# Spatial Complementarity of Forests and Farms: Accounting for Ecosystem Services

Subhrendu K. Pattanayak and David T. Butry

Our article considers the economic contributions of forest ecosystem services, using a case study from Flores, Indonesia, in which forest protection in upstream watersheds stabilize soil and hydrological flows in downstream farms. We focus on the demand for a weak complement to the ecosystem services—farm labor—and account for spatial dependence due to economic interactions, ecosystem processes, and data integration. The estimated models have theoretically expected properties across eight different specifications. We find strong evidence that forest ecosystem services provide economically substantive benefits to local people and that these services would be substantially undervalued if spatial dependence is ignored.

*Key words*: economic-ecological modeling, ecosystem services, Indonesian National Parks, nonmarket valuation, spatial econometrics, watershed protection, weak complementarity.

Forests provide an array of ecosystem services by sequestering carbon, maintaining habitat and biodiversity, stabilizing hydrological flows, mitigating soil erosion, and improving microclimates. Deforestation and forest degradation can irreversibly and substantively impair these ecosystem functions. This raises the question of why society and governments would allow rapid or excessive deforestation. One reason is the failure to consider the full range of goods and services provided by the forests, particularly any latent and complex ecosystem services (Dasgupta). The economic contributions of forest ecosystem services are not well understood and rarely quantified. This article illustrates a method for estimating the value of watershed services from protected tropical forests in Flores, Indonesia.

Specifically, we respond to three challenges posed in the literature. First, valuation studies have typically overlooked livelihood values of natural resources in developing countries, focusing largely on amenity values in developed countries (Deacon et al., Dasgupta). Second, a detailed consideration of the spatial aspects of ecosystems and ecological processes, such as spatial dependence, has been omitted from most valuation studies (Bockstael). Third, valuation of ecological services that are inputs into production processes has typically relied on data intensive approaches, such as the measurement of full profit functions, instead of focusing on demand for a weak complement, which substantially economizes on data requirements (Huang and Smith). Our article addresses these research issues with a case study from Indonesia in which forest protection policies in upstream watersheds in Flores stabilize soil and hydrological flows in downstream farms.

## Ecosystem Valuation

Adapting a definition by Daily, forest ecosystem services are the conditions and processes through which forest ecosystems, and their constituent species, sustain and fulfill human life.[1] The key to valuing a change in an ecosystem function lies in establishing the link between that function and some service flow valued by people. This is not a trivial endeavor because the analysis must reflect the intricate web of bio-geo-physical relationships between processes and conditions that link causes and effects in different parts of the ecosystem. If that link can be established, the economist's

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[1] See Pattanayak and Butry for further discussion of forest ecosystems, the goods, and services they provide, and a discussion of early valuation exercises.

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concept of derived demand can be applied (Freeman 1993, 1996). Ecosystem valuation is typically conducted to (*a*) evaluate changes in ecosystem management and (*b*) show that natural systems are represented in the policy process.

To our knowledge, most previous attempts to link ecosystem functions and the resulting services in an interdisciplinary framework have focused on some form of soil conservation. Empirical economic analyses of soil conservation have used resource accounting, mathematical programming, or econometric production function methods. In the econometric approach, the production functions are usually either aggregative (nation or statewide), thereby losing site-specific details or simple with just two or three arguments. In all cases, the value of soil erosion is estimated in terms of its effect on economic productivity. The critical distinction between these studies and our proposal relates to the link between ecosystem functions and the resulting services. The erosion studies focus on on-farm economic productivity losses from managed agronomic systems, rarely forest management. They do not discuss or rigorously analyze the off-site consequences, the linkages with up-stream ecological phenomena, or the spatial dimensions of ecological and economic process. Our review of the literature confirms Dasgupta's contention that economic valuation of nature's services is rare, particularly in tropical settings, thereby hampering the design and evaluation development and environmental policies.

### *Spatial Dimensions of Forest Ecosystem Valuation*

Economic models often do not exploit underlying spatial relationships, instead they tend to aggregate dispersed data (Bockstael, Anselin and Bera). In the case of forest ecosystem valuation, ignoring the spatial information could be especially costly in terms of statistical bias and inefficiency. This is because spatial links are inherent characteristics of both the ecological and the economic phenomena being studied, as well as the data integration techniques employed to study them. The ecosystem service flows can be conceived as "locational externalities that can set in motion a spatially dynamic domino effect" (Bockstael).

Spatial patterns can emerge as ecological services "flow" across the forest ecosystem, affecting the bio-geo-chemistry as well as socioeconomic activities. Spatial patterns also exist in pure economic behavior as economic agents (farmers in our case study) interact with, learn from, and copy their neighbors (Case 1991, 1992; Brock and Durlauf). The definition of a neighbor need not be restricted to Euclidean distances and can be extended to socioeconomic and cultural distances such as income levels and kinship ties and, perhaps more importantly, ecological distances such as proximity to streams. Clearly, if economic activities such as farming are conditional on the natural environment such as soil and moisture, the flow of ecosystem services across the landscape could induce similar behavior (i.e., farming activities) among farmers along an ecological gradient (i.e., watershed). A second, perhaps equally important, potential source of spatial pattern is the technique used in collecting and analyzing the data. Omitted variables are the most obvious source of spatial correlation because they are likely to capture important locational characteristics. Analysts can also induce spatial correlation by mismatching spatial units. For example, watersheds do not match socioeconomic or political clusters. Consequently, when we overlay watershed ecological data on village sociodemographics, we induce spatial patterns. This pattern also emerges from the spatial interpolation that is often used to match environmental and economic data.

Anselin and Bera suggest two more reasons for considering spatial issues. First, a number of important policies have taken on explicitly spatial dimensions, such as the designation of target areas (in our case, target watersheds). Perhaps a more practical reason is the availability of a large ecological and socioeconomic data with detailed spatial information. Recently, there has been a spurt of empirical analysis of spatially explicit processes in the field of environmental and resource economics (Anselin, Irwin and Geoghegan, Nelson). While much of this work has focused on modeling and predicting land use change, there are countably few rigorous empirical applications in developing countries—the focus of our article.[2]

From a modeling perspective, the challenge lies in addressing spatial dependence

[2] For reviews of spatial estimation in agriculture and resource economics, the interested reader is directed to Anselin and special issues of the journals Agriculture, Ecosystem and the Environment (Volume 85, Issues 1–3, 2001) and Agricultural Economics (Volume 27, Issue 3, 2002) that focused as much on theory and modeling as on econometrics.

in the data, which occurs when the value of variable $y$ for observation $j$ is correlated to the value of that variable for observation $i$ as a consequence of a spatial relationship. The existence of spatial autocorrelation implies that a sample contains less information than an uncorrelated counterpart sample, which limits our ability to carry out statistical inference. When we have a spatial relationship that results because of behavior of neighbors or because of biophysical process (e.g., water flowing across the landscape) or if an omitted variable is correlated with one of the model's regressors, we have the case of spatial lag dependence. Failure to estimate a spatial lag model when a spatial lag process exists may result in biased and inconsistent estimators (Anselin and Hudak, Anselin and Bera). The other, perhaps more innocuous, form of spatial autocorrelation is due to error correlation. Spatial error dependence is usually due either to measurement error or to omitted variables that spill over spatial units. A nonspatial model that contains spatial error will yield inefficient model estimators due to its nonspherical error covariance (Anselin and Bera). It is also possible to have a combination of lag and error. We return to these issues in the discussion of our model specification below.

## The Simple Analytics of Ecosystem Valuation: Weak Complementarity

As suggested by Freeman (1996) and Pattanayak and Kramer, the economic value of ecosystem services can be viewed as the outcome of three sets of functional relationships. First, public policies combined with private decisions affect forested watersheds, change watershed flows, and, thereby, generate changes in ecosystem services. Second, these services affect private production activities of economic agents. Third, this has consequences for their economic welfare. The change in welfare, evaluated in terms of market prices of private commodities, is the use value of ecosystem services.

Much of the environmental valuation literature has pivoted off Mäler's proposal to focus on a weak complement to the environmental good (Freeman 1993, Huang and Smith). Analysts estimate how the demand for the weak complement shifts in response to changes in environmental quality and measure willingness-to-pay (WTP) for environmental quality as the resulting changes in consumer surplus. Huang and Smith develop production analogs of this weak complementarity logic. They show that input demand can be used to measure values as changes in producer surplus that are induced by changes in environmental inputs ($E$) into production (e.g., total agricultural labor, $L$). In this approach, the value of ecosystem services ($E_1 - E_0$) is estimated from the input demand function, $L(P \mid E, \cdot)$, using Hotelling's lemma (1). Specifically, profits can be measured by integrating the input demand function from the market price, $P_0$, to the choke price, $P_C$, where the choke price is defined as the price at which the demand for the input becomes zero and depends on the ecosystem condition.

$$
\begin{aligned}
(1) \qquad \mathrm{WTP} &= \Delta\pi(P \mid \Delta E, Z) \\
&= \int_{P_0}^{P_C(E_1)} L(P_L \mid E_1, Z)\, dP \\
&\quad - \int_{P_0}^{P_C(E_0)} L(P \mid E_0, Z)\, dP \\
&= \int_{P_0}^{P_C(E_1)} -\frac{\partial\pi(P \mid E_1, Z)}{\partial P}\, dP \\
&\quad - \int_{P_0}^{P_C(E_0)} -\frac{\partial\pi(P \mid E_0, Z)}{\partial P}\, dP
\end{aligned}
$$

where WTP is the willingness-to-pay (or value) for the ecosystem service, $\pi$ is profit, $P$ is the input price (labor in this case), $E_1$ and $E_0$ are ecosystem conditions, $P_C(E_1)$ and $P_C(E_0)$ are the choke prices associated with the ecosystem conditions $E_1$ and $E_0$, respectively, and $Z$ denotes all other exogenous variables in the input demand equation including output prices.

An improvement in the ecosystem that generates ecosystem service will expand the demand for the weakly complementary production input, raise the choke price, and increase profits. WTP for the ecosystem service is, therefore, equal to the change in profits calculated from the two input demand curves. This logic is illustrated in figure 1 (note, we do not assume a parallel shift in demand—see the empirical specifications). The basic intuition is that increased ecosystem service raises the value of the marginal product of farm labor because it is a complement. Consequently, the value of an improvement in ecosystem services or a household's WTP is equal to the increased marginal value product of labor, which is equivalent to the profit increase.

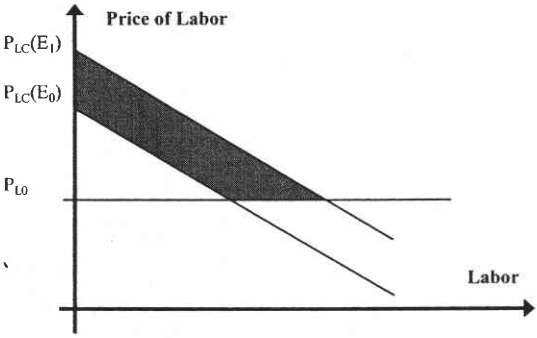


**Figure 1. Ecosystem contributions: Change in area under a demand for weak complement—farm labor (linear case)**

There are some important theoretical conditions for the applications of the weak complementarity logic in ecosystem valuation. The key issue is that ecosystem services—mitigation of droughts and erosion—contribute to rural farming by complementing an important element of rural livelihoods—the total labor employed in farming. That is, at the choke price, the marginal productivity of ecosystem service must be zero, implying that the production input is a necessary complement to using the ecosystem service. If this were not the case, then we could not value the ecosystem service by analyzing only this production input because the service would be productive irrespective of the demand for this input. Second, the production input in question must be nonessential such that we can define a choke price. The choke price establishes the initial position (where input demand equals zero) and determines the constant of integration (Mäler). Third, the weak complement must be traded in a functional and complete market at exogenously determined market prices. In addition, the induced change in demand for the weak complement should not be large enough to induce price effects. The implied separability of the production (profit) or consumption (expenditure) spheres of the household simplifies the analytical tasks for deriving welfare measures by allowing ecosystem values to be measured in terms of changes in producer surplus.[3] With separability, profit or quasi-expenditure functions can be used to value environmental services even for consumer–producer households (Pattanayak and Kramer). Huang and Smith suggest that by focusing on the demand function for weak complement (e.g., labor), analysts could substantially economize on the data demands for valuation by avoiding the estimation of full profit functions.[4]

## Forests Ecosystem Services in Flores, Indonesia

The forests of the Manggarai region on Flores island have been protected since the Dutch colonial rule. However, the degree of protection has varied across watersheds. In 1993, the government of Indonesia established Ruteng Park on 32,000 hectares with the primary goal of preventing further deforestation, initiating reforestation and land conservation, and enhancing watershed protection. Recent evaluations of water and soil resources in the region suggest that the forest conservation inside the Park maybe reducing soil erosion and mitigating droughts by protecting streams, rivers, and watershed in many Manggarai watersheds (Binnies, Swiss Intercooperation, Priyanto). Although the economic contributions of these ecosystem services are unknown, there is substantial biophysical evidence that Ruteng Park provides drought mitigation and soil conservation to the downstream farmers.

The drought mitigation and soil conservation services by Ruteng Park can be represented as changes in baseflow and erosion, respectively.[5] The forest hydrology literature posits that extensive tree cover helps maintain baseflow and soil levels in areas with environmental characteristics similar to Ruteng, that is, steep terrain, intense rainfall, and clay or compacted soil (Bonell and Balek). The studies by Binnies, Swiss Intercooperation, and Priyanto suggest that Ruteng forests are net "producers" of baseflow and soil.[6] The

[3] Scitovoszky was one of the first to recognize the importance of perfect markets in equating utility-profit-maximizing choices for owner firms. See Thorton and Eakin for further discussion of this issue.

[4] In a systems approach, we would estimate equations of profit, output supplies, and input demands as functions of prices and fixed inputs. Using weak complementarity, we could focus on one essential output supply *or* input demand and estimate it as a function of prices and fixed inputs; we would not need data on all quantities.

[5] Baseflow is the nonepisodic residual streamflow remaining after rain has cycled out of the hydrological system. The soil conservation service of forests results from a mitigation of the erosion process and an improvement in soil quality and quantity. See Hamilton and King for additional details.

[6] These findings are confirmed in supplementary analysis that we conducted in response to a referee's comments that our measures of ecosystem services may be endogenous. When we use forest cover as instruments for erosion and baseflow (based on forest ecology theory) in a Hausman exogeneity test (Hausman), we find strong statistical evidence that baseflow and soil conservation are correlated with forest cover.

studies do not, however, estimate precise increases in baseflow or reductions in soil erosion due to watershed protection. The primary economic role of baseflow and soil is as fixed inputs to agricultural production in the form of soil moisture and soil matter that enhance farm productivity. Improved agricultural production changes the economic welfare of agricultural households downstream of Ruteng Park. This change in welfare provides a measure of ecosystem values that can be derived from estimates of incremental producer surplus resulting from the incremental baseflow and soil. We focus on these watershed services to illustrate our methodology, while recognizing that they are just a subset of several potential benefits and costs of a large forested park.

The empirical model, presented next, is based on secondary hydrological and forest statistics and primary household data on the socioeconomic activities of the Manggarai people who live in the buffer zone of Ruteng Park. Priyanto describes the forest hydrological modeling to derive baseflow and erosion volumes for thirty-seven watersheds and sub-watersheds in the buffer zone of the park that resulted from the land uses (including forest protection) in the years preceding our household survey. We use these "lagged" sub-watershed level soil and baseflow in our econometric analysis because they reflect the approximate water and soil conditions that would have been experienced at each farm in each watershed. Thus, we capture the impact of broader ecological conditions (rather than farm-specific conditions) in a manner that is similar to the idea that rain is shared by several farmers in a rain shed.[7] While the Ruteng region receives on average 2.5 m of rainfall annually, only about 40% stays in the system as baseflow—suggesting drought conditions in many sub-watersheds. The average level of erosion is 2.1 tons/hectare/year. Although the variable we use in our empirical analysis is soil erosion, the forest ecosystem service, soil conservation, is the inverse of erosion.

The household data are drawn from a socioeconomic survey of 500 households that was conducted in the buffer zone of Ruteng Park in 1996. Because the hydrological effects of the park dissipate over geographical distance, the survey was restricted to all forty-seven buffer zone villages, contiguous to the protected area. The typical Ruteng household relies extensively on agriculture, growing primarily coffee and rice. Most of the local people (87%) are employed in agriculture. There are nonagricultural employment opportunities, including positions with the local government, NGOs, kiosks, and logging crews. The statistics on both hiring-in and hiring-out labor, the fact that a large proportion of households report input and output prices, and the proximity of roads and other market infrastructure provide some evidence that markets are complete for agricultural products and labor. For example, over 90% of the villages have easy access to paved roads and some form of credit facilities. About 80% of the villages have regular bus service and about 60% have one or more local stores. Furthermore, Pattanayak and Kramer conduct an econometric test described by Pitt and Rosenzweig to confirm the hypothesis that output and input markets are complete and functional (we repeat this test in this article).

We use geographical information system (GIS) to integrate the soil and hydrology data from the forest hydrology models with the socioeconomic survey data. By merging the two data sets within a GIS, we improve the general precision of the data set and compute spatially explicit ecological indices.[8] In addition, GIS allows us to calculate the spatial weights matrix, derived on the basis of distances between village centers.

## Empirical Strategy for Valuing Ecosystem Services of Ruteng Park

Applying the Huang and Smith logic and focusing on demand for agricultural labor, we see that baseflow and erosion can be conceived as weak complements to agricultural labor

[7] To our knowledge, this kind of sub-watershed level measurement of hydrological and agronomic indices represents one of the most spatially explicit indices of an ecological service in farm economics in a developing country context. While the level of resolution in this article causes some loss in precision, it is significantly more precise than typically used in most empirical work. Moreover, this sharing of ecological characteristics by groups of farmers is central to our contention that "spatial patterns" emerge as the ecosystem services "flow" across the landscape.

[8] For example, if portions of two streams contribute baseflow to a particular village, we use GIS to compute the fraction of the total baseflow from any one stream that goes to the particular village by first calculating the fraction of the total stream that passes over the specific village. The contributions of each stream can then be summed. Without GIS, we would calculate a crude weighted average of the baseflow in the two streams, based on visually estimated proportions.

because they satisfy the necessary conditions for weak complementarity. First, agricultural labor is nonessential, so that at a choke price of $P_{LC}$, demand for labor is zero. Because nonagricultural sources of income contribute to rural livelihoods, agricultural labor is a nonessential input to household full income as households switch to other activities when the price of labor is too high. Second, the marginal productivity of baseflow and erosion are zero at the choke price, implying that changes in ecosystem services have no welfare significance unless the effective wage is low enough to make labor demand positive. This follows from the fact that baseflow and soil are useful to the farming households only as farming inputs and it is impossible to farm without labor. Third, below we describe the econometric test we use for the assumption that labor markets are functional.

Our empirical study, therefore, is the first implementation of Huang and Smith's proposal regarding demand for weak complements to natural resources. We estimate the two most common functional forms of labor demand, linear and semilog, as described in (2) and (3) as

$$\text{(2)} \qquad \text{Linear: } L = \alpha + \beta P + \gamma \mathbf{Z} \quad \text{and}$$

$$\text{Welfare Est.} = \frac{\hat{L}_1^2 - \hat{L}_0^2}{-2\beta}$$

$$\text{(3)} \qquad \text{Semilog: } L = e^{(\alpha+\beta P+\gamma \mathbf{Z})} \quad \text{and}$$

$$\text{Welfare Est.} = \frac{\hat{L}_1 - \hat{L}_0}{-\beta}.$$

These equations also describe the formulas for the welfare estimates for each functional form. Note, $\hat{L}_1$ and $\hat{L}_0$ are the predicted baseline labor demand evaluated at mean wage with and without the ecosystem services (drought mitigation and soil conservation), $\beta$ is the regression coefficient for wage, $P$ is price of labor, $\mathbf{Z}$ is a vector of all other variables including output prices, and $\gamma$ denotes the corresponding regression coefficients.

The expressions for computing welfare estimates have to be modified to account for spatial dependence. These are derived and discussed in the Appendix. As shown in equations (A.5) and (A.8), ignoring spatial lags ($\rho$) can generate bias in estimates of ecosystem services by omitting indirect inputs via neighbors. For both the functional forms, $\partial \text{WTP}/\partial\rho > 0$, where WTP is the welfare estimate.

### *Specification of Labor Demand for Farming*

Annual labor demand is hypothesized to be a function of labor price; prices of the primary outputs (coffee and rice); and fixed inputs, including baseflow, farm size, soil condition (erosivity), and an irrigation index. Table 1 summarizes the expected relationships. The signs, sizes, and significance of the estimated coefficients provide the criteria for evaluating the theoretical performance of our models. We expect labor demand to be negatively correlated with the price of labor. Because prices of rice and coffee reflect returns to labor in farming or the effective productivity of labor, output prices should be positively correlated with labor demand. By similar logic, fixed inputs raise the return to farming and the productivity of labor, and therefore we expect all fixed inputs—farm size, irrigation, and baseflow—to be positively correlated with labor demand. Note that the coefficient on erosion will be

**Table 1. Descriptive Statistics and Expected Signs**

| Variables | Units | Mean | Expected Sign |
|---|---|---|---|
| Labor | Days | 115.38 | |
| Price of coffee | $ per kg | 1.78 | (+) |
| Price of rice | $ per kg | 0.18 | (+) |
| Price of labor | $ per day | 0.90 | (−) |
| Farm size | Hectares | 1.2 | (+) |
| Drought mitigation | Baseflow in m/year | 1.01 | (+) |
| Irrigation index | % of farm irrigated | 0.1 | (+) |
| Soil conservation | Erosion in tonnes/hectare/year | 4.19 | (−) |
| Family size | Number | 4.3 | ~ |
| Ratio of adults in family | Ratio | 0.77 | ~ |
| Ratio of ill in family | Ratio | 0.77 | ~ |
| Average age | Years | 26.7 | ~ |
| Ratio of males in family | Ratio | 0.49 | ~ |

negative because it is a negative fixed input. The key parameters in our model are the coefficients on the baseflow and erosion variables; their signs and the sizes will reflect the relative contribution of forest ecosystem services in the buffer zone of Ruteng Park.[9]

### *Tests for Complete Labor Markets*

Our labor demand specification also includes a set of household "compositional" characteristics—family size, average age, ratio of ill (the proportion of family members who had suffered from some form of illness in the previous year), adult (individuals over the age of sixteen, which is the age where family members begin to actively participate in nonhousehold livelihood activities), and male family members—to test the assumption that labor markets are functional (Benjamin). If this set of five variables is statistically unrelated to labor demand, it would suggest that production decisions are made independent of consumption decisions because the labor market is sufficiently complete and hired labor can be substituted for family labor. Using similar tests, Pitt and Rosenzweig, Benjamin, and Pattanayak and Kramer present evidence for functional markets in agrarian communities of Indonesia.

### *Tests for Spatial Dependence*

Above, we argued that spatial dependence is likely to exist in cross-sectional data sets such as the one used in this study. One of our main objectives is to explicitly address spatial lag and error dependence.

A key element of the spatial model is a weight matrix that captures the extent of "neighborliness" of and interactions among observations. It is an $N \times N$ matrix representing the spatial relationship between observations $i$ and $j$.[10] We construct an inverse distance spatial weight matrix, row-standardized to unity, to test and model the spatial processes in the Ruteng data. We use the inverse distance approach ($w_{ij} = 1/d_{ij}$, where $d_{ij}$ is measured between village $i$ and $j$) because we expect that the nearest neighbors are more likely to interact and share ecosystem inputs. Thus, as distance increases between villages, $w_{ij}$ approaches zero (little influence), and as distance decreases $w_{ij}$ approaches $+\infty$ (greater influence). The distances between village pairs, measured as the Euclidian distance between village centers, vary with a maximum of 53 km. Though unknown, intra-village distances are insignificant relative to distances between the forty-seven villages. Nevertheless, Anselin and Bera suggest that when multiple observations belong to the same aerial unit (e.g., different banks located in the same county), the distance between them must be set to something other than zero (or $1/d_{ij} \rightarrow +\infty$). We set intra-village distances to be 1/10 that of the nearest village.[11]

Least square estimation of a model with spatial lag dependence produces biased and inconsistent estimators. Simply because the dependent variable is itself spatially correlated does not necessarily cause misspecification. Misspecification occurs if the explanatory variables fail to capture the spatial variation—the omitted variable problem. A *spatial lag* model can be defined as

$$(4) \qquad \mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\delta} + \boldsymbol{\varepsilon}$$

where $\mathbf{y}$ is the $N \times 1$ vector of the dependent variable, $\rho$ is the spatial lag coefficient, $\mathbf{W}$ is the $N \times N$ spatial weight matrix, $\mathbf{X}$ is the $N \times K$

[9] One referee contends that erosion might be endogenous to our model of demand for agricultural labor. There are at least two reasons and one test why this is unlikely to be the case. First, we are using lagged values of the ecological data, that is, from years preceding the household survey, to capture overall environmental conditions. Second, as described above, erosion is measured at the sub-watershed level, which is orders of magnitude larger than any individual farm. While the activities on farm (including the amount of farm labor) will contribute to the overall level of erosion in the watershed, it is the collective actions of many farmers that determine the level of watershed erosion in this region. Third, we also conducted a Hausman test by using the primary forest cover, secondary forest cover, and slope as potential instrument for erosion and baseflow (confirmed by joint and individual statistical correlation with the ecosystem services and no correlation with the residuals). Results from the omitted variable version of the Hausman test suggest that we can reject the hypothesis that erosion and baseflow are endogenous in our model. The $p$-values associated with the predicted erosion and predicted baseflow variables were 0.95 and 0.71, respectively, using the linear specification, and 0.14 and 0.57, respectively, using the semilog specification.

[10] The simplest spatial weight matrix is a binary matrix where each element receives 1 if $j$ and $i$ are adjacent, and 0 otherwise. The appropriate spatial weighting scheme should be determined a priori and several different types of weight schemes exist (Anselin and Bera). GIS techniques facilitate the computation of these measures. The row-standardized approach is the recommended spatial weight matrix and the Wy term "becomes essentially a weighted average of observations at neighboring locations" (Anselin and Hudak). While "improperly specified" weighting may affect the power of the test for spatial autocorrelation, the potential for spurious conclusions is not as great as in the functional specification of a model (Anselin and Bera).

[11] Following Anselin and Bera, we want intra-village neighbors to have a distance greater than zero, but less than that the inter-village distance of the next nearest village. We found using other fractions instead of 0.1, that is 0.1–0.9, made little difference to the estimated nonspatial parameters. Setting the fraction to 0.1 yielded the highest log-likelihood value.

matrix of independent variables, $\boldsymbol{\delta}$ is the $N \times 1$ vector of coefficients, and $\varepsilon$ is the $N \times 1$ vector of the disturbance term.

On the other hand, an ordinary least square (OLS) model with spatially dependent errors will be inefficient. A *spatial error* model can be defined as

$$(5) \quad \mathbf{y} = \mathbf{X}\boldsymbol{\delta} + \lambda \mathbf{W}\boldsymbol{\xi} + \varepsilon$$

where is $\lambda$ the spatial error coefficient, $\xi$ is the $N \times 1$ linear model disturbance term, and $\varepsilon$ is the uncorrelated and homoscedastic error term. Anselin and Bera show that maximum likelihood (ML) methods can be used to produce unbiased and consistent estimators in the spatial lag case and efficient estimators in the error case.

The log-likelihood function for the spatial lag model is defined as

$$(6) \quad L_i = \ln(1 - \rho w_i) - 0.5\ln(2\pi) - 0.5\ln(\sigma^2) - 0.5(y_i - \rho(Wy)_i - x_i\beta)^2/\sigma^2$$

where $\rho$ is the spatial lag coefficient, $\sigma$ is the standard deviation, $w_i$ represents the eigenvalues of the weight matrix.[12] The statistical significance of ML estimates of $\rho$ offers evidence of spatial lag.

The log-likelihood function for the spatial error model is defined as

$$(7) \quad L_i = \ln(1 - \lambda w_i) - 0.5\ln(2\pi) - 0.5\ln(\sigma^2) - (y_i - \lambda(Wy)_i - x_i\beta + \lambda(Wx)_i\beta)^2/\sigma^2$$

where $\lambda$ is the spatial error coefficient. The statistical significance of ML estimates of $\lambda$ offers evidence of spatial error correlation. Equations (6) and (7) are perhaps the most common types of spatial models. Other models may resemble a combination of the two above or include higher order terms (Anselin and Bera). The most typical combination is a spatial lag and error model or the first order spatial autoregressive moving average model, defined as (Case 1991, 1992)

$$(8) \quad L_i = \ln(1 - \rho w_i) + \ln(1 - \lambda w_i) - 0.5(2\pi) - 0.5(\sigma^2) - 0.5(y_i - (p + \lambda)(Wy)_i + (\rho\lambda)(W^2y)_i - x_i\beta + \lambda(Wx)_i\beta)^2/\sigma^2.$$

The statistical significance of ML estimates of $\lambda$ and $\rho$ coefficients offers evidence of spatial lag and error correlation.

## Estimated Models of Demand for a Weak Complement

Eight labor demand models are estimated—four versions for each of the two functional forms (linear and semilog). The four versions consist of least square, spatial lag, spatial error, and a combined model with both spatial lag and error. The results are reported in tables 2 and 3, corresponding to the linear and semilog specifications.

In each of the four models estimated for each functional form, input prices (labor wages), output prices (rice), and fixed environmental inputs (baseflow, soil condition, and irrigation) have the expected signs and significance (soil condition is weakly significant in the linear lag/error model), with the exceptions of coffee price, which is statistically significant only in the linear models. The coefficients for all five household compositional variables are individually and jointly insignificant in all models, validating the complete market test as in Pitt and Rosenzweig, Benjamin, and Pattanayak and Kramer. The least squares models are statistically significant, with $P < 0.001$, and explain about 15% of the variation, which is not unusual in a small cross-sectional household survey data set.

Correcting for spatial dependence has the effect of producing more efficient and unbiased estimates. The spatial coefficients ($\rho$ and $\lambda$) are significant in all specifications, except the combined model, where they are individually insignificant but jointly significant.[13]

[12] Some of the eigenvalues of a row-standardize weight matrix will be imaginary, so we use Ord's method (Ord) for obtaining real eigenvalues, based on resymmetrized weight matrix. The resymmetrized matrix is constructed by $\mathbf{W}^* = \mathbf{D}^{1/2}\mathbf{W}_1\mathbf{D}^{1/2}$, where $\mathbf{W}_1$ is the original symmetric weight matrix (before it was row-standardized) and $\mathbf{D}$ is a diagonal matrix of the inverse of the row sums from the $\mathbf{W}_1$ matrix.

[13] Note that the $t$-statistics for the spatial parameters in the combined model are insignificant. These $p$-values, however, are based on the asymptotic $t$-tests, which rely on the standard errors that are four to twelve times bigger than those of the individual lag and error models. One potential problem is multicollinearity of the lag and error parameters. In contrast, if we rely upon the more robust likelihood ratio statistic, we find significant spatial parameters.

**Table 2. Parameter Estimates—Linear Model of Farm Labor Demand**

| | Least Squares | | Spatial Lag | | Spatial Error | | Spatial Lag and Error | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | *p*-Value | Coeff. | *p*-Value | Coeff. | *p*-Value | Coeff. | *p*-Value |
| Constant | −17.81 | 0.769 | −94.74 | 0.130 | −39.19 | 0.619 | −85.43 | 0.262 |
| Price of coffee | 23.02 | 0.107 | 18.74 | 0.194 | 19.43 | 0.187 | 19.03 | 0.197 |
| Price of rice | 382.74 | <0.001 | 262.63 | <0.001 | 348.73 | <0.001 | 285.74 | 0.001 |
| Price of labor | −109.69 | <0.001 | −68.17 | 0.006 | −83.05 | 0.009 | −72.55 | 0.020 |
| Farm size | 18.01 | <0.001 | 15.52 | <0.001 | 15.09 | <0.001 | 15.41 | <0.001 |
| Baseflow | 0.11 | 0.001 | 0.08 | 0.024 | 0.11 | 0.047 | 0.09 | 0.054 |
| Irrigation index | 49.22 | 0.004 | 45.58 | 0.010 | 48.48 | 0.008 | 46.89 | 0.010 |
| Erosion | −4.79 | 0.013 | −3.70 | 0.072 | −5.89 | 0.069 | −4.24 | 0.097 |
| Family size | −0.37 | 0.886 | 1.68 | 0.529 | 2.71 | 0.319 | 2.20 | 0.418 |
| Ratio of adults in family | 30.82 | 0.388 | 26.74 | 0.470 | 27.91 | 0.449 | 26.64 | 0.473 |
| Ratio of ill in family | −3.83 | 0.666 | −1.82 | 0.830 | −3.54 | 0.717 | −2.46 | 0.787 |
| Average age | −0.45 | 0.452 | −0.26 | 0.680 | −0.22 | 0.727 | −0.23 | 0.719 |
| Ratio of males in family | −6.26 | 0.809 | −1.04 | 0.966 | −0.33 | 0.989 | −0.58 | 0.981 |
| $\rho$ | | | 0.70 | <0.001 | | | 0.54 | 0.074[b] |
| $\lambda$ | | | | | 0.73 | <0.001 | 0.30 | 0.382[c] |
| Variance | | | 6,416.15 | <0.001 | 6,434.26 | <0.001 | 6,438.44 | <0.001 |
| Adj. $R^2$ | 0.150 | | | | | | | |
| $\chi^2$ statistic (model) | 92 | <0.001 | 119 | <0.001 | 117 | <0.001 | 120 | <0.001 |
| $\chi^2$ statistic (spatial parameters)[a] | | | 26.52 | <0.001 | 24.10 | <0.001 | 27.28 | <0.001 |
| Sample size | 494 | | 494 | | 494 | | 494 | |

[a]The spatial models are being compared to OLS, which is the most restricted model.
[b]Based on the likelihood ratio test with the spatial error model as the restricted model.
[c]Based on the likelihood ratio test with the spatial lag model as the restricted model.

The likelihood ratio statistics and the economic welfare estimates (next section) show that there is little in this data set to distinguish the three types of spatial models. Comparing the OLS model to the spatial lag model and spatial lag and error model (the spatial error model maybe biased), we find that when we account for spatial lag dependence, the coefficients for labor price are significantly smaller in absolute terms, whereas the coefficients for baseflow and erosion are somewhat smaller, relative to the OLS case.

### *Ecosystem Values: Contributions of Baseflow Increase and Erosion Decrease*

All the estimated models show that baseflow has a positive and significant impact on labor demand while erosion has a negative and significant impact. Together, these lend credence to the hypothesis that ecosystem services in the form of drought mitigation and soil conservation enhance agricultural profits. We assess the potential values of drought mitigation and soil conservation provided by Ruteng Park by considering two alternative forest hydrology scenarios—baseflow increase and erosion decrease by 5% and 10%, respectively. Welfare estimates, based on the formulas presented in (2) and (3) and the Appendix and the estimated coefficients, are reported in table 4.

For the spatial lag model, for example, we find that just a 5% increase in ecosystem services could increases agricultural profits by \$9–\$11 for the typical household (defined as the household with average characteristics). Similarly a 10% increase in ecosystem services would increase profits by \$19–\$24. Depending on the functional form, we find that spatial models generate welfare estimates that are 1.25–1.33 times larger that the OLS models. To put these ecosystem values in context, consider that the average household in this region earns just \$780 per year in terms of the cash value of its agricultural production plus any wage income (c.f. Yang and An for a similar measure of farm household value added). Thus, the ecosystem services make substantial contributions to rural livelihoods in this poor region.

**Table 3. Parameter Estimates—Semilog Model of Farm Labor Demand**

| | Least Squares | | Spatial Lag | | Spatial Error | | Spatial Lag & Error | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | *p*-Value | Coeff. | *p*-Value | Coeff. | *p*-Value | Coeff. | *p*-Value |
| Constant | 2.70 | <0.001 | 0.03 | 0.973 | 2.46 | <0.001 | 0.86 | 0.680 |
| Price of coffee | 0.10 | 0.456 | 0.06 | 0.669 | 0.07 | 0.643 | 0.07 | 0.666 |
| Price of rice | 3.12 | <0.001 | 2.27 | <0.001 | 3.00 | 0.001 | 2.57 | 0.005 |
| Price of labor | −0.97 | 0.001 | −0.62 | 0.014 | −0.71 | 0.026 | −0.65 | 0.037 |
| Farm size | 0.18 | <0.001 | 0.16 | <0.001 | 0.16 | <0.001 | 0.16 | <0.001 |
| Baseflow | 1.6E − 3 | <0.001 | 1.3E − 3 | <0.001 | 1.7E − 3 | <0.001 | 1.4E − 3 | 0.003 |
| Irrigation index | 0.74 | <0.001 | 0.67 | <0.001 | 0.69 | <0.001 | 0.68 | <0.001 |
| Erosion | −0.07 | 0.003 | −0.05 | 0.005 | −0.09 | 0.002 | −0.07 | 0.020 |
| Family size | 9.1E − 3 | 0.721 | 0.02 | 0.407 | 0.03 | 0.300 | 0.03 | 0.333 |
| Ratio of adults in family | 0.24 | 0.490 | 0.24 | 0.522 | 0.27 | 0.479 | 0.25 | 0.506 |
| Ratio of ill in family | −8.4E − 3 | 0.923 | 4.5E − 3 | 0.961 | −0.01 | 0.914 | −3.0E − 3 | 0.976 |
| Average age | −1.4E − 3 | 0.809 | −4.3E − 4 | 0.950 | −5.0E − 4 | 0.941 | −3.9E − 4 | 0.954 |
| Ratio of males in family | −4.8E − 3 | 0.849 | −6.6E − 03 | 0.978 | −0.02 | 0.941 | −0.02 | 0.947 |
| $\rho$ | | | 0.64 | <0.001 | | | 0.41 | 0.193[b] |
| $\lambda$ | | | | | 0.68 | <0.001 | 0.38 | 0.240[c] |
| Variance | | | 0.63 | <0.001 | 0.63 | <0.001 | 0.63 | <0.001 |
| Adj. $R^2$ | 0.16 | | | | | | | |
| $\chi^2$ statistic (model) | 100 | <0.001 | 120 | <0.001 | 120 | <0.001 | 122 | <0.001 |
| $\chi^2$ statistic (spatial parameters)[a] | | | 19.85 | <0.001 | 19.54 | <0.001 | 21.23 | <0.001 |
| Sample size | 494 | | 494 | | 494 | | 494 | |

[a]The spatial models are being compared to OLS, which is the most restricted model.
[b]Based on the likelihood ratio test with the spatial error model as the restricted model.
[c]Based on the likelihood ratio test with the spatial lag model as the restricted model.

**Table 4. Economic Contributions of Ecosystem Service to Typical Household: Simulated Average Values for 5% and 10% Increase in Services (Baseflow and Erosion) in U.S. Dollars per Year**

| | Linear | | Semilog | |
|---|---|---|---|---|
| | 5% | 10% | 5% | 10% |
| OLS | 7.15 | 14.71 | 8.72 | 18.33 |
| Spatial Lag | 8.93 | 19.05 | 10.96 | 24.45 |
| Spatial Error | 9.52 | 19.59 | 12.42 | 26.18 |
| Spatial Lag and Error | 9.04 | 18.98 | 11.57 | 24.96 |

## Summary and Conclusions

Hydrological and soil stabilization, such that downstream droughts and erosion are mitigated, are among several ecosystem services of the forested watersheds within Ruteng Park, established in 1993 by the government of Indonesia on Flores island to reverse deforestation and initiate reforestation and afforestation. Hydrological responses to modifications of forest cover are manifested in quantities of water flow and soil at specific downstream locations. These ecosystem services can be measured in terms of baseflow and erosion and are considered to be fixed inputs into farm production in the immediate downstream of the park. Thus, values of forest ecosystem services can be measured in terms of profits accruing to downstream farmers. By applying the logic proposed by Huang and Smith, these changes in profits can be measured by focusing on the demand for a weak complement such as farm labor.

GIS is used to integrate farm budget data with baseflow and erosion data to improve precision and calculate a spatial weights matrix, derived on the basis of inter-village distances.[14] Because of both conceptual reasons (socio-economic interactions and bio-geo-chemical flows) and analytical imperatives (data collection and integration), we can expect to find spatial lag and error correlation in our data. Farm labor demand is estimated as a function of labor price, coffee and rice prices, baseflow, erosion, and other fixed inputs using ML estimation, with spatial weights to account for spatial lags and error correlation. The estimated labor demand model has theoretically expected properties and shows that baseflow and erosion are complements to labor demand for coffee and rice production. The estimated equations also offer clear evidence of both forms of spatial dependence in the data.

Let us revisit the three challenges posed at the beginning of the article. First, we find that, irrespective of the type of spatial model, forest ecosystem services can make substantial economic contributions to the farming households living downstream from protected forest watersheds in Flores, Indonesia. Second, we approach the spatial dimensions of the problem from a practical policy-oriented perspective, asking if there is spatial dependence, and if so, how it changes estimates of ecosystem values. In the Ruteng case, we find evidence of both kinds of spatial dependence, lag and error correlation. Failure to recognize the spatial nature of the processes and the data could lead to underestimation of true benefits from ecosystem services. That is, each farmer's labor productivity improves because of direct increases in ecosystem inputs as well indirect impacts through the enhanced productivity of their neighbors. Third, our estimated value of ecosystem services are close—on the order of only a few dollars—to estimates obtained from estimating full profit systems. Thus, weak complementarity presents significant methodological efficiencies by allowing accurate estimation of values using considerably fewer data.[15]

In conclusion, although forests are widely believed to generate watershed protection benefits, the magnitude of these benefits is typically unknown. By applying a transparent economic model, testing for and modeling spatial dependence, and finding credible estimates of values for two forest ecosystem services,

[14] Consider further contributions of GIS: In the Ruteng example, we compare two definitions of baseflow and erosion, a non-GIS version that is based on visually estimating the overlay of villages and watersheds, and a GIS stream-weighted measure. Because of space constraints, the results of the analysis using the non-GIS ecosystem variables are not reported in this article. The GIS version adds precision in that it uses the data in a hydrologically defensible manner. Welfare differences between the non-GIS and GIS versions are substantial—the non-GIS version appears to overestimate the importance of ecosystem services.

[15] Estimates based on demand for a weak complement may be a lower bound of ecosystem services when there are more than one such complement. In this case, the weak complementarity logic could be applied to multiple market complements. We would estimate demand for each weak complement, calculate the welfare change for each, and additively aggregate to generate overall ecosystem values. In our case, agricultural labor productivity is the primary economic contribution of hydrological stabilization in the Ruteng area. Another advantage of this approach in the production setting, unlike the consumption setting where weak complementarity is a maintained hypothesis, is that the analyst can test for the complementarity given that the relationship is a physical or technological association. Our results show that this physical complementarity of labor, baseflow, and erosion holds.

this research takes an important step toward quantifying the contribution of forests to poor farmers in Indonesia. Both the weak complementarity logic and spatial econometrics approach illustrate the potential for efficiency and precision in estimation. For a variety of factors, however, not least the precision of economic and ecological data, the estimated values should be treated as indicative rather than absolute.

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## Appendix

### *Derivations of Welfare Estimates for Spatial Dependence Models*

Row-standardization of the spatial weights plays an important role in these derivations. As shown below, **W** drops out of all subsequent calculations when row-standardized to sum to 1. Suppose we have the following linear model:

$$\text{(A.1)}\quad \mathbf{L} = \rho\mathbf{W}\mathbf{L} + \alpha + \beta\mathbf{P} + \gamma\mathbf{Z} + \varepsilon$$
$$= [\mathbf{I} - \rho\mathbf{W}]^{-1}[\alpha + \beta\mathbf{P} + \gamma\mathbf{Z} + \varepsilon]$$

where **L** is $(N \times 1)$, **I** is a $(N \times N)$ identity matrix, $\rho$ is a scalar, **W** is $(N \times N)$ weight matrix, $\alpha$ is the constant term, **P** is a $(N \times 1)$ vector of labor prices, $\beta$ is the (scalar) parameter estimate for labor prices, **Z** is a $(N \times (K-2))$ matrix of other exogenous factors, $\gamma$ is a $((K-2) \times 1)$ vector of parameter estimates for the exogenous factors, and $\varepsilon$ is $(N \times 1)$ disturbance term. Thus, we can rewrite this in scalar notation as

$$\text{(A.2)}\quad L_i = \left[1 - \sum_{j=1}^{N} \rho w_{ij}\right]^{-1} * \left[\alpha + \beta P_i + \sum_{j=1}^{K-2} z_{ij}\gamma_j\right] \forall i.$$

Since by construction $\{w_{i1} + w_{i2} + \cdots + w_{iN} = 1, \forall i\}$, then the above can be rewritten as

$$\text{(A.3)}\quad L_i = \left[\frac{1}{1-\rho}\right] * \left[\alpha + \beta P_i + \sum_{j=1}^{K-2} z_{ij}\gamma_j\right] \forall i.$$

Thus, for the representative household, the spatially adjusted labor demand equals the labor demand multiplied by a spatial multiplier (Kim, Phipps, and Anselin)

$$\text{(A.4)}\quad \hat{L}_{\text{Spatial}} = \frac{1}{1-\rho}\hat{L}.$$

Applying the weak complementarity logic as in (1) based on Hotelling's lemma, welfare change associated with an improvement in ecosystem inputs $(E_1 - E_0)$ can be computed as follows:

$$\text{(A.5)}\quad \text{WTP} = \Delta\pi(P \mid \Delta E, Z)$$
$$= \int_{P_0}^{P_C(E_1)} \frac{1}{1-\rho} L(P \mid E_1, Z)\, dP$$
$$- \int_{P_0}^{P_C(E_0)} \frac{1}{1-\rho} L(P \mid E_0, Z)\, dP$$
$$= \frac{1}{1-\rho}\left[\frac{\hat{L}_1^2 - \hat{L}_0^2}{-2\beta}\right].$$

The welfare calculation in the lag and error combined case reduces to the lag case because $E[\lambda\mathbf{W}\xi] = 0$. The welfare calculations for the spatial error model are equivalent to (2) because $E[\lambda\mathbf{W}\xi] = 0$.

In the semilog case, we have

$$\text{(A.6)}\quad \mathbf{L} = e^{(\alpha + \beta\mathbf{P} + \gamma\mathbf{Z} + \varepsilon)}.$$

For the representative household, the spatially adjusted labor demand equals the labor demand raised to a spatial power

$$\text{(A.7)}\quad \hat{L}_{\text{Spatial}} = \hat{L}^{\frac{1}{1-\rho}}.$$

Repeating the previous calculations, the welfare change associated with an improvement in ecosystem inputs $(E_1 - E_0)$ can be computed as follows:

(A.8)

$$\begin{aligned}\mathrm{WTP} &= \Lambda\pi(P|\Lambda E, Z)\\ &= \int_{P_0}^{P_C(E_1)} L_{\text{spatial}}(P \mid E_1, \bullet)\, dP\\ &\quad - \int_{P_0}^{P_C(E_0)} L_{\text{spatial}}(P \mid E_0, \bullet)\, dP\\ &= \left[\frac{(1-\rho)}{-\beta}\right] * \left[\hat{L}_1^{\frac{1}{1-\rho}} - \hat{L}_0^{\frac{1}{1-\rho}}\right].\end{aligned}$$

As before, the welfare calculation for the lag and error combined case reduces to the lag case, whereas the welfare calculations for the spatial error model are equivalent to equation (3).

For both cases, when $\rho = 0$, (A.5) and (A.8) reduce to (2) and (3). For the linear and semilog functional forms, the spatial welfare calculations have desired properties with respect to the spatial parameter ($\rho$), in that $\partial\mathrm{WTP}/\partial\rho > 0$, where WTP is welfare. WTP approaches $+\infty$ as $\rho$ goes to 1 and approaches some value less than the "nonspatial WTP" in the instance when $\rho$ approaches $-1$, however, it will not be $-\infty$.[16]

[16] Examining the spatial welfare measure for the semilog functional, it might appear that while the limit of $(1-\rho)$ as $\rho \to 1$ is 0 and the limit of $[\hat{L}_1^{\frac{1}{1-\rho}} - \hat{L}_0^{\frac{1}{1-\rho}}]$ as $\rho \to 1$ is $+\infty$, thus implying that the limit for the entire function is 0, as 0 multiplied by $+\infty$ equals 0. However, this is incorrect. This is because 0 and $\infty$ are not actual numbers in this case but are statements of the limit (Anton). It can be shown that the limit of this function is in fact $+\infty$ when $\rho \to 1$. The asymmetry makes intuitive sense, if as $\rho \to -1$ drove welfare to $-\infty$, this would actually imply positive autocorrelation. Positive autocorrelation implies similar neighboring values, whereas negative autocorrelation implies dissimilar neighboring values, producing a checkerboard-like pattern. Thus, welfare cannot go to $-\infty$, and still be consistent with negative autocorrelation. In our example, $-\infty$ would occur from positive autocorrelation if the welfare effect from an ecosystem change was negative.