ECONOMIC CAUSES OF TROPICAL DEFORESTATION – A GLOBAL EMPIRICAL APPLICATION[1]

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Abstract: The paper investigates the complex system of causes affecting tropical deforestation at a worldwide level. There is no generally accepted theory in the deforestation literature to indicate which variables should be included in a model of deforestation at an aggregate global level. The paper begins, therefore, by presenting an analytical structure based on formal farm household economic modelling literature. The empirical findings derived from a global regression model tend to confirm the profit maximising market approach to deforestation, *i.e.* policy and structural variables at the macro-level that stimulate agricultural production provide farmers with incentives to deforest and expand their arable land areas. However, subsequent statistical tests suggest that the causes of tropical deforestation are difficult to identify and quantify at a global level, and that these should be analysed at a more disaggregated level.

Keywords: global tropical deforestation, farm household models

JEL classification: C23, Q23

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1. Introduction

Deforestation refers to the removal of trees from a forested site and the conversion of land to another use, most often agriculture (van Kooten, 2000). Deforestation is primarily confined to developing countries, and mainly in the tropics (Myers 1994). There is growing concern over shrinking areas of tropical forests (Barraclough and Ghimire 2000). The livelihoods of over two hundred million forest dwellers and poor settlers depend directly on food, fibre, fodder, fuel and other resources taken from the forest or produced on recently cleared forest soils. Furthermore, tropical deforestation has become an issue of global environmental concern, in particular because of the value of tropical forests in biodiversity conservation and in limiting the greenhouse effect (Angelsen *et al* 1999). This has led economists to increase their efforts to model the process of deforestation and conversion of forests to other land uses.

The rationale of this paper is to investigate the set of driving forces that might induce tropical forest depletion. The focus is on the socio-economic macro-level factors, for which a global regression model has been constructed in order to analyse empirically and test the existence of macroeconomic explanations of deforestation and the channels through which these might work. The global regression model is constructed using panel data on macro-level variables across 50 tropical countries over an 18-year period.[1]

The main findings confirm the validity of a market profit maximising approach to tropical deforestation. In other words, factors that stimulate production and profits such as increased agricultural output prices, decreased input prices and increased flow of technology into agriculture, have a negative effect on the preservation of forestland, and contribute to its conversion to agricultural uses. However, after a thorough statistical analysis, the model correctness and the validity of the initial findings are critically evaluated and the significance of estimated coefficients is questioned. The validity of generalised macroeconomic explanations of deforestation is questioned therefore, emphasising the importance of microeconomic and case study work.

The paper is structured as follows. Section 2 considers a conceptual analysis of the driving forces of deforestation. Section 3 discusses the theoretical underpinning. Section 4 constructs a global regression model and presents the main results obtained. Finally, section 5 concludes.

2. The driving forces of deforestation - a conceptual framework.

Pearce and Brown (1994) identify two main forces affecting deforestation:

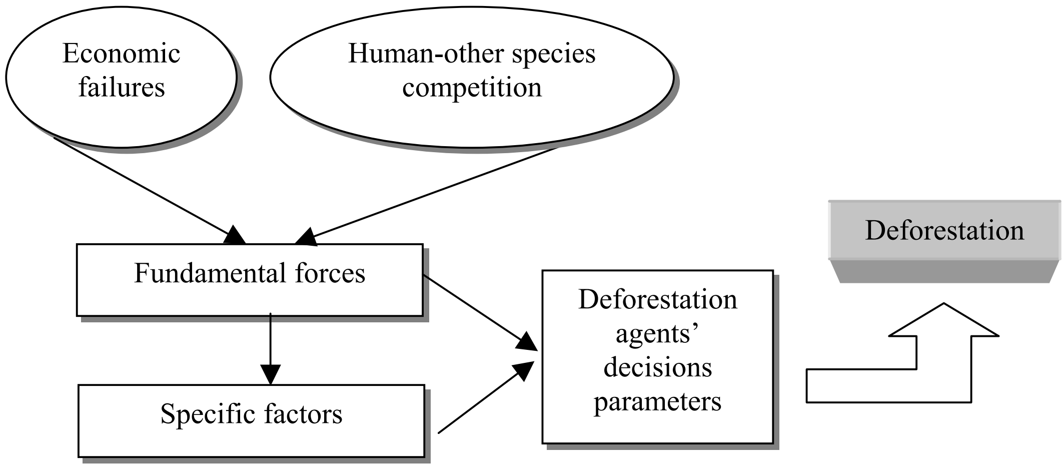
- Competition between humans and other species for the remaining ecological niches on land and in coastal regions. This factor is substantially demonstrated by the conversion of forest land to other uses such as agriculture, infrastructure, urban development, industry and others.
- Failures in the workings of the economic systems to reflect the true value of the environment. Basically, many of the functions of tropical forests are not marketed and, as such, are ignored in decision-making. Additionally, decisions to convert tropical forests are themselves encouraged by fiscal and other incentives.

The second of these fundamental forces nurturing deforestation has been intensively analysed by the environmental economics literature. Poor farm households or commercial loggers have little incentive to care about the environmental effects of their actions. Such unaccounted costs give rise to so-called economic failures, which could be classified into local market failures, policy failures and global appropriation failures (Panayotou 1990). Market failures are present because an unregulated market economy will fail to produce an optimal outcome where prices generated by such markets do not reflect the true social costs and benefits from resource use and convey misleading information about resource scarcity, providing inadequate incentives for management, efficient utilisation and enhancement of natural resources. Policy failures or market distortions are present where misguided intervention or unsuccessful attempts to mitigate failures result in worse outcomes (Panayotou 1990). For example, lack of respect for traditional land rights make property rights to forestland uncertain, and could encourage short-term exploitation of forests rather than long-term sustainable use. Finally, global appropriation failures are present because, in the case of tropical forests, the benefits of preservation, of biodiversity, and the value of the genetic pool in developing new medicines, crops, and pest control agents, are poorly reflected in market allocations. These provide services that extend far beyond the borders of the host country, reducing incentives to implement globally efficient policies (von Amsberg 1998).

Thus, the existing institutional and legal framework leaves forests outside the domain of markets, unowned, unpriced and unaccounted for (von Amsberg 1998), fostering their excessive use and destruction, despite their growing true economic values.

The absence of first-best policies that could effectively internalise the externalities arising from the economic failures previously described reinforces the factors shaping the decisions of agents to deforest. Thus, fundamental forces combine with specific factors to influence the decisions made by the deforestation agents. These interconnections are illustrated in figure 1.

Figure 1: The driving forces of deforestation

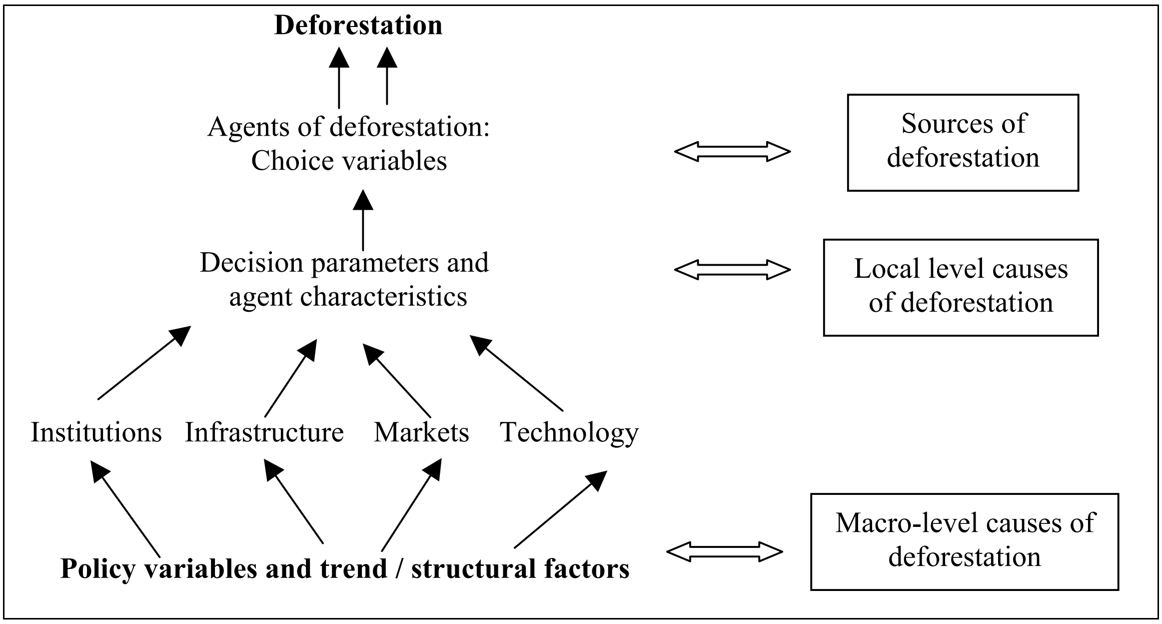


Source: Author's diagram.

Most of the existing literature typically distinguishes between two levels of specific factors: direct and indirect causes of deforestation. The direct causes of deforestation are also typically referred to as sources of deforestation (Caviglia 1999), first-level or proximate causes (Panayotou 1992; Barbier *et al.* 1994). These, as Shafik (1994) observed, are fairly obvious: forests are cleared either to harvest timber or other forest products or they are cleared to use the land for agriculture or livestock.[2] However, as a practical matter, the interaction between different types of agents frequently makes it difficult to separate their impacts and determine their relative importance. Often, ranchers and loggers facilitate small farmers' entrance into forested areas, farmers engage in logging to finance agricultural expansion, and ranchers follow small farmers into agricultural frontier areas (Angelsen and Culas 1996). The indirect causes of deforestation are more complex and controversial. These include both factors that immediately affect the decisions of agents to deforest (such as output and input prices) and those that have a delayed impact on agents' decision-making (such as underlying terms of trade and technological progress). The major drawback of the direct-indirect classification is that it merges the immediate and underlying causes under the label of indirect or second-level. Since the underlying causes determine the decision parameters, mixing these two levels flaws the cause-effect relationship and creates serious problems in empirical investigations and regression models, such as high levels of multicollinearity (Angelsen *et al* 1999). In order to avoid this, the specific factors can be more appropriately classified into three distinct groups: sources of deforestation, local-level causes, and macro-level causes of forest depletion.

A first step is to identify the agents of deforestation, *i.e.* small farmers, loggers, ranchers, and their relative importance in forest clearing. Their actions are considered to be the *sources of deforestation*.[3] In the second step, the agents make decisions about certain choice variables based on their own characteristics and given decision parameters (Kaimowitz and Angelsen 1998). The authors give examples of endogenous choice variables such as land allocation, labour allocation and migration, capital allocation, consumption and other technological and management decisions. The characteristics of deforestation agents are mainly described by their objectives and preferences, initial resource endowments, knowledge and cultural attributes. The agents' decision parameters are external to individual agents and consist of output, labour and other factor input prices, accessibility, available technology and information, risk, property regimes, government restrictions and physical environmental factors (Kaimowitz and Angelsen, 1998). Thus, the characteristic and decision parameters determine the set of permissible choices and constitute the *local level causes of deforestation*.[4] Finally, broader policy variables and trend and structural variables such as demographic and technological forces indirectly influence the agents' characteristics and decision parameters. These are grouped under the label of *macro-level causes of deforestation*.[5] Hence, the conceptual framework as depicted in figure 2 provides a distinction between local-level and macro-level causes that makes it a useful and necessary basis from a methodological point of view.

Figure 2: Conceptual framework of the causes of deforestation



Source: Adapted from Kaimowitz, D. and A. Angelsen (1998) *Economic models of tropical deforestation. A review,* Centre for International Forestry Research.

3. Theoretical underpinnings

There is no consensus around a theory of deforestation indicating which explanatory variables at the macro-level should be included in an empirical model (Andersen 1996). The derivation of such a model is not the intention of this paper. However, the paper will rely on the deforestation literature providing economic theories at the farm household level related to the links between deforestation, proxied by agricultural land expansion, and changes in agents' decision parameters (*i.e.* local-level causes of deforestation). This delivers a theoretically underpinning for the empirical analysis and systematic guidance as to which macro-variables might be inserted in the regressions. The section outlines two different and extreme models of agricultural land expansion: the subsistence (population or *full-belly*) approach and the market (open economy or profit maximising) approach.[6]

3.1 THE SUBSISTENCE APPROACH

The subsistence approach assumes an extreme case, *i.e.* that no markets exist. This theoretical approach begins from the assumption that a person's objective is to satisfy his subsistence requirement by producing agricultural commodities (Angelsen *et al*., 1999). The economic problem is to minimise the labour efforts given a subsistence target, implying that consumption beyond that level has no value. This is labelled by Dvorak (1992) as the *full belly* version of clearing fields.

Production is determined by:

$$X = Af(L, H, F)$$

where X is production in physical units, A represents the technological level, L is (on the field) labour input, H is total land area (land assumed to be of homogenous quality), and F is fertiliser input. The production function is assumed to be concave, with positive but decreasing marginal productivity of all inputs. All inputs are normal and any pair of inputs is complementary.

Because no market for land is assumed, uncultivated land (forest) can be brought into cultivation on a "first come first served" basis (Angelsen *et al* 1999). There are, however, costs related to the clearing of new land, and also costs from having a large area to cultivate, for example, in terms of walking, transport of inputs and output. These additional costs are represented by a convex function $h(H)$. Hence, the optimisation problem is to minimise $L + h(H)$ subject to the constraint $sN = pX - qF$, where the subsistence target is given by subsistence consumption (equal to income) per capita (s), multiplied by the total population (N), and p and q are output, and, respectively fertiliser (input) prices.

The Lagrangian (denoted by G) of this minimisation problem is:

$G = L + h(H) - \lambda[pAf(L,.H, F) - qF - sN]$, where λ is the Lagrangian parameter.

Setting the first-order conditions (*i.e.* the derivatives of the Lagrangian G with respect to its arguments, L, F, H and λ) to zero, the following are obtained:

FOC1: $pA = \frac{1}{\lambda f_L} = \frac{h_H}{\lambda f_H} = \frac{q}{f_F}$

FOC2: $pAf(L, H, F) - qF = sN$

The term ($1/\lambda$) in the first-order conditions (FOC1) can be interpreted as the shadow wage of labour (social opportunity cost of labour), which is endogenous in the respective model. Thus, at the optimum the marginal costs per output unit of the three inputs equal the price of output (p), multiplied by the technological level (A) (Angelsen *et al.*, 1999).

The effects of exogenous changes on the land area under cultivation are relatively obvious. An output price increase or technological progress makes it attractive for farmers to meet the subsistence target by producing from a smaller land area. Lower fertiliser prices will induce farmers to use more fertilisers and less land and labour inputs, and thereby reduce the pressure on forests. Improved accessibility, in terms of lower costs of bringing new land into cultivation, has the opposite effect, namely, an increase in forest depletion. Finally, population growth increases the overall consumption requirement, and therefore leads to increased area of cultivation and deforestation.

A major limitation of this model is the key assumption that households only seek to meet a pre-established consumption target and lose all interest in working once they have reached that goal (Kaimowitz and Angelsen 1998). Nevertheless, the model could be empirically relevant in those situations where producers are virtually isolated from markets or where norms require any production beyond subsistence levels to be shared, which greatly reduces the incentives to produce more.[7]

3.2 THE MARKET APPROACH

The key change in the underlying model assumptions is the introduction of a perfect labour market where labour can be sold or hired at a fixed exogenous wage rate (*w*), which determines the opportunity cost of labour used in agriculture. This, in turn, implies that the level of population is endogenous (whereas in the subsistence model it was exogenous), since labour must be allowed to move freely between the farm and off-farm sectors to ensure labour supply and demand converge at the predetermined wage rate. The land expansion decisions can thus be studied as a profit maximising problem, where the household maximises total profits or land rent.

Maximize: $pAf(L,H,F) - qF - w[L + h(H)]$

Setting the first-order conditions (*i.e.* the first derivatives of the profit function with respect to its arguments, L, H, F) equal to zero the following is obtained:

$$pA = \frac{w}{f_L} = \frac{wh_H}{f_H} = \frac{q}{f_F}$$

Although the first-order conditions look similar in both approaches, the interpretation of the impact of exogenous changes on agricultural land area expansion in the market approach differs greatly from that in the subsistence approach. This is because in the subsistence model the population variable was assumed to be exogenous (and the shadow wage endogenous), whilst in the market model the wage rate is exogenous (and population endogenous). In other words, agricultural production and land use within the market approach are determined by the relative profitability of agriculture and not by any subsistence requirement.

Therefore, higher output prices or technological progress will increase the relative profitability of agriculture, which puts pressure on forests through an increase in land cultivation. Increased fertiliser prices will, assuming complementarity between fertiliser and land area, reduce the area of cultivation. Better access to the forest margin will, as in the subsistence case, lead to an area expansion. A key variable for the determination of the extent of deforestation is the wage rate - higher opportunity costs of labour will make cultivation on the forest margin unprofitable. Finally, population does not enter the market approach model directly. However, by extending the approach to include general equilibrium effects, a population increase will have indirect negative effects on forested areas through lower wages and higher food prices (Angelsen *et al.* 1999).

The main criticism of this model is associated with the strong perfect labour market assumption. In many contexts this is unlikely to hold, especially in the short run when there is no migration and given the hypothesis that family labour is completely interchangeable with hired labour is violated.

The comparative static results of the two theoretical approaches are summarised in table I.

Table I: Hypotheses derived from the subsistence and market approaches

Effect on def. of an increase in…	*…on land expansion and deforestation*	
	Subsistence approach	*Market approach*
Output price (p)	decrease	increase
Input /fertiliser price (q)	increase	decrease
Wage /alternative employment (w)	not applicable	decrease
Agricultural productivity / technology (A)	decrease	increase
Population (N)	increase	increase
Costs of clearing and access (h(H))	decrease	decrease

Source: Angelsen, A., E. Shitindi and J. Aarrestad (1999) "Why do farmers expand their land into forests? Theories and evidence from Tanzania", *Environment and Development Economics* 4 (03): 313-31.

It is important to note that the predicted effects of changes in the technological level and in output and fertiliser prices are different across the two models. Furthermore, the subsistence approach highlights the effect of population growth, whereas the market approach highlights the role of alternative employment, as expressed through the wage rate. In other words, while the subsistence approach focuses exclusively on the agricultural sector, the market approach draws attention to linkages with the rest of the economy.

4. Empirical analysis

The empirical analysis estimates multi-country regression models using national-level data from a large number of countries. The findings from the statistical analysis would eventually support regional or global generalisations regarding the major processes affecting tropical deforestation (see Appendix for data description).

4.1 VARIABLES USED, HYPOTHESES AND ASSUMPTIONS

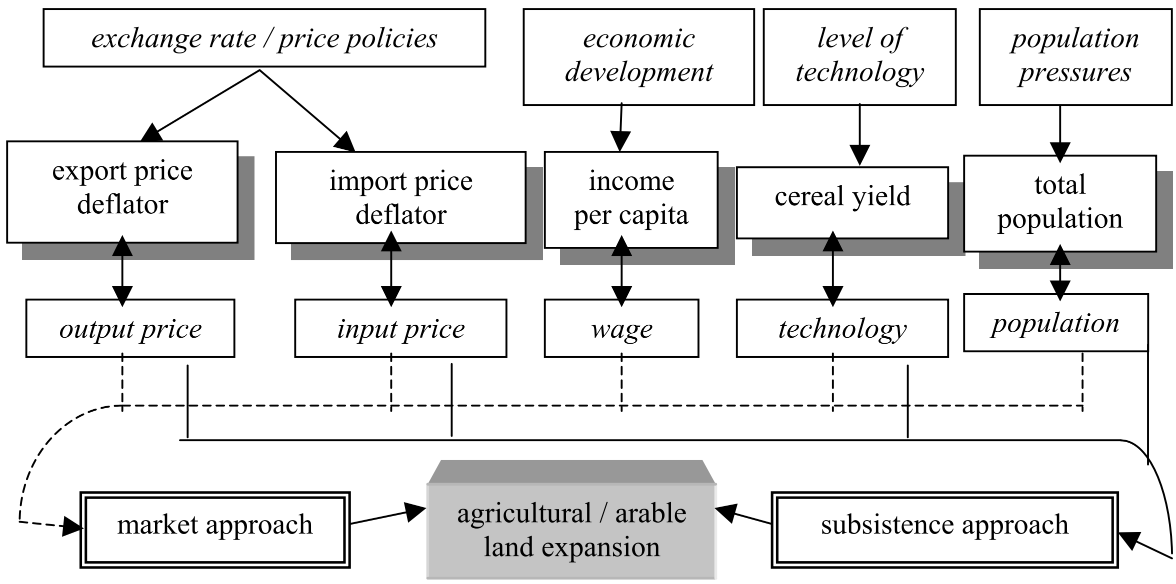
The empirical analysis tests the market and subsistence models of agricultural land expansion using macro-level variables. For this purpose, five macro-scale variables were chosen to reflect the decision parameters that were theoretically modelled, two policy variables, export and import price deflators, and three trend variables, income per capita, cereal yields, and population.

Countries undertaking structural adjustment usually rely on policies such as devaluation, price liberalisation and removal of subsidies to boost their exports, reduce the demand for imported goods and improve their terms of trade (Young and Bishop 1995).[8] Hence, agricultural output and input prices might be proxied by variables reflecting such exchange rate and price policies. This would assume that as tropical developing countries undertake adjustment programmes, open up their economies and integrate into the global markets, the effects of improved terms of trade on farm households would result in increased competition and prices within the agriculture sector and a rise in farm incomes. Such an assumption depends on the transmission channels of price shocks to the variables determining household welfare, and the behaviour of the agents and institutions comprising them (Winters 2000). In other words, it is assumed that the changes in domestic marketing arrangements that accompany adjustment reforms do not lead to the disappearance of market institutions and farm households are not isolated from the market. The variables chosen to proxy output and input prices are the *export and import price deflators*, as they are most likely to reflect price changes due to adjustment policies. But in the case of trade from one country with many countries, it is very difficult to specify one export price for agricultural outputs and one import price for agricultural inputs for each country (Kant and Redantz 1997). Hence, overall exports and imports were used to construct the price deflators, assuming that economy wide price deflators do reflect agricultural price deflators in the countries under study. To note that most authors that investigate the impact of exchange rate and price policies on deforestation use as a proxy the terms of trade. For example, it is argued that improved terms of trade for agricultural and forest product exports and higher real exchange rates make it more profitable to convert forests to other uses (Capistrano, 1994, Southgate, 1994, Kant and Redantz, 1997).[9] However, in order to construct an empirical model consistent with the theoretical framework, the terms of trade where split into two variables, export and import price deflators that would eventually capture the impact of changes in agricultural output and input prices on deforestation. Wages or employment alternatives are proxied by *income per capita*, as a measure of economic development. This assumes that national product represents off-farm income (*w* in the market approach). This type of approach is taken from Angelsen, Shitindi and Aarrestad (1999). The authors note that this macro-level variable may also reflect farm income, which should be determined by output prices and production, the latter being a function of land, labour and other inputs. If farmers are cash constrained, increased income could allow them to spend more on purchasing inputs. Under the subsistence framework this would lead to reduced pressure on forests, whereas the effect would be the opposite in the market approach. Technological level and population pressures are the only macro-scale variables in this study to directly reflect the hypotheses derived from the subsistence and market approaches. The proxy used for technology is *general cereal yields*. This was chosen due to its tendency to reflect an underlying variable, so that the recommendation that all the variables should be on the same level of analysis is respected. In addition, cereal yield reflects the whole set of inputs that farmers might use in their agricultural production (fertilisers, agricultural machinery and other agricultural requisites). With respect to the *population* variable, as previously mentioned, this is hypothesised to have the same increasing effect on deforestation under both approaches.[10] Finally, deforestation is proxied by the *expansion of agricultural land*. This is because agricultural land expansion is generally viewed as the main source of deforestation, accounting for around 60 percent of total tropical forest depletion.

Besides, according to the World Resources Institute (2000), deforestation is technically defined as the conversion of forested land to non-forested land, or the reduction of forest cover within a forest, whereas harvesting, which is the term used for commercial logging is viewed as a separate process from deforestation. However the proxy is not perfect mainly due to two main reasons: first, it does not cover all sources of deforestation and second, some agricultural expansion may not be into forest but, for example, grasslands and savannah. Yet, this might be the best proxy available, as the data on forest cover and deforestation first, reflects not only recent deforestation, but earlier deforestation as well, and current independent variables cannot explain past activities, and second, it is rather limited and unreliable (Southgate 1994).[11]

Figure 3 illustrates the proxies (shadow boxes) that are used to construct the initial regression model of deforestation (see Appendix for data description).

Figure 3: Proxies to be used in the initial empirical model



Source: Author's diagram.

Bearing in mind these assumptions and the theoretical constructions previously presented, the specification of the statistical model is as follows:

$$(\ln AL)_{it} = FE_i + \beta_1(\ln EPD)_{it} + \beta_2(\ln IPD)_{it} + \beta_3(\ln GNPPC)_{it} + \beta_4(\ln CY)_{it} + \beta_5(\ln POP)_{it} + \varepsilon_{it}$$

Equation 1

i = country index:1,2,3......50; t = time index:1980,.....,1997 (18 years); FE are the fixed effects, which can be re-written as: $FE_i = \alpha_1 D_1 + ... + \alpha_{50} D_{50}$; α_i is the constant term for the *i*th cross-sectional unit (country-specific coefficient) and D_i are country dummies, which could also be labelled as $d_{ij}=1$ if i=j and 0 elsewhere. AL is arable land area and is a proxy for deforestation; EPD and IPD are the export and import price deflators and proxy agricultural output prices and, respectively, input prices; GNPPC is the real gross national product per capita and is a proxy for off-farm income (the wage variable in the market approach); CY is cereal yield and is a measure of agricultural productivity that proxies technology; and POP is total population. All variables are expressed in natural logs so that the coefficients are interpreted as elasticities. The values for the β_k slope coefficients are assumed the same for all *i* and *t*; ε_{it} is the error term with the classical main assumptions.[12]

The model pools cross-section and time-series data using a one-way fixed effects linear model, *i.e.* it introduces intercept terms to account for the effects of those omitted variables that are specific to individual cross-sectional units but stay constant over time. In addition to differences in land size, the group effects could also reflect differences in climatic conditions and topography between countries (Angelsen *et al.* 1999), and/or differences in the distribution of forests, proximity to rivers, and the density of trees (Cropper and Griffiths 1994). For example, the proximity of forests to rivers would affect the profitability of converting them into arable land. Likewise, forest area that is clustered is likely to be less vulnerable to deforestation than fragmented forest that is interspersed with other land uses.

Based on the underlying assumptions, the *a priori* expectations about the sign of the coefficients can now be formulated. That is, under the subsistence approach, coefficients β_1, and β_4 are expected to be negative, β_2 and β_5 are expected to be positive. The sign of β_3 is not predicted by the subsistence approach as the income per capita variable is taken to reflect off-farm opportunities, which is not modelled under this theoretical perspective. Under the market approach, coefficients β_1,

β_4, and β_5 are expected to be positive, while β_2 and β_3 are expected to be negative. These are summarised in table II.

Table II: *A priori* expectations about the sign of the coefficients

	Subsistence approach	Market approach
β_1	-	+
β_2	+	-
β_3	NA	-
β_4	-	+
β_5	+	+

β_1, β_2, β_3, β_4 and β_5 are regression coefficients described in equation 1.

4.2. EMPIRICAL RESULTS AND DISCUSSION

The main results of the long-run static regression analysis corresponding to equation (1) are reported in table III.[13] All the signs of the coefficients are in line with the *a-priori* expectations corresponding to the market approach that were displayed in table II.

Table III: Results obtained in the initial static model

Dependent variable	*Sign and size of coefficients*	*t-ratios (p-values)*
lnEPD	+0.06*	+4.07* (0.00)
lnIPD	-0.02	-1.08 (0.28)
lnGNPPC	-0.08*	-3.05* (0.00)
lnCY	+0.03	+1.53 (0.13)
lnPOP	+0.29*	+8.93* (0.00)
Adj-R^2	0.895	
No. of observations	900	
Degrees of freedom	845	

*Significant at a one-percent level.

Three out of five variables are significant at a one-percent level, *i.e. lnPOP, lnEPD, lnGNPPC*.[14] Thus, the population takes the leading position variable; a one-percent increase in the number of people is translated into 0.29 percent increase in arable land. The result for population is important in both models; higher population is associated with more agricultural land, although the elasticity is less than one third. The second most significant parameter is the export price deflator. The positive sign supports the market approach hypothesis that an increase in the price of agricultural output reflected by an increasing export price deflator induces farmers to respond by expanding the area of arable land. Although the size of the coefficient (the elasticity of arable land area with respect to the price deflator for exported goods) seems rather small (0.06), this might not be outside expectations. For example, an increase in export prices might encourage some agents to use more fertilisers, seeds, irrigation or labour and farm more intensively (*e.g.* double-cropping) that would increase output without necessarily increasing land under cultivation. However, this hypothesis might apply for large farm households and commercial loggers for which the means of land intensification are more at hand. For small farmers this might not hold, as modern varieties have not generally spread to "needy" areas, especially where water supply is insecure and where most poor people's livelihoods still depend mainly on growing food (Lipton and Longhurst 1989). The next significant coefficient is for the GNP per capita variable. To the extent it reflects off-farm income, this result suggests that the demand for arable land tends to decrease with increasing real income. This factor is strongly connected with the population variable as both of them might reflect the availability of off-farm jobs. In other words, according to Angelsen *et al* (1999), a plausible approach in line with the market approach is that improved opportunities for income outside agriculture would reduce pressure on land, whereas population pressures depresses off-farm income opportunities. The last two factors, technology and import price deflator, are insignificant at a 10-percent level, but the cereal yield variable becomes significant at a 13-percent level, again supporting the market approach. That is, increasing yield on cereal crops and decreasing input prices reflected by the import price deflator, contributes to expansion of the area of temporary crops.

Although the results provide support for the market approach to deforestation, further statistical tests were carried out to verify the correctness and validity of such estimates. The issue of autocorrelation, in particular, was extensively addressed as the key issue in the empirical investigation.[15]

Provided that the explanatory variables are strictly exogenous, the presence of autocorrelation in the error term does not result in inconsistency of the standard estimators (Verbeek, 2000). It does, however, invalidate the standard errors and resulting tests, implying that the estimators are no longer efficient.[16] Traditional econometric practice interprets autocorrelation as a problem of the model's error term, while in fact the residuals may well display a pattern of autocorrelation as a result of model misspecification, *i.e.* either wrong proxies, omitted variables or incorrect functional form (Mukherjee, White and Wuyts 1998). Further econometric analysis was undertaken in an attempt to find whether an improved model would fit the supposed relationship between macroeconomic forces and deforestation. In other words, the response to the issue of autocorrelation was to carry out more specification searches by using other proxies, including time-period effects, other macro-level variables and quadratic terms, and constructing dynamic models.[17] In each case the significance of the coefficients obtained loses its importance and the explanatory power of deforestation at the global level becomes diffusive.[18] The exception was the population variable that was significantly positive.[19] However, this does not provide any significant support for any of the two theoretical approaches as the sign is interpreted differently in each approach. According to the subsistence approach population growth has a direct effect on agricultural land expansion through increased total consumption requirement, whereas the market approach emphasises its indirect effect through higher food prices and lower wages.[20]

Basically, without correcting for serial correlation the results *tend* to give support to the market approach, whereas when solving for autocorrelation four out of five variables lose their explanatory power, pointing towards the difficulty in quantifying the underlying macroeconomic causes that might induce tropical forest depletion.

5. Conclusions

The initial empirical analysis appears to confirm that tropical deforestation is caused by the drive for maximising profits within the agricultural sector. In other words, the policy and structural variables at the macro-level that stimulate agricultural production, such as improved output-input price ratios, access to technology and less opportunities for off-farm activities, provide the farmers with incentives to deforest and expand their arable land areas. This would be particularly valid in the short to medium term when liberalisation policies are implemented and the economy does not have sufficient time to develop that would increase the income of the population and offer better off-farm opportunities. Nevertheless, when further statistical tests are undertaken to verify the correctness of the model and critically evaluate the results, the initial findings lose their importance and the significance of the estimated coefficients is questioned. Thus, the empirical search would tend to indicate towards an apparent absence of generalised macroeconomic explanations of tropical forest depletion and the difficulty in capturing and generalising the macro-level causes of deforestation.

In addition, the inconclusive results found after correcting for autocorrelation could also be attributed to data limitations and model drawbacks. The data limitations are mainly associated with its quality, especially with reference to the dependent variable that attempts to proxy deforestation. Perhaps with modern technology (satellite techniques) direct information on levels of forest covers and rates on deforestation could be obtained without any questionable extrapolations. Even though such data collection has already began, in order to draw solid conclusions a long time-span is necessary, which is not what one prefers, as the process of deforestation requires to be addressed immediately. With respect to the model drawbacks, although other proxies might be found (*e.g.* irrigated land area for technology) the variables used and the rather simplifying assumptions made could be regarded as being reasonable and acceptable. In addition, the regression model has been carefully constructed according to the theoretical underpinnings that explain the process of deforestation and several specifications have been attempted. Nevertheless, there are several shortcomings associated with global regression models. For example, the models generally encounter difficulties with limited degrees of freedom, selectivity problems, their weak capacity to distinguish between correlation and causality or to the determine the direction of causality, their often inappropriate and strong assumption that each variable affects all countries in roughly the same manner and, finally, their tendency to lose track of strong micro-level relations, which evaporate in the process of aggregating data.

The final results may be interpreted as confirming the complex and indirect effects of macroeconomic forces on deforestation. For example, Barraclough and Ghimire (2000) argue that macro-scale market factors induce numerous sub-processes that respond to different dynamics. Moreover, local level deforestation processes differ greatly from place to place and generalisations based on global /national data might not be helpful in understanding the complex causes of deforestation. Kaimowitz and Angelsen (1998) also conclude that generally it is hard to find any clear-cut relationship between macroeconomic variables and policies, and deforestation. Other modelling strategies might hold more promise for offering significant insights and inferences about deforestation than global regression models. For example, since the factors encouraging deforestation are relatively location specific, Angelsen *et al.* (1999) expect to find a much stronger correlation between deforestation and the micro-level decision parameters, than between deforestation and macro-level variables. Barbier *et al.* (1994) point out that these micro-level variables that mostly overlap with sectoral level variables, have the most immediate and visible effect on deforestation. Moreover, the findings that the regression model is significantly explained by country dummies (*i.e.* the fixed effects) would suggest that the causes of deforestation reside more at a local rather than global level.

In conclusion, the analysis has offered relevant insights into the complex system of causes affecting tropical deforestation at a global level, with the empirical research findings pointing towards the profit maximising market approach to deforestation. Subsequent statistical tests tend to diminish however, the significance of the results, and suggest that the causes of tropical deforestation are rather country or local specific and that these should be analysed at a more disaggregated level, with a focus on the profit maximising model of clearing forests. Although the analysis displays a limited story of tropical deforestation at a global level and about how causality works – about the who, how, and where of forest depletion, it does argue, however, that liberalisation and structural adjustment policies that provide incentives for agricultural producers to increase their output have a negative impact on the environment through cultivated agricultural land expansion and deforestation, calling for mitigation measures to be provided and implemented. In addition, it offers guidance and clears the way for further research to be undertaken at a regional and local or household / firm level.

Notes

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[1] The software programme used in the empirical analysis is Limdep and the data is taken mainly from the World Development Indicators 2000.

[2] A literature review undertaken by Duraiappah (1996) identified logging, agricultural /pastoral encroachment and expansion, and fuelwood collection, as main sources of deforestation. Studies suggest agricultural expansion as the leading direct cause accounting from roughly 50-percent (UNEP, 1995; Myers,1994) to around 60-percent of the annual forest loss (Panayotou, 1992). The second direct cause is commercial logging, about 20-percent, and the rest is attributed to fuelwood collection, ranching and other uses, such as urban development and infrastructure (Shafik, 1994, Southgate, 1998).

[3] Theoretically, the magnitude of their effects can be directly measured and no economic analysis, per se, is required.

[4] The label of "local level causes of deforestation" is equivalent to that of "immediate causes of deforestation" used by Kaimowitz and Angelsen (1998). However, the term the authors use might be misleading due to its time dimension, which is not characteristic to the variables grouped under the label.

[5] Kaimowitz and Angelsen (1998) use here the term of "underlying causes of deforestation". Yet again, such variables have been relabelled to "macro-level causes of deforestation" as they are more consistent with the present analysis.

[6] A description of the approaches can be found in Angelsen (1996), Angelsen *et al.*(1999), Dvorak (1992) and Kaimowitz and Angelsen (1998).

[7] For example, Holden (1996) finds that the subsistence model is appropriate for traditional Zambian society, where there was little market integration and institutions for risk sharing are largely absent.

[8] Here we assume that all tropical countries under investigation have generally been exposed to some degree to liberalisation and adjustment programmes and that import and export prices have a major influence upon

agricultural input and output prices. In other words, these are small open economies and economic agents involved in external trading behave as price takers.

[9] Nevertheless, this may not apply in the case where tree crops rather than field crops are exported, which is the focus of country case studies. For example, in the uplands of the Philippines, tree crops are exported whereas annual crops are produced for the domestic market, and, a devaluation would therefore have negative effects on deforestation and positive effects on the level of soil erosion as tree crops are stimulated (Coxhead and Jayasuriya, 1994 as cited in Angelsen and Culas, 1996).

[10] Debt and other macro-level variables have not been included in my initial empirical model, as the way in which the decision parameters are affected by these are too indirect and it is difficult to find appropriate proxies. For example, Angelsen and Culas (1996) conclude that deriving some general linkages between debt and immediate causes is a tedious and often not fruitful process. Also the clearing and access decision parameters are not discussed as they are difficult to quantify and in addition they provide the same explanations of deforestation in both models.

[11] Furthermore, according to FAO (2001), agricultural land can be subdivided into arable land, permanent crops and permanent pastures. The variable chosen to measure agricultural land was the area of arable land or land under temporary crops. This is because, farmers generally respond to market forces such as price increases by expanding their farmland (arable land), while the area under perennial (permanent) crops is less likely to be expanded (Angelsen et al., 1999). The authors find this argument plausible since permanent crops are less soil erosive, and productivity can be improved from rehabilitating existing plantations. Therefore, it is easier for farmers to respond quickly to price incentives in the short-run for temporary crops by expanding arable land area. Further, because most temporary crops deplete soil fertility faster than perennial crops, they require more new fertile land.

[12] $E(\varepsilon_{it})=0$; $E(\varepsilon_{it}^2)=\sigma^2$; and $E(\varepsilon_i\varepsilon_j)=0$, that is mean zero, constant variance, and, respectively, zero covariance. Given these assumptions, it is well-known that the ordinary-least-squares estimator is the best linear unbiased estimator.

[13] When interpreting the results from a fixed effects regression, it is important to realise that the parameters are identified through the within dimension of the data, reflecting variation across countries (Verbeek, 2000).

[14] The brief interpretation of the coefficients provided is made with reference to the estimates obtained when corrected for heteroscedasticity.

[15] A very high autocorrelation coefficient is reported by *LIMDEP*, ρ=0.808. A hint regarding the autocorrelation problem might also be inferred from observing the residual sum of squares (RSS), which is relatively high, 7.823, before correcting for autocorrelation as compared to the figure, 0.957, after correcting for autocorrelation. Once the estimation is corrected for autocorrelation using the Cochrane-Orcutt iterative technique, all the coefficients become insignificant, with the exception of *lnPOP* that remains positive and significant at a one-percent level.

[16] The initial assumption that the covariance is zero ($E(\varepsilon_i \varepsilon_j)=0$) is violated.

[17] Other proxies used included arable land as a percentage of land use and as a proportion with respect to population as a proxy for agricultural land expansion, fertiliser consumption per hectare of arable land as a proxy for technology, and terms of trade as a proxy for both output and input prices. Other macro-variables included in the regression model consisted of a indebtedness measure, real exchange rate, and the square of income per capita. Finally, the dynamic models included a simple dynamic model in terms of first differences, capturing only short term effects, and an unrestricted error correction model (UECM) capturing both short and long term effects and accounting for any potential problem of endogeniety. A detailed description of the alternative approaches undertaken to deal with the issue of autocorrelation and the results obtained are provided in an extended version of this paper, available upon request from the author or, alternatively, from the main library of the University of Sussex Catalogue (http://catalogue.sussex.ac.uk/home).

[18] This was confirmed by assuming that the initial static model was correctly specified, and using the Cochrane-Orcutt procedure to obtain efficient estimates. Again inconclusive results were found.

[19] Moreover, a regression model excluding population as a variable in absolute terms and including arable land per capita as a dependent variable expressed in relative terms was undertaken. The results obtained and the associated statistical problems were similar to the initial regression.

[20] In addition, population is a demographic factor and not a macroeconomic force that would be relevant for the respective analysis.

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Appendix

Data description

The data set in the initial static model (equation 1) comprises 50 countries repeatedly observed over 18 years. However, this is not a balanced panel data set, as 22 observations out of 900 possible observations were reported missing. To avoid an unbalanced panel data set that complicates the estimation techniques, the 22 missing values were extrapolated by fitting a trend for each country to the existing values. This results in a database with 900 observations and 55 parameters (50 country dummies plus 5 modelled independent variables), which implies 845 degrees of freedom.

The selection of the countries included in the empirical analysis is based on the methodology developed by Palo, Mery and Salmi (1987) in the pilot scenarios that they construct in order to assess deforestation in the tropics. Their starting point is the revised FAO/UNEP 1981 assessment of tropical forest resources, which includes 72 countries (half of each analysed country had to be located in the tropical zone). The authors further include Mauritania, which had been omitted by FAO/UNEP, and then reduce the list of countries by eliminating 5 outliers according to a thorough residual analysis (Trinidad and Tobago, Papa New Guinea, Madagascar, Mozambique and Cuba). Thus their final analysis includes 68 countries. Out of this set of countries, 18 countries were excluded in this paper due to data limitations, as the respective data was not available for at least one modelled variable throughout the whole period analysed (the countries are: Angola, Belize, Benin, Brunei, Cambodia, Equatorial Guinea, Ethiopia, French Guyana, Guinea, Guyana, Lao, Liberia, Myanmar, Namibia, Somalia, Sudan, Suriname, and Vietnam). Hence, assuming the double selection bias (the first stem from the fact that only tropical countries were selected and the second arises from the exclusion of countries for which data were not available), the final data set includes 50 countries. The full list of countries, 17 from Latin-America, 27 from Africa and 6 from Asia, is made available below.

The period covered is from 1980 until 1997. This is because, over the last two decades adjustment policies - that is a move toward a more market-based development strategy - have been implemented in virtually all developing countries (White and Leavy, 2000).

The source for almost the majority of the data was the World Bank (*i.e.* data used for calculating import and export price deflators, GNP per capita, cereal yield and the population variable).The data were taken from the 2000 World Development Indicators made available on CDROM by the Institute of Development Studies at the University of Sussex. Additional data was obtained from the FAO statistical database (FAOSTAT) made available on the Internet.

The 6 variables (1 dependent variable and 5 independent variables) were derived as follows:

Arable land is the land under temporary crops, temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow, less than five years (FAO, 2001). The dependent variable is expressed in hectares because it is assumed that the fixed effects control for the variability of cultivable area across countries (the absolute area of forest cleared can be expected to be higher in larger countries). Furthermore, it is assumed that total land use does not change significantly over the rather short time period under study. The reasonable approach for expressing arable land in hectares is later confirmed, when the dependent variable is normalised and expressed both as a percentage of total land use and as a ratio to total population for which similar results are obtained.

In what regards the **import and export price deflators**, I have constructed these using the data on exports and imports expressed in current and constant 1995 US dollars. That is, the export (import) price deflator was created by taking the ratio of the nominal value of exports (imports), *i.e.* current price times the quantity for exported (imported) goods, to the real value of exports (imports), i.e. constant price times the quantity for exported (imported) goods. The deflators are thus constructed according to a Paasche index, *i.e.* changing weights are used (the quantity of exports /imports recorded for each year). The deflators using US dollars have been preferred to those using local currencies, as the latter incorporate large variations due to domestic inflation (some countries like Bolivia and Mexico experienced even hyperinflation in the period analysed).

Gross national product per capita is obtained by dividing gross national income by midyear population (WDI-2001). The indicator is expressed in real terms, *i.e.*constant 1995 US dollars.

Cereal yield is a measure of agricultural productivity and is expressed in kilograms per hectare of harvested land. Production data on cereals refer to crops harvested for dry grain only (WDI-World Bank, 2001).

The **population** variable represents midyear estimates and is based on the *de facto* definition of population, which counts all residents regardless of legal status or citizenship.

<u>List of countries used in the analysis (50):</u> Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Colombia, Congo, Dem. Rep, Congo, Rep., Costa Rica, Cote d'Ivoire, Dominican Republic,

Ecuador, El Salvador, Gabon, Gambia, Ghana, Guatemala, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Jamaica, Kenya, Malawi, Malaysia, Mali, Mauritania, Mexico, Nicaragua, Niger, Nigeria, Panama, Paraguay, Peru, Philippines, Rwanda, Senegal, Sierra Leone, Sri Lanka, Tanzania, Thailand, Togo, Uganda, Venezuela, Zambia, Zimbabwe.