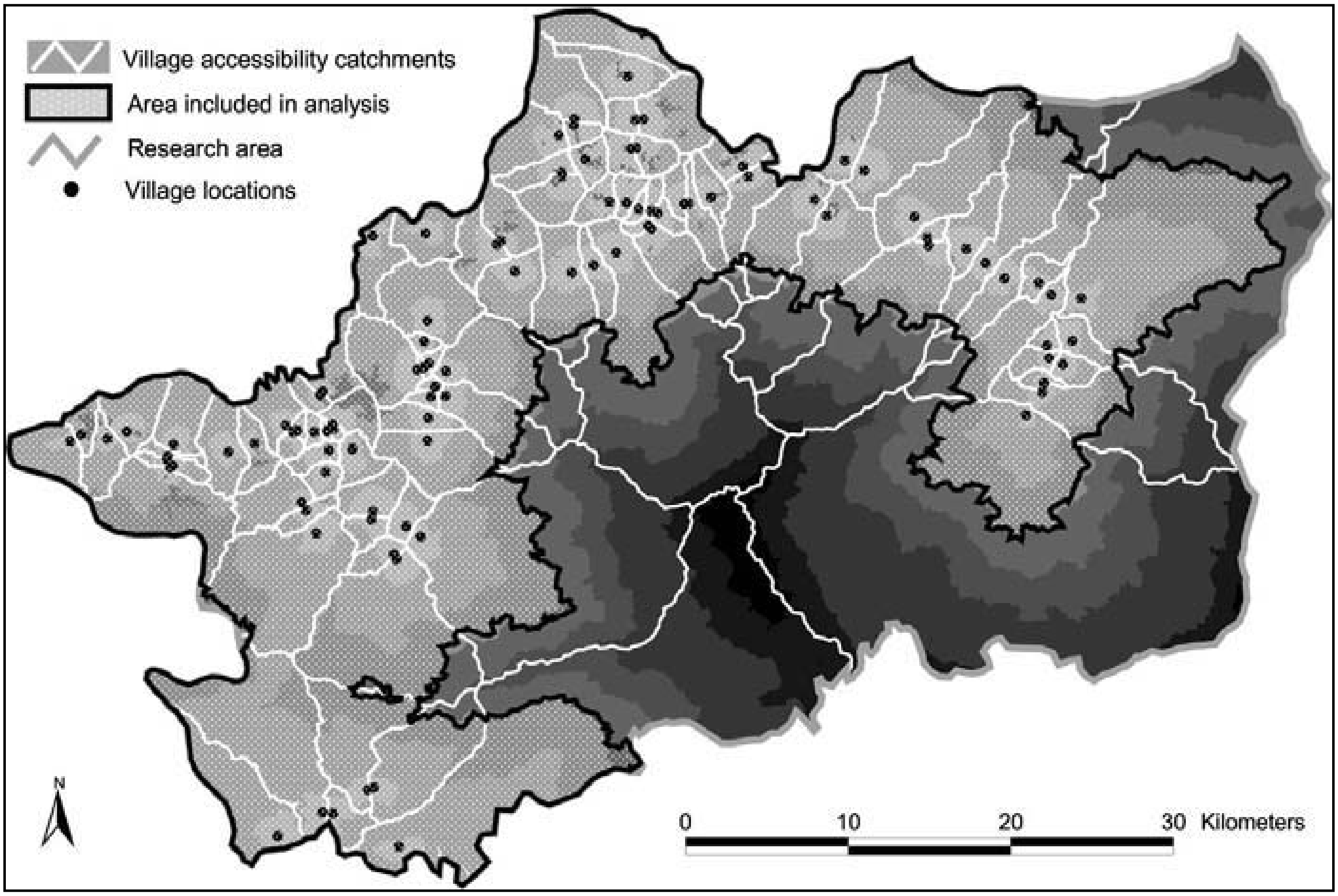
[5] For an example of spatial data integration using purely Euclidean distance measures, see Müller & Zeller (2002).
[6] The land-cover data from the Landsat images have a spatial resolution of 30 by 30 meters. The land-cover maps were then resampled to the resolution of the DEM, i.e. to square pixels of 50 by 50 meters.

on the probable land use of a given pixel. These techniques help to reduce spatial autocorrelation although they do not totally eliminate it (de Pinto and Nelson 2002).

Figure 2: Transportation cost surface with spatial sample and approximated village



Source: authors

5 Models and Results

5.1 Econometric estimation

To explore relationships between exogenous and predetermined variables and the land cover categories as left-hand side variables, a multinomial logit specification was applied. MNL models estimate the direction and intensity of the explanatory variables on the categorical dependent variable by predicting a probability outcome associated with each category of the dependent variable. MNL is based on the assumption that the probabilities are independent of other outcomes. In this analysis, socioeconomic data are measured at the village level; therefore, it is important to account for village-level effects shaping the mixture of land uses. Assuming that pixels are independent across villages, but not necessarily within, we cluster all pixels based on approximated village areas.[7] This affects the estimated standard errors and the variance-covariance matrix of the estimators, but not the estimated coefficients (StataCorp 2003). Further, we employ the Huber and White sandwich estimator to obtain robust variance estimates. The sampling procedure outlined in section 4 resulted in 22,300 observations, which we use to estimate the coefficients of the MNL. These coefficients are then used to predict outcomes for the entire dataset (558,000 observations) in order to generate continuous prediction and simulation maps.

5.2 Empirical results

The MNL has three land cover classes as categorical, unordered dependent variables. To control for potential endogeneity problems, only lagged values for time-variant independent variables such as population growth and spatial connectedness are considered in the empirical applications. In addition, all independent variables were tested for multicollinearity. We assess the assumption of independence of irrelevant alternatives using the Hausman test and can accept the null hypothesis that outcomes are independent of other alternatives. Model results are reported as raw coefficients in Table 4 of the appendix for non-agricultural land as the comparison group. Overall predictive power is 87%, measured as the locations predicted correctly (Table 2). Equivalent to Nelson et al. (2001) we found that wrong predictions frequently lie on the border

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[7] We are grateful to John L. Pender for this recommendation.

between land use classes, which is likely to be related to spatial errors in the source data and unavoidable artifacts inherent in spatial data integration.

Coefficients for the geophysical variables are mostly significant at the 1% level and show the expected signs with high predictive power. Agriculture is more likely at lower altitudes, flatter land, and on more suitable soils. Surprisingly, access to all-year roads does not have a significant effect on the probability of a certain land use class. This is due to the relatively large areas under paddy and mixed agricultural use far away from the predetermined all-year road network. Earlier introduction of mineral fertilizer and more irrigated area increases the likelihood that pixels are under paddy production. Lagged population, as a measure of initial demand for land, does not seem to have an influence on the amount of area cultivated as it was probably outweighed by effects from agricultural intensification. In addition, large numbers of migrants were settled in areas with high proportions of land suitable for paddy cultivation, especially in the period after the end of the war in 1975 until the beginning of the nineties. Therefore, lagged population has little influence on the amount of land used for cultivation. The dummy on ethnic composition is significant at the 5% level and negatively affects the probability of paddy land. Our landscape indicators for patch isolation and fragmentation significantly decrease the likelihood of observing mixed agriculture. A significant amount of the more fragmented agricultural plots did indeed regenerate into non-agricultural uses. The amount of paddy land does not seem to be related to the landscape structure, but mainly emerges in areas with favorable geophysical conditions. Forest protection has a strong effect on the likelihood to observe both mixed agriculture and paddy land, significant at the 1% level.

Table 2: Prediction matrix for base estimation

Observed land use, 2000	Base scenario: *Mixed agriculture*	*Paddy*	*Non-agricultural land*	Total	Correct
Mixed agriculture	*255.1*	28.5	55.2	***338.7***	75.3%
Paddy	36.2	*71.8*	3.0	***111.0***	64.6%
Non-agricultural land	57.2	2.4	*885.7*	***945.3***	93.7%
Total	**348.5**	**102.7**	**943.9**	***1,395***	86.9%

Source: authors

5.3 Policy simulations

Changes in socioeconomic variables are simulated by changing values of specific explanatory variables of interest to policy makers. The estimated coefficients from the base estimation were applied to the entire data set, new predictions were computed, and the probabilities for land use with the simulated values of explanatory right-hand-side variables generated. Comparing simulated predictions of land use to the base predictions yields an approximation of the effects of varying levels of explanatory variables on land use (Nelson et al. 2001). The main advantage of the spatially explicit estimation employed is the opportunity to assess locational changes and to identifiy potential hot spots of land-use change following certain policy interventions.

We hypothesize three policy scenarios for rural development interventions (Table 3). The first scenario assumes a five-years earlier introduction of NPK fertilizers. Governments can influence such technology adoption by increasing extension services and by supporting fertilizer application through price incentives. The 'forest protection scenario' follows a government guideline that discourages agricultural production above slopes of 15 degrees. Empirically, we assume that slopes greater than 15 degrees and, in addition, all primary forest with closed crown cover is added to already existing protected areas. The last policy option combines 'earlier introduction of NPK' with the 'forest protection scenario' to assess the effect of this predominant policy strategy in Vietnam.

Table 3: Simulated policy scenarios

Description		Proxy
1. Earlier introduction of fertilizer	→	introduction of NPK 5 years earlier
2. Forest protection	→	a) protection of existing primary forest
	→	b) protection on slopes >15 degrees
3. Earlier introduction of fertilizer and forest protection	→	scenarios 1 and 2 combined

Source: authors

A comparison of simulated changes with the baseline predictions is expected to shed light on the impact of the rural development policy scenarios on land use. The spatially explicit framework allows for an assessment of both the magnitude as well as the location and spatial arrangement of the simulated changes. This will enable the identification of areas, which are more likely to change into other forms of land use under a certain policy setting.

6 Simulation Results

The scenario of 'earlier introduction of fertilizer' resulted in a reduction in non-agricultural land uses by 21.5 km^2 and an intensification of mixed agricultural land into paddy of 10 km^2 (Table 5). A visual comparison of the underlying land-cover map with the prediction map reveals that most of the converted land switches from non-agriculture into agriculture was bare soil and grass land. The simulated increase in areas under forest protection decrease agricultural land use by 5.1 km^2. Significant changes in the spatial patterns of land use result from a combination of policies to boost the introduction of yield-increasing technologies combined with forest protection (Table 5 and Figure 4 in the appendix). It induces a reduction in area under mixed agriculture by 15 km^2. Figure 4 in the appendix shows the spatial changes resulting from this policy intervention. On flat land and in suitable areas agriculture is intensified as can be observed in the northwestern part of the analyzed area. Agricultural production is left abandoned in marginal sloping areas adjacent to the lowland fields as in the south and northeast. The identification of such potential hot-spots calls for more in-depth field visits to monitor resulting land-use outcomes. The number of patches in the third policy scenario is increasing by 10%. This leads to more scattered spatial arrangements, which is less desirable from an ecological viewpoint. This result suggests that forest protection strategies ought to be combined with ecological valuations that explicitly take into account the value of contiguous protection areas conserving precious biodiversity.

7 Discussion and Policy Implications

The potential value of spatially explicit land-use modeling to policy makers lies in not only explaining observed patterns with regard to hypothesized causal processes, but also in quantitatively examining the impacts of policy on the landscape. Governments of developing countries face tough choices regarding how to alleviate rural poverty without further harming local natural resources such as forests. It has often been hypothesized that land-saving technologies such as fertilizer can of great benefit to forests, by reducing the need to clear additional land. However, as Angelsen (1999) states, the assumptions under which such a clear relationship would exist are too restrictive: no market effects are considered. This framework allows us to examine the tradeoffs between intensification and protection, and the simulations clearly indicate that even with the adoption of likely additional forest protection measures, further conversion of non-agricultural land occurs. Furthermore, the spatially explicit framework allows the policy maker to determine *where* those changes are likely to occur, both in absolute space, and also relative to the factors that influence spatial returns to land use.

Agricultural land uses are concentrated on lower altitudes, flatter land, and on better soils. Forest protection has a strong negative effect on the likelihood to observe land under agricultural cultivation. An earlier introduction of yield-increasing fertilizers and higher investments in irrigation increase the probability of paddy land, while in ethnic villages paddy land is less likely. Both population densities and the predetermined distance to the nearest all-year roads are insignificant determinants of present land use. Population densities are highest in paddy-growing areas with a low land-labor ratio and high levels of external input use. The predetermined road network, established under the French colonial rule, probably influenced market access at that time, but is relatively unimportant to the spatial arrangement of land use at present. Improved means of transportation as well as (potentially endogenous) further road construction opened up additional areas suitable for agricultural cultivation.

The spatially explicit simulations demonstrate possible land-use changes resulting from rural policy interventions. Government investment in agricultural intensification, proxied by an earlier introduction of NPK fertilizers, has a strong positive influence on the area under paddy rice, by far the most important food crop for farmers in the research area. The forest protection scenario induced higher pressure on agricultural land uses within the simulated additional areas under forest protection and resulted in the abandonment of more marginal lands. Combining the two scenarios results in significant changes, both in quantitative terms and in the spatial arrangement. However, the alterations in spatial patterns, which can be observed from the simulation maps, might demonstrate a higher landscape fragmentation following the policy interventions. This result suggests that forest protection strategies ought to be combined with ecological valuations that explicitly take into account the value of contiguous protection areas conserving precious biodiversity. This methodology facilitates a spatial assessment of land-use changes to allow policy makers the detection of local hot-spots, which possibly require additional conservation efforts. Likewise, areas with yet untapped agricultural potential due to beneficial natural or socioeconomic conditions can be identified.

The two districts in our study were purposively selected and can, therefore, not be generalized for the whole of Dak Lak province. Nonetheless, the policy implications of this study call for an increasing use of spatial planning to assist in the geographical targeting of conservation and rural development efforts. A spatially explicit simulation of land-use changes following rural development interventions, especially in locations with crucial watershed and biodiversity functions, might promote sustainable pro-poor management of natural resources and of globally valuable environmental services. As the simulations indicate, even with additional forest protection methods, new clearings with intensification exceed the extent of additional protected areas. Therefore, we suggest that a better long-term rural development strategy would to be create off-farm employment opportunities. As Angelsen (1999) demonstrates, increases in the market wage rate, ceteris paribus, will reduce the demand for clearing additional land.

With respect to implications for further research, we conclude that problems for spatially explicit modeling and spatial statistics are found more frequently in the combination of data on natural resources with socioeconomic information at an acceptable scale and under reasonable assumptions and simplifications. Our attempt to combine land use data with accessibility catchments at the village level addresses this issue. However, this aggregation masks decision-making processes at the farm and plot levels. More disaggregated data are needed to consider the effects of rural development policies on cropping patterns and micro-level changes in a spatially explicit framework. Still, the identification of hot-spots using our data is reasonably accurate and indeed showed changes in susceptible areas.

To obtain better spatial information for socioeconomic indicators, village censuses would yield more variation in explanatory indicators, improve the strength of the estimations and facilitate more sophisticated spatially explicit policy simulations. Combined with landscape metrics, more disaggregated data can yield additional insights into the spatial composition and arrangement of potential land-use changes resulting from investments in rural development. In that way, spatially explicit econometric modeling can enhance the geographical targeting of rural development interventions and facilitate the assessment of the magnitude and location of their economic and environmental consequences.

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Appendix

Table 4: Multinomial logit results with non-agricultural land as comparison group

	Agriculture	**Paddy**
Spatial lag slope (degrees)	**-0.069**	**-0.128**
	(9.28)***	(6.75)***
Elevation (100m)	**-3.379**	**-5.993**
	(5.93)***	(5.52)***
Soil suitability for paddy	**1.207**	**2.618**
	(6.31)***	(9.59)***
Soil suitability for mixed agriculture	**1.548**	**1.099**
	(5.70)***	(2.73)***
Population, 1990	0.006	0.006
	(-0.73)	(-0.49)
Ethnic minority village (0/1)	-0.253	**-0.903**
	(-0.72)	(2.38)**
Hero village	**0.794**	-0.104
	(2.69)***	(-0.22)
Km to all-year road	-0.024	-0.03
	(-0.58)	(-0.35)
Years since establishment of NEZ	-0.001	**-0.082**
	(-0.05)	(2.84)***
Years since introduction of NPK	0.048	**0.1**
	(-1.35)	(2.38)**
Increase in irrigated area (ha), 2000	-0.004	**0.018**
	(-0.59)	(2.01)**
Protection dummy (0/1)	**-2.062**	**-1.363**
	(6.47)***	(3.23)***
Distance to nearest neighboring patch (100m), 1992	**-0.127**	-0.101
	(1.77)*	(-0.71)
Shape complexity, 1992	**-0.18**	-0.033
	(4.59)***	(-0.4)
Constant	**17.849**	**27.207**
	(7.98)***	(5.03)***
Observations	22278	22278

Robust z statistics in parentheses; significant coefficients in bold;
* significant at 10%; ** significant at 5%; *** significant at 1%

Source: authors

Table 5: Land use implications of policy scenarios

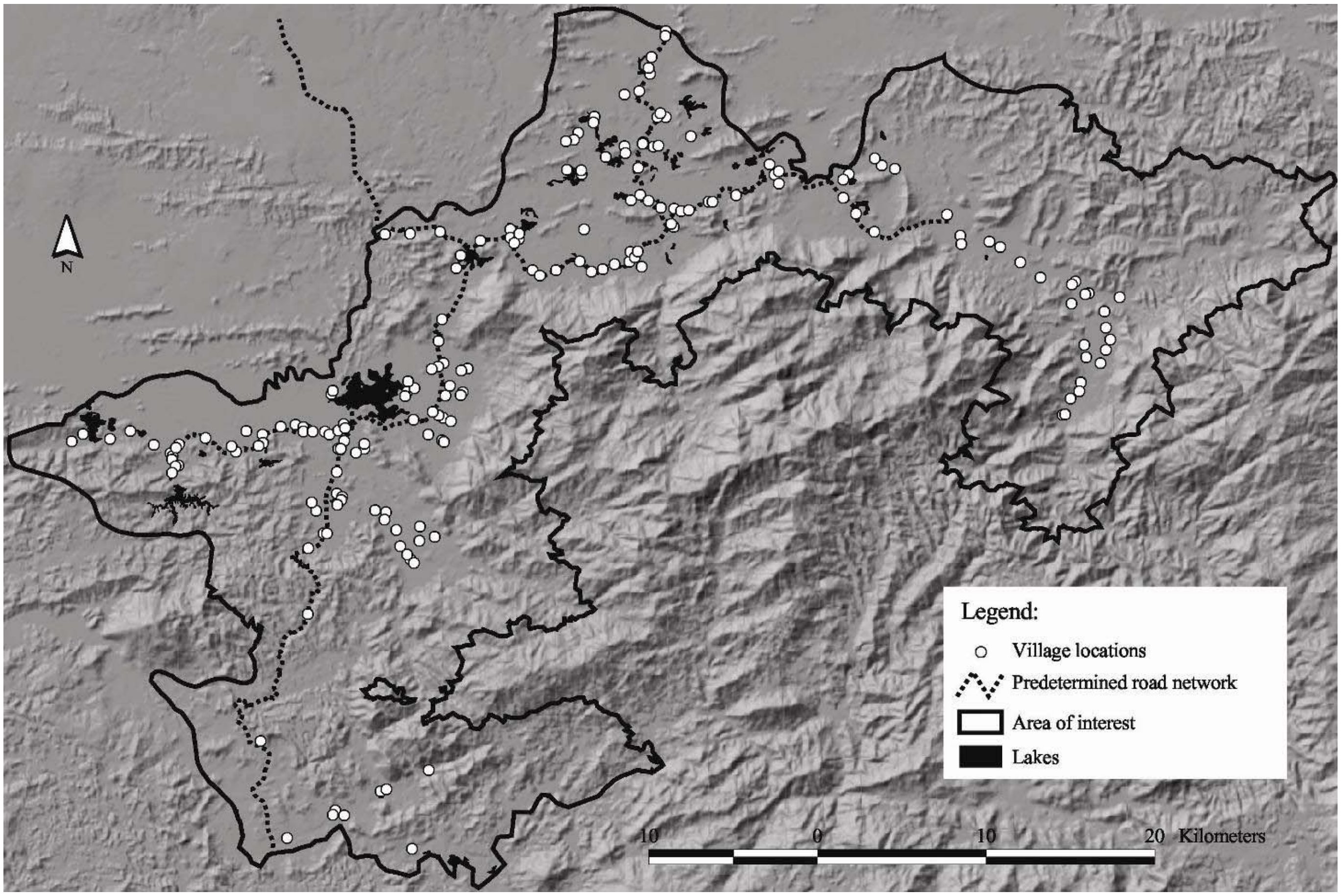
Base scenario	Early introduction of NPK: *Mixed agriculture*	*Paddy*	*Non-agricultural land*	Total
Mixed agriculture	*338.5*	10.0	0	***348.5***
Paddy	0	*102.7*	0	***102.7***
Non-agricultural land	21.2	0.3	*922.4*	***943.9***
Total	**359.7**	**113.0**	**922.4**	***1,395***

Base scenario	Forest protection: *Mixed agriculture*	*Paddy*	*Non-agricultural land*	Total
Mixed agriculture	*343.4*	0	5.1	***348.5***
Paddy	0	*102.7*	0	***102.7***
Non-agricultural land	0	0	*943.9*	***943.9***
Total	**343.4**	**102.7**	**948.9**	***1,395***

Base scenario	Combined NPK and protection scenario: *Mixed agriculture*	*Paddy*	*Non-agricultural land*	Total
Mixed agriculture	*333.5*	10.1	4.9	***348.5***
Paddy	0	*102.7*	0	***102.7***
Non-agricultural land	19.6	0.3	*924.0*	***943.9***
Total	**353.1**	**113.0**	**928.9**	***1,395***

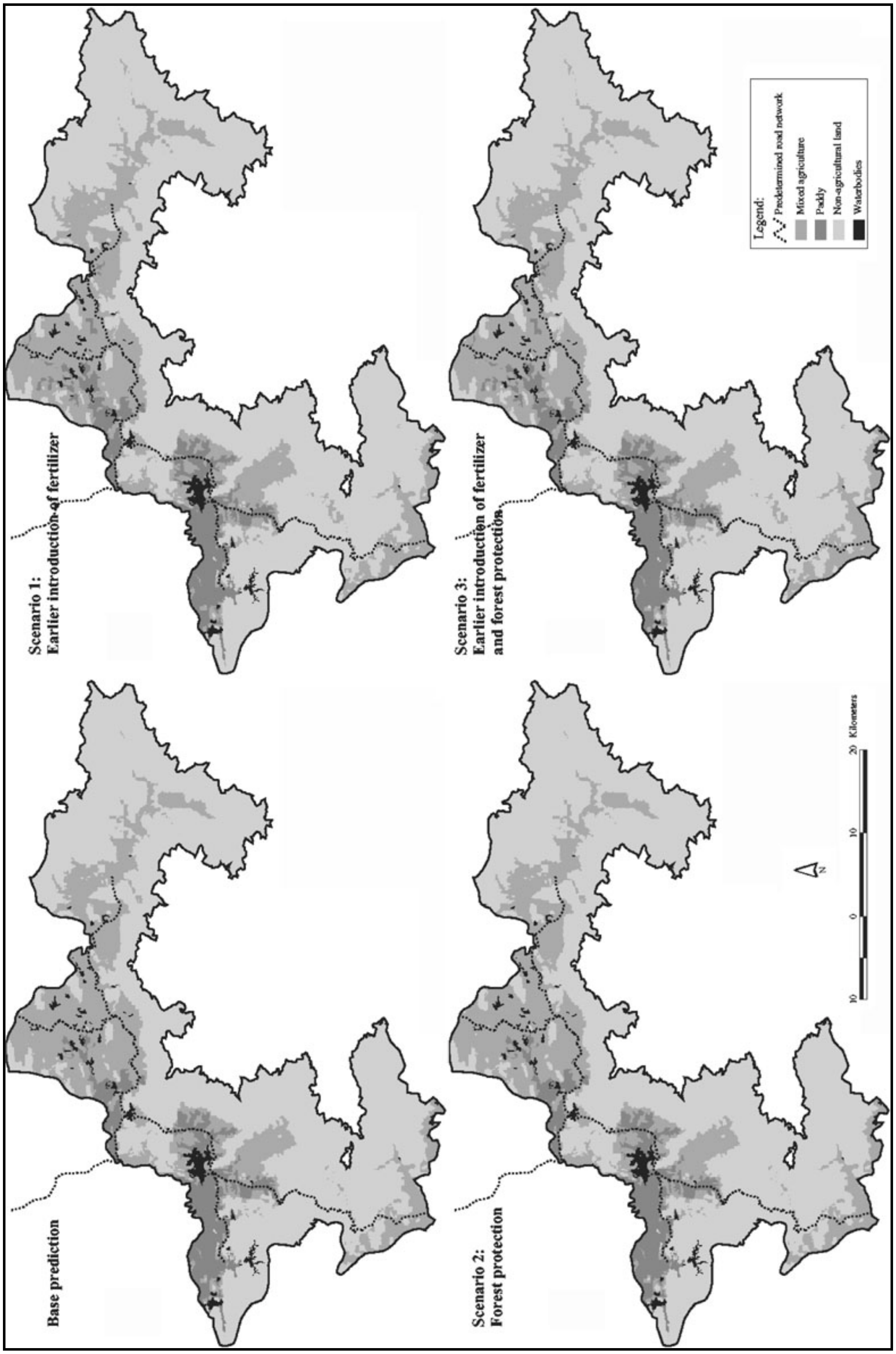
Source: authors

Figure 3: Location of villages, topography and road network



Source: authors

Figure 4: Prediction maps of policy scenarios on land use compared to base predictions



Source: authors

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