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A Comparison of Microeconomic and Macroeconomic Approaches to Deforestation Analysis

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Abstract

The economics of deforestation has been explored in detail. Generally, the frame of analysis takes either a microeconomics or macroeconomics approach. The microeconomics approach assumes that individual decision makers are responsible for deforestation as a result of utility maximizing behavior and imperfect property right regimes. The macroeconomics approach explores nationwide trends thought to be associated with forest conversion. This paper investigates the relationship between these two approaches by empirically testing the determinants of deforestation using the same data set from Thailand. The theory for both the microeconomics-based and macroeconomics-based approaches are developed and then tested statistically. The models were constructed using established theoretical frames developed in the literature. The results from both models show statistical significance consistent with prior results in the tropical deforestation literature. A comparison of the two approaches demonstrates that the macro approach is useful in identifying relevant aggregate trends in the deforestation process; the micro approach provides the opportunity to isolate factors of those trends which are necessary for effective policy decisions.

Keywords: deforestation; land conversion; Environmental Kuznet's Curve; economics

1. Introduction

Deforestation impacts environmental conditions on multiple spatial and temporal scales. Understanding the causes of deforestation can help us understand the relationship between human activity, forest health, biodiversity, and greenhouse gas emissions (Culas, 2007). Uncontrolled deforestation can also impact the livelihoods of local forest users by removing economic opportunities and damaging the environment. While deforestation rates have gone down in recent years the current rates remain unsustainable (Hansen *et al.,* 2010).

Economic analysis on deforestation began by exploring macro relationships between aggregate country-wide indicators including GDP, imports and exports, population, and deforestation for specific countries (Barbier *et al.,* 1991). Development of micro-based approaches then considered the economic behavior of households, or individual agents (Cropper *et al.,* 2001). Both microeconomics-based and macroeconomic approaches have contributed to an improved understanding of the factors leading to deforestation. While the different approaches have allowed researchers to analyze the relevant trends as well as the shortcomings of their methodologies (Angelsen and Kaimowitz, 1999; Rudel, 2007), a comparison between micro and macro approaches has not been performed.

This paper provides this comparison by developing and testing models for the two approaches. The first section outlines the mathematical theory of the microeconomics-based and macroeconomics-based approaches to deforestation and empirical models. The data used in the analysis is then described in the second section. Results from the two approaches are found to be consistent with the literature. Comparison of the two approaches finds that the macro approach is good finds deforestation trends in Thailand while the micro based focuses on results more applicable towards policy recommendations.

2. Materials and Methods

2.1. Microeconomics-based approach

The microeconomic literature on deforestation builds from the land conversion model developed in Cropper *et al.* (1999). The land conversion model assumes a supply and demand framework for land conversion, where individuals can sell or purchase forested land. In this model, agricultural households' demand land contributes to changes in land use. This can lead to the specification of an econometric model that isolates those characteristics driving this change (Miller and Plantinga, 1999; Kelly and Huo, 2013). Cropper *et al.* (1999) assume that a farmer's demand for new agricultural land can be represented by profit maximizing behavior such that,

$$Maximize\ \pi_{l,k,L_C} = (p_A - tc) * y(l,k,L_C,s) - wl - rk - p_C L_C \quad (1)$$

where p_A is the price of agricultural outputs, tc is transportation costs, y is the agricultural output, l is labor, with its wage w, k is capital, with its rent r; L_c is cleared land, with p_c as its rental price, and s represents soil quality and slope.

2.1.1. Demand and supply

The first order conditions from equation (1) can be solved to yield the following demand function for cleared land:

$$L_C = L_C(p_A, tc, w, r, p_c, s) \quad (2)$$

Equation (2) shows the amount of land that is demanded (for conversion) by a single farmer. An estimate for the population is then generated by multiplying the results for the representative agricultural household in equation 2 by the agricultural population size, N.

$$C^D = NL_C(p_A, tc, w, r, p_C, s) \quad (3)$$

The supply of cleared land will depend on the costs associated with clearing or supplying this land. These costs include labor, soil quality, and slope. The price of timber is included because timber resulting from the conversion can be sold. The marginal cost of the clearing function will be:

$$C^S = C^S(s, w, p_r, p_c) \quad (4)$$

Where C^s is the supply of cleared land and is the price of timber.

2.1.2. Equilibrium

The demand and supply functions dictate the equilibrium quantity of cleared land. This can be found by using equations (3) and (4) to determine an equation for C^E (the equilibrium value of cleared land):

$$C^E = C(N, tc, Q, p_A, w, r, s, p_r, p_c) \quad (5)$$

Equation (5) captures the factors determining land conversion. Prior literature demonstrates that land conversion is determined by population density, wages, agriculture output prices, agriculture input prices, transportation costs, and suitability of land (slope and soil type) for agriculture (Panayotou and Sungsuwan, 1994; Cropper *et al.,* 1999; Cropper *et al.,* 2001; Barbier and Cox, 2004).

2.1.3. Microeconomics-based empirical model

Equation (5) forms the basis for the microeconomics-based empirical model, and proxies need to be developed for the agricultural households and the price of agricultural commodities. The number of agricultural households within a province are estimated by multiplying the population of a province in a time period by the proportion of gross province product (GPP) that is devoted to agriculture $(\frac{GPP_A}{GPP_T})$ (Cropper *et al.,* 1999).

$$N = Population * (\frac{GPP_A}{GPP_T}) \quad (6)$$

The export price of rice is used as a proxy for the price of agricultural commodities (Gingrich, 1994). The distance to Bangkok variable and the presence of a commercial center within a province serve as proxies for transportation costs (Barbier and Cox, 2004). To control for province size, the amount of land cleared and agricultural population are divided by the area of the province. Assuming a linear form, the cleared land equation becomes:

$$(C^E/A)_{it} = a_0 + a_1(\frac{N}{A})_{it} + a_2 p_{Ait} + a_3 tc_i + a_4 w_{Lit} + a_5 s_i + a_6 B_{it} \quad (7)$$

Two econometric models are used to estimate equation (7). The first uses the two-way random effects method, which includes the agricultural population density, the distance to Bangkok, a two year lag of the logging ban, labor wage, slope, and the presence of a commercial center. The second uses a one-way random effects model, which allows the inclusion of the export price of rice, the import price of fertilizer, and the export price of timber.

2.2. Macroeconomics approach

The theoretical framework for the macroeconomic approach to deforestation analysis is based on the Environmental Kuznet's Curve (EKC) literature. The EKC literature tests the hypothesis that income per capital causes deforestation. These analyses of deforestation have found that households initially use wood as fuel and consumables, but switch to other forms of fuel such as oil and higher quality consumables as incomes rise (Panayotou and Sungsuwan, 1994).

The EKC predicts that deforestation will rise (at a decreasing rate) as incomes rise until a turning point is reached (Choumert *et al.,* 2013; Naito and Traesupap, 2014). The result is an inverted U-shaped relationship between income and deforestation rates (Bhattarai and Hammig, 2001; Lantz, 2002; Raunikar and

Buonglorno, 2008). While there is no unified theoretical framework for the EKC model in the literature, Dinda (2005) introduces a theoretical approach using dynamic optimization and models a representative agent that will maximize her present value welfare given the following function (subject to economic constraints):

$$\max_c W = \int_o^\infty e^{-pt} U(C(t), E(t))dt;$$
$$U_c, U_E > O; U_{cc}, U_{EE} < O; U_{cE} > O \quad (8)$$

where U is the utility derived from the composite consumption bundle C and the stock of the environment E. Increases in consumption and environment, as well as the cross partial effects, are assumed to be positive but diminishing. The variable ρ is the discount rate.

The production function demonstrates the economic constraints and is assumed to be:

$$Y=Y(K,E);\ Y_K, Y_E>O; Y_{KK}, Y_{EE}<O;\ Y_{KE}=O \quad (9)$$

where Y represents production, and K represents capital stock. The transition equations for K and E are determined from the agent's choices of consumption *(C)* and reforestation *(A):*

$$\dot{E} = A - \gamma Y = A(t) - \gamma Y(K(t),E(t));\ O < \gamma < 1 \quad (10)$$

$$\dot{K} = Y - A - C = Y(K(t),E(t)) - A(t) - C(t) \quad (11)$$

Equation (10) assumes that a one to one relationship holds between the environmental stock and the abatement term, and that a certain percentage *(γ)* of output results in pollution which damages the environment. Equation (11) demonstrates how capital investment is equal to the amount of production remaining after abatement and consumption expenditures. Equations (8) through (11) can be combined into a current value Hamiltonian with choice variables A and C.

$$\max_{A,C} H=U(C,E)+\lambda[Y(K,E)-A-C]+\mu[A-yY(K,E)] \quad (12)$$

By rearranging the first order conditions derived from equation (12), we get[1]:

$$\frac{\dot{E}}{E} = \frac{U_C}{EU_{CE}} \left[\frac{CU_{CC}}{U_C} * \frac{C}{C} + Y_K(1-\gamma) - \rho \right] \quad (13)$$

Equation (13) demonstrates the rate of change for the environmental stock, which depends on the functional form of the utility function and on consumption's rate of change. It also depends on the marginal productivity of capital, represented as the coefficient on the $Y_K(1\text{-}y)$ term, which describes the fixed proportion of production that negatively affects the environmental stock.

2.2.1. Macroeconomics empirical macro

Equation (13) demonstrates that the rate of change in the environment is a function of the marginal utility of consumption, the growth rate of consumption, the marginal product of capital, the pollution coefficient, and time preference. A linear form for equation (13) is shown below:

$$DF_{it} = a_1 + a_2 I_{it} + a_3 I^2_{it} + a_4 AgYield_t + a_5 B_i + a_6 PopulationDensity_{it} + a_7 t \quad (14)$$

where DF_{it} is the deforestation rate of a province i in time period t and corresponds to the change in the level of the environmental stock. The variables L_{it} and L^2_{it} represent the GPP per capita and the gross provincial product per capita squared and are used to represent the nonlinear nature of consumption. The $AgYield_t$ variable shows the agricultural yield in tons per hectare which is used as a proxy for the marginal product of capital. Agricultural yield is determined for Thailand as a whole so it only varies over time. The commercial center variable is included as a proxy both for consumption and marginal rate of capital. Population density plays a role in the Υ by controlling how influential the marginal rate of capital will be on in determining the rate of deforestation.

Two models were also estimated for the macro approach. The first, a two-way random effects model that includes the variables: gross provincial product per capita, gross provincial product per capita squared, the commercial center variable, population, and dummy variables representing the four provinces in Thailand (the central province is omitted). The four regional dummies are included to capture the different institutional structures (Cropper *et al.,* 1999). The second model uses a one-way random effects model, which includes the two-year lag of the logging ban dummy variable[2] and the yield per hectare variable.

[1] Methods shown in appendix.
[2] The ban was not instituted immediately and uniformly in Thailand. Robustness tests show that lagging the logging ban variable results in a negative and significant coefficient.

Table 1. Macro data descriptive statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
GPP per capita	864	23,082.49	17,787.00	20,179.16	5,622.00	251,257.00
GPP per capita squared	864	9,395.27	3,163.55	33,881.97	316.00	631,301.00
Northeast	864	0.26	0.00	0.44	0.00	1.00
North	864	0.30	0.00	0.46	0.00	1.00
South	864	0.22	0.00	0.42	0.00	1.00
Logging Ban	864	0.63	1.00	0.48	0.00	1.00
Commercial center	864	0.26	0.00	0.44	0.00	1.00
Population density	864	91.47	84.96	39.95	10.72	220.49
GPP from agricultural	864	0.32	0.31	0.12	0.04	0.65
Agricultural yield	864	21,900.63	21,604.00	1,611.47	19,555.00	24,655.00

Source: Royal Thai Land Development Department, Royal Thai Forestry Department, Royal Thai Department of Provincial Administration, Royal Thai Ministry of Interior, Royal Thai Department of Labor Protection and the International Rice Research Ins

2.3. Data

To compare the two approaches, a high quality data set was needed. This paper uses data from Thailand over the 17 year period between 1982 and 1998. The forest cover data comes from Royal Thai Department of Forestry (Department of Forestry, 2008). This data was converted from Landsat images, which were subject to random verification by members of the local Department of Forestry. Forest cover estimates in other tropical countries were estimated using a process developed by the United Nations Food and Agricultural Organization (FAO). To offer a complete forest database for certain countries and regions, the FAO bases its Global Forest Resource Assessment on population growth projections (Barbier and Burgess, 2001). The use of satellite imagery and random ground verification removes potential endogeneity problems with the forest cover data.

The transportation costs and access to markets data were controlled for by creating a commercial center variable. A province is assumed to have a commercial center if there was a city within its border that was one of the largest 25 cities in Thailand in 2000[3]. This is used as a proxy for development, presence of roads, or access to markets.

The population and GPP data are from the Department of Provincial Administration, Ministry of Interior Royal Thai Government (Ministry of Interior, 2005). Provincial wage data were used from Thailand's Department of Labor Protection and Social Welfare (Ministry of Labour, 2012). World rice and fertilizer prices came from The International Rice Research Institute (International Rice Research Institute, 2012). Distance to Bangkok was measured in kilometers from the capital for each province using Google Earth (Google Inc., 2012). All GPP, pricing, and wage data

[3] To be one of the 25 largest cities in Thailand, a city must have had a population of more than 55,000. The next largest city had a population of 35,000. Source: Department of Provincial Administration, Ministry of Interior, Royal Thai Government.

Table 2. Micro data descriptive statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
Agricultural population	864	201.93	174.13	122.59	21.72	718.85
Agricultural population density	864	0.03	0.03	0.01	0.00	0.07
International price of rice	864	286.90	294.50	41.28	209.42	357.50
Distance to Bangkok	864	358.24	327.50	205.54	55.00	790.00
Provincial minimum wage	864	3,795.06	3,522.50	1,290.08	1,706.00	6,389.00
Slope/Soil variable	864	2.24	2.00	1.66	0.00	4.00
Commercial center	864	0.26	0.00	0.44	0.00	1.00
International price of fertilizer	864	12.44	12.50	2.29	8.00	16.00
International price of timber	864	216.64	205.63	58.23	115.68	326.99
Logging Ban	864	0.63	1.00	0.48	0.00	1.00

Source: Royal Thai Land Development Department, Royal Thai Forestry Department, Royal Thai Department of Provincial Administration, Royal Thai Ministry of Interior, Royal Thai Department of Labor Protection and the International Rice Research Institute

are reported in 1988 Thai Baht. A binary variable was created for having relatively flat or mountainous terrain. The slope data are from the Thailand's Land Development Department and Kasetsart University (Moorman and Rojanasoonthon, 1967). Summary tables for the data used in both approaches are presented in Tables 1 and 2.[4]

3. Results and Discussion

The results from the micro-based approach are reported in Table 3. Agricultural populations, as well as agricultural population density were found to be significant in both models. However, the agricultural population density has a negative effect on deforestation. This suggests that higher density numbers mean that the population is using the land more intensively, which can lower the pressure for land conversion. The slope variable is negative, which means the mountainous regions experienced lower rates of deforestation. Finally, the minimum wage for each province is only found to be significant in the second model and has the expected sign.

3.1. Micro-based approach

The micro models find that the commercial center variable negatively impacts deforestation with statistical significance at the 10 percent level in both models. The distance to Bangkok variable is found to be significant in both models, and suggests provinces further away from the capital city experience higher rates of deforestation. This correlation could exist for a number of reasons including a lower likelihood of country wide enforcement of laws, or fewer opportunities to find better paying jobs in the capital city (due to increased transportation costs).

In the second model the sign on the rice variable was negative meaning that higher rice prices result in lower demand for land conversion. The import price of fertilizer was found to be insignificant, which could be the case if the marginal productivity of fertilizer use is low (Hossain and Singh, 2000). These counterintuitive results could be due to a lack of viable substitute crops and little fertilizer use, which is common in the northern regions (Babel *et al.,* 2011). Finally, the export price of timber and the logging ban variables were found to be

[4] Thailand currently consists of 76 provinces. Of these, three did not exist prior to 1982; three changed borders between 1982 and 1995 (due to the creation of the previously mentioned provinces) and 11 had no forest cover. To perform regression analysis, 17 provinces were dropped from the original data set of 76. This analysis utilizes data from 59 provinces that remained unchanged after 1982 and have forest cover. The Thai Royal Forest Department measured forest cover eight times during this 17-year period. The absent forest cover observations were linearly imputed.

Table 3. Land conversion model results

Variables	Model 1	Model 2
Agricultural population	0.003***	0.003***
	-0.001	-0.001
Agricultural population	-14.030**	-15.040**
density	-6.888	-7.128
Distance to Bangkok	0.002***	0.002***
	-0.000	-0.000
Wage	-2.55E-06	-0.000189***
	-0.000	-4.92E-05
Slope	0.151***	0.146***
	-0.050	-0.051
Commercial center	-0.320*	-0.314*
	-0.176	-0.179
Export price of rice		-0.005***
		-0.001
Import price of		0.010
fertilizer		-0.019
Export price of		0.005***
timber		-0.001
Logging ban		-0.700***
		-0.137
Constant	-8.016***	-5.828***
	-2.252	-0.403
Model	Two Way RE	One Way RE
Observations	833	833
Number of Provinces	54	54
Wald statistic	558	329.9

Standard errors in parentheses *** *p<0.01*, ** *p<0.05*, * *p<0.1*

statistically significant. This suggests that agents make decisions over time by not immediately adjusting to price fluctuations.

3.2. Macro approach

The macro approach results (Table 4) are consistent across both models, and they both fail to reject the EKC hypothesis at the 10% level of significance. This result suggests that the EKC relationship may hold in Thailand over this time period. The regional dummies were found to be significant at the 1% level in both models, the southern region having a smaller effect than the north and north east regions. This result is consistent with the prior results that found the northern provinces have had the largest deforestation rates (Panayotou and Sungsuwan, 1994; Cropper *et al*., 1999; Cropper *et al.,* 2001).

Additionally population density and percent of GPP devoted to agriculture are found to be statistically significant. This is consistent with prior literature that found that increased population density forces conversion of marginal lands near the fringes of developed areas. Similarly, a higher percentage of the population or production devoted to agriculture also increases pressures on conversion and therefore deforestation (Barbier and Burgess, 1997; Rosero-Bixby and Palloni, 1998; Cropper *et al.,* 1999; Deininger and Minten, 1999; Pfaff, 1999; Barbier and Burgess, 2001; Patarasuk and Fik, 2013).

Table 4. EKC model results

Variables	Model 1	Model 2
GPP per capita	9.19e-06***	9.24e-06***
	-3.14E-06	-3.19E-06
GPP per capita	-2.23e-06*	-2.60e-06*
Squared	-1.35E-06	-1.43E-06
Northeast	0.519***	0.513***
	-0.095	-0.095
North	0.465***	0.466***
	-0.0921	-0.091
South	0.264**	0.276***
	-0.104	-0.105
Population density	0.003***	0.003***
	-0.001	-0.001
GPP from	1.178***	1.100***
agriculture	-0.281	-0.295
Commercial center	-0.039	-0.045
	-0.071	-0.071
Logging ban		-0.227***
		-0.057
Yield per hectare		-6.56e-05***
		-1.79E-05
Constant	-0.730***	1.177***
	-0.176	-0.411
Model	Two way RE	One way RE
Observations	864	864
Number of Provinces	54	54
Wald statistic	488.4	221.9

Standard errors in parentheses *** *p<0.01,* ** *p<0.05,* * *p<0.1*

Contrary to the micro model the commercial center variable is not statistically significant but is consistently negative in the macro approach. This suggests that at the macro level, the presence of a commercial center within a province has an ambiguous effect on deforestation and that other factors may be more important in determining deforestation rates.

In the second model the effect from the logging ban is negative and significant as expected. The agricultural yield per hectare variable is significant but has low economic significance. This suggests that efforts to increase farming productivity will have little effect on deforestation rates.

3.3. Comparison

Using the same dataset, the two economic approaches to analyzing deforestation offer two different stories. Despite these apparent differences, it is likely that the two methods describing the same process. The macro approach, with its focus on aggregate variables, analyzes the trends occurring with respect to deforestation. The micro approach identifies the specific variables impacting farmer's decisions.

The first link between these approaches stem from income and income opportunities. The macro approach captures the effect of rising incomes having a positive, then negative effect on deforestation rates. This is consistent the Environmental Kuznet's Curve framework. While aggregate income per capita has little effect on the individual farmer, measures such as minimum wages and access to local commercial centers would have an effect. The presence of a commercial center may lead to increased opportunities for local farmers who decide to convert less forest because of those opportunities. This could explain the positive significance in the micro approach results.

Second, population is found to be a contributor to deforestation. The macro approach demonstrates the effect of population density on deforestation rates. The micro approach focuses on the agricultural population. While the agricultural population does have a positive effect on land conversion the agricultural population density has a negative effect. This distinction helps policy makers encourage forest friendly growth strategies, which could be accomplished by incentivizing intense or efficient land use by subsidizing agricultural technology, increasing access to credit and institutions, and by promoting efficient input use (Helfand and Levine, 2004).

A third comparison between the approaches shows the role of provincial location and its effect on deforestation. In the macro approach each region (using the central region as the base) was found to be statistically different. Both approaches show that provinces further from Bangkok have larger deforestation rates. The macro approach identifies the aggregate trends for deforestation occurring in the specific regions. The micro approach suggests that the distance to Bangkok plays a significant role in determining deforestation rates, either through lack of local opportunities, increased transportation costs, or less national government oversight.

Finally, the lagged logging-ban also plays a significant role in mitigating deforestation in both approaches. This countrywide policy has similar effects on both the aggregate trends and individual decision makers.

4. Conclusions

The micro approach lends itself well to public policy analysis, by helping to understand what causes individual farmers to engage in land conversion. This knowledge allows policymakers to evaluate current policies and formulate new ones. Several of the relationships described in this paper have made their way into Thai public policy including the development of commercial centers, improvements in agricultural technology, and enforcement of the logging ban. The logging-ban is the most direct method to reduce deforestation. However, the difficulty lies with enforcement. Over the past decade the Thai government has reported continuous declines in illegal harvesting rate, which suggests that enforcement is working (Felardo, 2013). Improved transportation infrastructure and the creation of commercial centers have created opportunities for those engaged in subsistence farming. Other policies include subsidizing agricultural technology, increasing access to credit for small scale farmers, and by promoting efficient use of agricultural inputs.

The macro approach provides insight into the trends related to deforestation rates. The analysis contributes to the EKC literature, and shows that deforestation rates in Thailand differ across regions. Additionally, population factors increase the pressure to deforest while provinces with high GPP from agriculture experience similar results.

Two approaches for investigating the determinants of deforestation have been analyzed. The macro approach investigates the aggregate trends of factors influencing deforestation, while the micro approach gave more insights to potential causes of deforestation. Depending on the type of information needed, both approaches have strengths and weaknesses.

Appendix

Econometric considerations

The data include variables that vary over province but not over time. A fixed effects approach would create a variable that would be co-linear with these variables. Because using a fixed effects model would require dropping these potentially significant variables, a random effects method is preferred[5]. Using random effects gives the advantage of testing the specific variables for significance between the provinces.

The presence of heteroskedasticity in the models was tested using a likelihood ratio test. It was found that the data were indeed heteroskedastic both within panels and overall, which could be corrected for by using feasible generalized least squares or allowing for robust estimators (Greene, 2012). Serial correlation was tested for and found. This was corrected for by using the Prais-Winsten FGLS approach to the random effects model (Greene, 2012). The four models were analyzed using three regression techniques: the pooled OLS method from Driscoll and Kraay (1998), a random effects method controlling for heteroskedasticity, and a Prais-Winsten FGLS method. Each method resulted in estimates with the same sign and found nearly all of the same variables to be significant. The results from the random effects model with a robust variance matrix are reported to be consistent with the prior literature. for by using feasible generalized least squares or allowing for robust estimators (Greene, 2012). Serial correlation was tested for and found. This was corrected for by using the Prais-Winsten FGLS approach to the random effects model (Greene, 2012). The four models were analyzed using three regression techniques: the

[5]The Hausman test was run on each model to test whether fixed effects or random effects was more appropriate. The test found that the random effects model was the most appropriate with a p stat of .97.

pooled OLS method from Driscoll and Kraay (1998), a random effects method controlling for heteroskedasticity, and a Prais-Winsten FGLS method. Each method resulted in estimates with the same sign and found nearly all of the same variables to be significant. The results from the random effects model with a robust variance matrix are reported to be consistent with the prior literature.

Macro model derivation

Optimizing equation (12) results in the following first order conditions

$$\frac{\partial H}{\partial C} = U_C - \lambda = 0;\ U_c = \lambda \qquad \text{(A-1)}$$

$$\frac{\partial H}{\partial A} = \mu - \lambda = 0;\ \mu = \lambda \qquad \text{(A-2)}$$

$$\dot{K} = \frac{\partial H}{\partial \lambda} = Y(K,E) - C - A \qquad \text{(A-3)}$$

$$\dot{E} = \frac{\partial H}{\partial \mu} = A - \gamma Y(K,E) \qquad \text{(A-4)}$$

$$\dot{\lambda} = -\frac{\partial H}{\partial K} = Y_K(\lambda - \mu\gamma) + \rho\lambda \qquad \text{(A-5)}$$

$$\dot{\mu} = -\frac{\partial H}{\partial E} = -U_E + \lambda Y_E(\lambda - \mu\gamma) + \rho\mu \qquad \text{(A-6)}$$

Now we set equations (A-5) and (A-6) equal to each other (using equation A-2) and rearrange them to get:

$$Y_K(\Omega) = Y_E(\Omega) - U_E;\ \Omega = \lambda(\gamma - 1) \qquad \text{(A-7)}$$

Equation (A-7) tells us that the marginal product of capital must be equal to the marginal product of the environment minus the marginal utility of the environment. Both of the marginal products are multiplied by a scalar Ω, which represents the shadow price of the good multiplied by the net effect it has on the economy (taking into account the negative externality of production).

We can take the time derivative of equation (A-1) to get

$$\dot{\lambda} = U_{CC}\dot{C} + U_{CE}\dot{E} \qquad \text{(A-8)}$$

References

Angelsen A, Kaimowitz D. Rethinking the causes of deforestation: lessons from economic models. The World Bank Research Observer 1999; 14(1): 73-98.

Babel MS, Agarwal A, Swain DK, Herath S. Evaluation of climate change impacts and adaptation measures for rice cultivation in Northeast Thailand. Climate Research 2011; 46(2): 137-46.

Barbier EB, Burgess JC. The economics of tropical forest land use options. Land Economics 1997; 73(2): 174-95.

Barbier EB, Burgess JC. The economics of tropical deforestation. Journal of Economic Surveys 2001; 15(3): 413-33.

Barbier EB, Burgess JC, Markandya A. The economics of tropical deforestation. Ambio 1991; 20(2) 55-58.

Barbier EB, Cox M. An economic analysis of shrimp farm expansion and mangrove conversion in Thailand. Land Economics 2004; 80(3): 389-407.

Bhattarai M, Hammig M. Institutions and the environmental Kuznets curve for deforestation: a crosscountry analysis for Latin America, Africa and Asia. World development 2001; 29(6): 995-1010.

Choumert J, Motel PC, Dakpo HK. Is the environmental Kuznets curve for deforestation a threatened theory? A meta-analysis of the literature. Ecological Economics 2013; 90: 19-28.

Cropper M, Griffiths C, Mani M. Roads, population pressures, and deforestation in Thailand, 1976-1989. Land Economics 1999; 75(1): 58-73.

Cropper M, Puri J, Griffiths C. Predicting the location of deforestation: the role of roads and protected areas in North Thailand. Land Economics 2001; 77(2): 172-86.

Culas RJ. Deforestation and the environmental Kuznets curve: an institutional perspective. Ecological Economics 2007; 61(2-3): 429-37.

Deininger KW, Minten B. Poverty, policies, and deforestation: the case of Mexico. Economic Development and Cultural Change 1999; 47(2): 313-44.

Department of Forestry, R. T. G. Forest Cover by Province. Bangkok. 2008.

Dinda S. A theoretical basis for the environmental Kuznets curve. Ecological Economics 2005; 53 (3): 403-13.

Driscoll JC, Kraay AC. Consistent covariance matrix estimation with spatially dependent panel data. The Review of Economics and Statistics 1998; 80(4): 549-60.

Felardo J. Temporal and spatial analysis of forest management: a case study of Kam Cha i, Thailand. Dissertation of Doctor of Philosophy (Economics). The University of New Maxico, New Maxico, 2013.

Gingrich CD. GATT and the Thai agricultural economy. Ames, Center for Agricultural and Rural Development. 1994.

Google Inc. Google Earth. Mountain View, CA, Google Inc. 2012.

Greene WH. Econometrics analysis. Prentice hall. 2012.

Hansen MC, Stehman SV, Potapov PV. Quantification of global gross forest cover loss. Proceedings of the National Academy of Sciences 2010; 107 (19): 8650-55.

Helfand SM, Levine ES. Farm size and the determinants of productive efficiency in the Brazilian Center-West. Agricultural Economics 2004; 31(2-3): 241-49.

Hossain M, Singh VP. Fertilizer use in Asian agriculture: implications for sustaining food security and the environment. Nutrient Cycling in Agroecosystems 2000; 57(2): 155-69.

International Rice Research Institute, I. Wholesale Export Price of Milled Rice. Manila. 2012.

Kelly P, Huo X. Do farmers or governments make better land conservation choices? Evidence from China's sloping land conversion program. Journal of Forest Economics 2013; 19(1): 32-60.

Lantz V. Is there an environmental Kuznets curve for clearcutting in Canadian forests?. Journal of Forest Economics 2002; 8(3): 199-212.

Miller DJ, Plantinga AJ. Modeling land use decisions with aggregate data. American Journal of Agricultural Economics 1999; 81(1): 180-94.

Ministry of Interior, D. O. P. A. R. T. G. Gross Domestic Product Classified by Regions. Bangkok. 2005.

Ministry of Labour, R. T. G. Minimum Wage and Enforcement. Bangkok. 2012.

Moorman FR, Rojanasoonthon S. The applied scientific research corporation of Thailand and FAO. Kasetsart University, Thailand.1967.

Naito T, Traesupap. The relationship between mangrove deforestation and economic development in Thailand. Mangrove Ecosystems of Asia 2014; Springer: 273-94.

Panayotou T, Sungsuwan S. An econometric analysis of the causes of tropical deforestation: the case of Northeast Thailand. *In:* The causes of tropical deforestation: the economic and statisical analysis of factors giving rise to the loss of tropical forests (*Eds:* Brown K, Pearce D). University College London Press, London, UK. 1994: 192-210.

Patarasuk R, Fik TJ. Spatial modelling of road network development, population pressure and biophysical properties of upland crop and forest conversions in Lop Buri province, Thailand, 1989-2006. Singapore Journal of Tropical Geography 2013; 34(1): 120-36.

Pfaff ASP. What drives deforestation in the Brazilian Amazon? Evidence from satellite and socioeconomic data. Journal of Environmental Economics and Management 1999; 37(1): 26-43.

Raunikar R, Buongiorno J. Ecological integrity as an economic variable: an application to forested landscapes in the southern United States. Journal of Forest Economics 2008; 14(1): 29-45.

Rosero-Bixby L, Palloni A. Population and deforestation in Costa Rica. Population and Environment 1998; 20(2): 149-85.

Rudel TK. Changing agents of deforestation: from state-initiated to enterprise driven processes, 1970-2000. Land Use Policy 2007; 24(1): 35-41.

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