AN ECONOMETRIC ANALYSIS OF FACTORS AFFECTING TROPICAL AND SUBTROPICAL DEFORESTATION

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In most developing countries deforestation has reached alarming rates. In view of their relevance for the local economy (e.g., as a source of foreign exchange earnings and supply of fuelwood), an adequate management of forest resources should be pursued. In these economies forest exploitation and land conversion have often been seen as a temporary solution to structural problems. In this way, however, the same problems are even aggravated in the long run. The study first reviews recent explanations of tropical deforestation: a distinction is drawn between areas of substantial agreement on the one hand, and discordant results and interpretations on the other. In the main part of the analysis, based on cross-country data for the 1980s, regression models incorporating different sets of determinants of deforestation are applied. Compared to previous studies, the analysis tries to better account for the sequential timing of some of these determinants. Different patterns are identified among country groups, according to specific features of economic activities, macroeconomic and political environments, and climatic conditions.

'N EKONOMETRIESE ANALISE OOR FAKTORE WAT TROPIESE EN SUBTROPIESE ONTBOSSING BEÏNVLOED

In die meeste ontwikkelende lande het ontbossing kommerwekkende groeikoerse bereik. In die lig van hul belang vir die plaaslike ekonomie (b.v., as 'n bron van buitelandse valuta en voorsiening van brandhout), sou geskikte bestuur van boshulpbronne nagestreef moet word. In hierdie ekonomieë is die bosuitbuiting en grondomskakeling dikwels as 'n voorlopige oplossing vir strukturele probleme aangesien. Op hierdie wyse word dieselfde probleme egter in die lang termyn selfs vererger. Die studie kyk eerstens na nuwe verklarings vir tropiese ontbossing: 'n onderskeiding word gemaak tussen gebiede van duidelike ooreenstemming enersyds, en nie-ooreenstemmende resultate en interpretasies andersyds. In die hoofdeel van die analise, wat op data van verskillende lande vir die 1980's gebaseer is, word regressiemodelle met verskillende stelle bepalingsfaktore toegepas. In vergelyking met vorige studies, probeer hierdie analise, om die volgorde gebeure van enkele van hierdie determinante beter te beskou. Verskillende patrone word volgens spesifieke eienskappe betreffende ekonomiese bedrywighede, makro-ekonomiese en politieke omgewings, en klimaatstoestande onder landelike groepe geïdentifiseer.

1.   INTRODUCTION

Tropical forests are estimated to have been losing nearly 17-20 million hectares p.a. in recent years. In the 1980s, this resulted in a loss equivalent to a land area larger than Botswana (although one should bear in mind that these estimates include woodlands which are likely to be reforested in the future). Africa and Latin America have been the most affected regions, while in Asia serious losses are concentrated in a limited number of countries, especially in the South East. This loss amounts to an annual deforestation rate of at least 0.8-0.9% (Sharma 1992: 10; Barbier *et al.*, 1994:7; Pearce-Brown, 1994:9). Even if they have received less attention by the literature concerned, subtropical regions have also been severely affected by deforestation. Unlike the recent performance in industrial countries, in less developed countries (LDCs) the rate of reforestation, including the rate of natural regeneration, has lagged behind the rate of deforestation: this imbalance has led to a gradual reduction of the tropical and subtropical[1] forest cover (Sharma *et al.,* 1992:22).

This depletion has not always necessarily been associated with negative net economic and social effects, since in some cases the welfare loss may be offset by improvements in urban development and greater scope for agricultural activities (*Ibidem* : 34). However, in most cases welfare benefits tend to be of a short-run nature, and are often confined to certain population groups and institutions (Klemperer, 1996:507). Tropical deforestation as presently experienced is believed to generally imply a waste of resources and impair producer countries' long-term growth potential.

Partly due to the lack of homogeneous, suitable and reliable indicators at the national level, specific features related to the causes of tropical deforestation, such as the biochemical and climatic determinants of soil erosion and degradation, lie practically outside the scope of cross-country studies (De Graaf, 1993:25). However, even with more general indicators available, the relationship between development and forest utilization has often been treated in a descriptive way, by comparing various indicators, such as rate of deforestation and population pressures, across LDCs or developing regions. This type of analysis does not allow an assessment of the relative importance of direct and underlying causes of tropical deforestation, nor does it provide any solid base for distinguishing between different regional or sub-regional patterns. Econometric studies on the subject are rare and often unpublished (Barbier *et al.*, 1994)[2]. These studies find conflicting empirical evidence relative to the role of some of the possible determinants of deforestation.

This study aims at reassessing the relevance of these determinants for LDCs as a whole and according to developing regions and climatic environments, based on recent cross-country data. Section 2 presents a review of literature contributions, by specifically pointing at some areas of consensus, and possible reasons for contradictory evidence and discordant views. Following a discussion of the database and variables utilised, and some methodological questions, statistical and econometric estimates are examined in section 3. Conclusions are drawn in section 4.

2.   AN OVERVIEW

2.1   Some common assumptions

Within the recent literature on the subject, distinctions have been drawn between direct or proximate, and underlying causes of deforestation (Sharma, 1992), and between and within developing regions (sub-Saharan Africa, Asia, Latin America) (De Graaf, 1993). Less clear appears to be a distinction according to type of forest/wood: tropical forests are classified between moist and dry varieties, with the former further subdivided between rain and deciduous forests. A detailed classification is hampered by the effects of climatic changes, droughts, and overgrazing, whereby tropical moist forests can gradually be replaced by dry forests, especially in Africa and South America (WRI, 1990:111). Until the 1990 FAO assessment of tropical forests by ecosystem, cross-country international forestry data were not disaggregated according to this criterion[3].

Most authors seem to agree that market and policy failures, coupled with demographic pressures and poverty, have been the most relevant structural determinants of deforestation in LDCs. Without denying the relevance of market and policy failures, some empirical analyses focus almost exclusively on population pressures and poverty as underlying causes of all sources of deforestation (Cropper-Griffiths, 1994), while others test for a wider range of basic determinants. In the latter view, these structural or underlying causes have a bearing on a set of direct factors of deforestation, which can be grouped under four headings (Table 1).

With regard to commercial logging, incorrect pricing of forests, compared to public programmes for other sectors, reduces the incentives to sustainable development. These distortions are revealed by the low level of rents out of forest exploitation (or *stumpage* value), relative to the real costs of reforestation. If associated with a permanent loss of forest areas, tropical timber prices should include the cost of the foregone economic value entailed by deforestation

(Barbier *et al.,* 1994:22). A signal of these distortions is represented by the imprudent

Table 1:   Determinants of tropical deforestation: literature findings and hypotheses

Direct causes	Underlying causes	Possible statistical indicators	
		Direct *	Indirect
LDCs			
1. Commercial logging	Distorted costs/prices	Average duration of logging concessions. Production and exports of tropical wood.	Indicators of economic performance (foreign indebtedness, unemployment, inflation)
2. Fuelwood and/or shifting cultivation	Poverty. Population pressures.	Fuelwood consumption. ADC of tropical wood.	Arable land (ha)/EAP_a. Arable land ha)/ agricultural population. Sociodemographic indicators
3. Agricultural expansion and overgrazing	Incentives for large-scale mechanised agriculture.	Subsidised rural credit programmes.	Degree of concentration in major export crop. Inflation rate.
4. Infrastructure and industrial/mining development	Incentives for other sectors. Relief from population pressures.	Changes in road density. Growth of production by sector.	Foreign exchange earnings from alternative exports. Sociodemographic indicators.
Sub-groups of LDCs			
5. Low productivity in agriculture	Scope for/quality of irrigation Fertilisers (Africa). Climatic changes (Sahel).	Low average grain yield.	Irrigated cropland. Fertiliser use (nutrients/ha arable land). Desertification .
6. Restrictions applied to log exports.	Incentives for processed timber products (Indonesia, Philippines; Côte d'Ivoire)	Elasticity of substitution between suppliers.	Trade share for timber products. Level of development and size of the economy. ODA receipts.

*   *Direct* indicators may refer to both sets of causes
ADC   apparent domestic consumption
EAP_a economically active population in agriculture

ODA official development aid

forestry policies of several LDCs, which have granted logging concessions with a short duration, compared to the average time of timber regeneration (20-50 years). In Côte d'Ivoire, for instance, a country with one of the highest deforestation rates, logging concessions have tended to be granted over maximum periods of 5 years. In Gabon, by contrast, concessions are awarded for a period of at least 30 years, thus encouraging logging companies to contribute to a more efficient forest management (Gillis, 1988b).

Increasing urban and rural poverty have led numerous LDCs, especially in West Africa, to high rates of deforestation, due to shifting cultivation and fuelwood harvest. Shifting cultivation consists in successive clearing of forest areas for the purpose of food supply for subsistence and regional markets. In some cases, shifting cultivation has also been practised by relatively better off farmers, and in several middle-income economies these activities have increasingly been integrated with larger market-oriented agricultural holdings (Gillis, 1988; Amelung-Diehl, 1992). In the countries of the Sahel region nearly 90% of domestic energy requirements is covered by fuelwood (Barraclough-Ghimire, 1995:23). Inefficient burning of wood and production of charcoal have led to a permanent loss of woodland in some city outskirts, thus inducing a replacement of dung for fuel. This has reduced in turn the availability of manure for agricultural land (Lee-Zawdie, 1996:15).

Government policies favouring logging and land conversion have often attempted to redress pressing macroeconomic constraints, such as the decrease of foreign exchange earnings from alternative sources (e.g., mineral exports) and the need to service foreign debt obligations. An emblematic case of macroeconomic and policy-related circumstances which could turn a country highly endowed with tropical forests currently subject to a low rate of deforestation (0.1% p.a. in the 1980s) into a situation of severe depletion of these resources within the next few years, is believed to be Suriname. While being affected by a serious fiscal crisis, declining revenues from bauxite exports, a high inflation rate, and lacking adequate forest protection laws, Suriname's government has recently started negotiations with foreign timber companies to discuss the eventual granting of 25 to 40% of the national land area for logging (WRI, 1996:208-209).

In some cases, government policies have targeted specific population groups, through the implementation of subsidised employment programmes, or subsidised rural credit programmes. The latter programmes have tended to be more common in LDCs with high inflation rates (Repetto, 1990:23 and Browder, 1988:254), where deforested land has been seen as a hedge against inflation by investors. These programmes are regarded to have often exacerbated the

dualistic pattern of agriculture in LDCs, by fostering the expansion of monocultural plantations for export and national markets, besides livestock production, in relatively more fertile areas (frequently lowlands), with traditional farmers and landless households being mostly displaced onto upper watersheds and tropical forests (Rowe *et al.,* 1992; De Graaf, 1993:54).

High population pressures in urban and rural areas have stimulated many governments to embark on large-scale infrastructural projects, typically for hydroelectric power, irrigation, and the transport system. Although, by hindering the feasibility of timber exploitation programmes, the presence of a weak infrastructure network can impair a socially efficient harvest level, these projects have often been associated with internal migration (often implying a resettlement of poor communities) and expansion of mining and agricultural activities, and may facilitate logging in new areas. While, in the absence of other ways of transport, logs harvested in the interior have so far been transported to the main Gabonese coastal centres by river, the envisaged completion of the Trans-Gabon Railway is expected to accelerate the rate of deforestation in the interior regions (Gillis 1988b). Similarly, in several LDCs, in contrast with the previous experience of smaller dams, there has been a tendency over the last two decades to build fewer and larger dams, with consequent more severe effects in terms of flooding and clearing of forest land for land conversion into reservoirs (Amelung-Diehl, 1992:114).

Among the direct factors of deforestation, land conversion for agricultural activities is empirically found to be the most relevant determinant of tropical deforestation by cross-section and pooled econometric studies[4]. Whereas in Latin America this conversion tends to be associated with large-scale plantations and livestock production, in other developing regions shifting cultivations, along with logging, assume greater importance (Amelung-Diehl, 1992:61-62). However, these results should be interpreted with caution, in view of certain methodological constraints as discussed in subsection 2.2. Furthermore, the role of some of the non-forestry policies and macroeconomic features examined above seems to be questioned by contradictory empirical findings. Part of these controversies may be explained by cross-country structural differences, which are likely to render results sensitive to sample selection.

2.2   Controversial issues and statistical evidence

With regard to the methodological problems encountered by statistical studies on deforestation, different definitions of deforestation have proved to lead to partly different conclusions: the broader is the concept adopted, eventually encompassing forest degradation and *modifications*, the more important appears

to be the role of the forest industries. A broad definition would also imply that, in countries with large forest fallows (land covered by woody vegetation deriving from shifting cultivation, where reconstitution of the forest is still possible), such as typically in Africa, greater relevance would be attributed to rural population pressures as an underlying cause, with subsistence farming, grazing, and wood extraction as direct agents of this change (WRI, 1996:211).

For empirical purposes, on the one hand, the definition of deforestation by FAO[5] is considered to be too narrow by some authors (Amelung & Diehl 1992:10). On the other hand, alternative deforestation estimates following broader criteria, provided by a 1989 study by Myers (quoted by Amelung & Diehl), are based only on extrapolations, besides being outdated and possibly too broad. This may lead to an overstatement of the role of logging activities (I*bidem* : 19) and demographic pressures, as mentioned above. An FAO study, based on satellite imagery scanning 10% of the world's tropical forests, found that in the last decade more than half of the changes affecting these forests have actually been represented by "moderate to severe forms of degradation", mostly not accounted for by FAO-WRI deforestation estimates (WRI, 1996:210-211).

Secondly, even when the stricter FAO definition is adopted, the expansion of cropland, especially for shifting cultivation, frequently follows commercial logging. In some cases a three-stage deforestation process is observed, whereby initial logging is replaced by widespread forest clearing for subsistence agriculture, which is succeeded in turn, in the presence of decreasing agricultural yields, by livestock activities (Persson, 1995). Some other cases are characterised by a rotation pattern: deforestation would then turn out to be a periodic, rather than a permanent or near-permanent, phenomenon, since non-forest land uses would not severely clear or degrade the forest area. An example is represented by part of the Brazilian Atlantic coastal forests, which have experienced a natural regeneration after undergoing some clearing for temporary agricultural activities (Barraclough-Ghimire, 1995:10). However, secondary forests, growing out of abandoned pastures, usually have a lower biomass than the primary ones (Myers, 1994). Econometric results would therefore be more robust if sufficiently long time series were available, and if more disaggregate forest statistics were collected[6].

Thirdly, possible *feedback* effects of deforestation on soil and water resources should not be ignored, even if they are more difficult to model with cross-section data. Particularly if deforestation occurs in sloping areas, these effects include a negative impact in terms of aspects such as irrigation capacity and conditions of water supply, increased risks of flooding, and reduced crop productivity (de Graaff, 1993: 104-107). This points to a need to test for both directionalities in this

chain of causation-effects. For instance, poor health standards, along with low education levels, can be assumed to "inhibit the adoption of appropriate technologies... and conservation activities" (*ibidem* : 55), but they can also be further worsened by the process of soil degradation accompanying deforestation[7].

Further controversial aspects arise from the interaction between factors, such as that between infrastructure development and fuelwood requirements. The role of infrastructure development is particularly difficult to assess, not only due to the selection of a suitable *proxy* variable, but also in terms of its various implications. National infrastructures are often improved thanks to a more efficient institutional setting, such as extension services, which can encourage local communities in forest areas to better comply with conservation measures (de Graaff, 1993: 55). Similarly, in LDCs which are heavily reliant on charcoal and firewood for mineral processing, the expansion of hydropower infrastructures may have positive, instead of negative, implications for forest management, despite implying itself a highly land-intensive energy generation process. In this respect, some authors suggest an inverted U-shaped *environmental Kuznets* curve (Cropper-Griffiths, 1994:251; Rudel-Roper, 1997:61-62): with increasing levels of development, deforestation rates tend to increase first, and decrease later (once a more diversified industrial structure has been achieved, with a greater reliance on alternative sources of energy).

The role of mining activities can be misinterpreted by the kind of proxy variable utilised. Export specialization statistics refer to the exports of ores. The downstream contribution of mining to domestic industries, especially in economies with a larger industrial base including metal processing activities (India, Brazil), is not accounted for by these statistics. In this respect, mining is believed to have substantial indirect effects on deforestation, such as the use of charcoal for mineral processing industries. Moreover, mineral supply and export figures do not allow a distinction according to the location of mineral reserves and the geological features of the deposits: alluvial and openpit mining in relatively accessible regions is bound to affect the forest area more extensively than underground mines, at least directly (Amelung-Diehl, 1992:99-100).

Besides national forestry policies, the role of the general institutional setting has not been empirically assessed: different implications can be suggested. In broad terms, LDCs with a high political instability and/or authoritarian regimes seeking legitimisation from certain population groups are likely to have suffered a more uncontrolled depletion of domestic forest resources by local authorities, with these authorities often giving priority to short-term gains (Browder, 1988:255; Gillis, 1988b; Palo 1994:44; Panayotou-Ashton, 1995:268). Moreover,

sudden changes in the institutional setting governing national forest resources can create insecurity on forest rights by the local population, and can therefore contribute to accelerate deforestation, as occurring in Nepal subsequent to the nationalisation of the forest land (Barraclough-Ghimire, 1995:97). Political stability, by contrast, could assure a more effective public protection and control over the use of forest resources. Conversely, however, political instability tends to discourage foreign involvement in logging activities, which may explain a lower rate of deforestation in, e.g., Zaire (de Graaff, 1993:38).

In terms of macroeconomic policy factors, empirical results of studies on tropical deforestation do not reach the same conclusions. The impact of foreign debt exposure is found to be as expected by Kahn & McDonald (1994), but the opposite result is indicated by another study, which shows a negative relationship between debt service ratios and deforestation (Capistrano, 1994). Rudel & Roper (1997:61) distinguish between a deforestation effect in LDCs with small forests, and a neutral or even forest-conservation effect in LDCs with large and remote forests (following the curtailment of large public infrastructure projects under debt-induced fiscal austerity). The analysis is complicated by the implementation in recent years, although to a still limited extent, of debt-related financial instruments geared to foster natural resource management and conservation in highly indebted LDCs (*debt-for-nature* swaps) (Repetto, 1990:24; WRI, 1992:123).

Similarly, official development aid (ODA), although ignored by the econometric studies on the subject, is regarded to possibly have ambivalent effects (Amelung-Diehl, 1992:3; 126). On the one hand, by financing large-scale infrastructure projects, or livestock development and other export-oriented production projects, ODA can contribute to deforestation (for the case of Central American LDCs: Barraclough-Ghimire, 1995:67). On the other hand, aid flows are often linked to compensation arrangements with LDCs, geared to target the use of forestry and agriculture resources according to sustainable growth.

Devaluation of the exchange rate appears to stimulate logging activities for export, thus enhancing deforestation. Policy measures implemented by structural adjustment programmes, such as exchange rate realignments, can also indirectly contribute to land conversion and deforestation, by fostering export crops (Dine, 1993), and the demand for agricultural land for domestic food supply (Capistrano, 1994:72). *Ceteris paribus*, upward-misaligned exchange rates could therefore be expected to be associated with relatively lower rates of deforestation. In some LDCs, however, timber exports have been found to be less responsive to real exchange rate devaluations, compared to, e.g., traditional agricultural products (Gillis, 1988:79). Furthermore, the maintenance of an

overvalued exchange rate may also be assumed to be responsible for deforestation, by allowing a misallocation of productive resources and the strengthening of a dualistic agricultural production structure. In Indonesia, long periods of exchange rate overvaluation have resulted in "a decline of the forest's value as a source of non-wood products relative to its value in producing wood" (*ibidem*: 81) and, as such, are believed to have played some role in promoting deforestation. In Ghana, the overvaluation of the domestic currency did discourage official exports of timber, but it also favoured increased smuggled timber exports, in amounts possibly equivalent to official flows (Gillis, 1988b:306).

Agricultural population pressures on land vary substantially between LDCs, with no clear distinctions between developing regions (de Graaff, 1993:44-45). These pressures are aggravated in several LDCs, especially in sub-Saharan Africa, by a low average productivity of arable land. Besides the cultivation of lower-yield average grain varieties compared to Asian countries, agricultural supply in most African LDCs is affected by a more limited support from irrigation and much lower rates of fertilization, even once the different crop and soil nutrient requirements are accounted for (*ibidem* : 24-25, 37, 45) (Table 1). An econometric study on 53 LDCs finds that lower agricultural yields seem to accelerate the pace of deforestation, although this is not proved at a high level of statistical significance (Barbier *et al.*, 1994:31-32). The role of average productivity and profitability in agriculture for tropical deforestation, through its impact on agricultural expansion into forested areas, is controversial. While *push* factors can be represented by low average levels (as in the expansion of marginal farming in Africa), high average levels may exercise *pull* factors (Pearce-Brown, 1994:17), especially in the absence of technological improvements allowing for agricultural intensification.

Sub-Saharan African countries are also believed to have a higher ratio of *open* to *closed* forests, with the former constituting woodland and the latter term referring to real forests in terms of percentage crown cover (de Graaff, 1993:35-37). This 'African' pattern is considered to have partly been the result of a process of degradation from closed to open and fragmented forests in the 1980s (WRI, 1996:211). This may widen the scope for non-commercial logging in the continent, since fuelwood is mainly extracted from open forests, shrubs and plantations (Amelung-Diehl, 1992:118). However, no indications are provided in this respect by the available statistical evidence[8]. The interaction between long-term climatic and anthropogenic factors is a controversial issue. The southward drift of the Sahara, with its connected increased risks of fires and droughts, is considered responsible for deforestation in countries such as Ghana (Gillis, 1988b), while negative feedback effects between forest clearance and

desertification have been observed along the coastal north-central Chile (Barraclough-Ghimire, 1995:17).

Producer countries with a higher market power and a relatively more diversified production base, such as Indonesia, have set restrictions to unprocessed log exports, with the aim of promoting domestic processing activities. This would eventually allow these countries to undercut the price of other producers and enlarge their export market shares in processed timber products. In theory, the search for increased market power might encourage a conservationist approach by these countries, provided that it is supported by international financial assistance (Barbier *et al.*, 1994:123-124). In other cases, such as the Philippines, the move towards finished products has been motivated by the shrinking forest resource, although log export restrictions have not continuously been applied due to periodic balance of payments problems (Boado, 1988). In Thailand a radical approach was adopted in 1989, with a government ban on logging: in the absence of a favourable social and institutional environment, the plan has not been effective (WRI, 1992:47). In view of present rates of deforestation, all forests in Thailand and Vietnam may virtually disappear by the beginning of the next century (Myers, 1994).

In practice, log export restrictions have often been accompanied by an export tax structure biased against these exports, and subsidisation of domestic sawnwood and plywood producers. As such, they are regarded to have contributed to inefficient, high-cost local wood-processing industries, characterised by low production capacity utilisation (Repetto-Gillis, 1988:404). Whether this has had a negative impact in terms of deforestation, has not been empirically tested. Indirectly, this might have been the case, since log export bans in, e.g., Indonesia, are likely to increase the demand for logging in neighbouring countries, while not substantially contributing to reducing the rate of deforestation in the producer country concerned. Subsidised and inefficient wood-processing industries can also be expected to cause a higher waste of logs (hence deforestation) relative to wood produced (Pearce-Brown, 1994:14).

High substitution elasticities of import demand for tropical timber (especially for plywood, but also for sawnwood) from different countries of origin (Barbier *et al.*, 1994:49) suggest ample scope for changing market shares among timber-exporting LDCs, in favour of the most competitive producers, in spite of rather low price elasticities. This also contrasts with relatively low cross-price elasticities between temperate and tropical wood products. The consequences are likely to be felt especially by producer LDCs with small open economies and a relatively heavier reliance on forest product exports, such as the Central African Republic and Congo.

In section 3, some major hypotheses and findings on tropical deforestation are reappraised in the light of a cross-country econometric application. The analysis is preceded by some explanations about sources, country sample and selection of variables.

3.   ECONOMETRIC APPLICATION

3.1   Database and variables

3.1.1   Deforestation data and LDC coverage

Deforestation is assessed by the FAO once a decade: the first global assessment was carried out in 1980 (and completed in 1982), the second one in 1990-92. In view of the relatively strict definition by FAO (subsection 2.2 and note 5), an analysis based on FAO data is likely to downgrade the role of logging activities. However, selective logging, which allows a natural regeneration of the forest cover, appears to be the exception in most LDCs. In these countries logging operations tend to affect from 40% to 70% of the trees of a forest area, even if only 10-20% of the trees are cut, and to cause severe soil degradation (WRI 1990: 107)[9].

Econometric studies on tropical deforestation tend to focus exclusively on LDCs with moist forests. Besides being economically more valuable for commercial timber, these forests are regarded as environmentally more sensitive than the dry ones, in view of their richer biodiversity and higher degree of irreversibility of deforested land (Amelung-Diehl, 1992:7). In this way, the analysis is not suited to identify possible different deforestation patterns among LDCs, according to the predominant type of forest, even if this distinction is hindered by the statistical constraints mentioned earlier, in subsections 2.1 (note 3) and 2.2. Fuelwood collection, e.g., is likely to be a more serious factor of deforestation for dry forests (Panayotou-Ashton, 1995:267). While most tropical deforestation concerns rain and deciduous forests in lowlands, deforestation in dry areas, such as in the Sahel, Southern Africa, or Pakistan, can affect even more severely the local carrying capacity (WRI, 1990:107; WRI, 1994).

Moreover, no distinction is generally drawn in terms of different reliability of forestry data across LDCs. At an individual country level, particular attention in the debate on tropical deforestation has been devoted to the three LDCs with the largest tropical forest resources, namely Brazil, Indonesia and Zaire, which alone account for over half of closed tropical forests (Brugess, 1993). However, these countries lack reliable statistical information for forest resources, except for

northern Brazil (Zaire also for social and economic indicators in general). Relative to other developing economies, they also present lower deforestation rates, although in terms of absolute changes they account for a large share of global loss of tropical forests (45% of this loss relative to rainforests in the 1980s is attributed to Brazil and Indonesia) (WRI, 1994:ch. 7).

For this analysis, FAO forest resource data published biennially by WRI (1992, 1994) were relied upon. These data are collected and estimated by the FAO, based on population and socioeconomic variables, maps on vegetation zones, forest surveys, and satellite imagery. The sample can be distinguished in three country groups (Appendix). The first two groups include LDCs to which a 1988 FAO evaluation of national estimates and inventories on forest cover and deforestation attributed relatively good statistical reliability within the developing world (group A), or a medium level of reliability (group B) (WRI, 1992:292). Despite being included by the FAO in either one of these categories, a number of LDCs were not considered because of insufficient statistical information for variables other than the forest sector (e.g., Haiti), or due to the unreliability of forest estimates for a large portion of their territories (Brazil and India)[10].

The third group (group C) comprises a small number of LDCs heavily reliant on tropical timber exports or with a high proportion of arid lands (as defined by the FAO : WRI, 1992, 284). In the latter respect, Ethiopia lies in an intermediate position between dry-forest LDCs and other countries of the sample, since it registers similar proportions of arid and humid soil. The small number of observations in each of the three groups suggested the use of dummy variables on the whole LDC sample, while a separate analysis of group A countries was limited to simple correlation coefficients.

3.1.2   Selection and interpretation of variables

A list of variables used in the statistical and econometric analysis, mainly based on FAO and World Bank data, is given in the Appendix. Variables other than those listed were originally included in the analysis, since they tried to incorporate some of the hypotheses discussed in section 2. However, the latter variables prove to be either statistically insignificant, or spuriously or more indirectly related to the dependent variable[11].

Deforestation data were available for both the whole reference period, i.e. 1980-90, and the first half of the decade (WRI, 1992 and 1994: Table 19.1). In terms of intertemporal effects of the explanatory variables, time lags can be supposed to concern tropical deforestation (especially if deforestation is defined according to

FAO criteria: note 5) induced by commercial logging and fuelwood collection, relative to the time of occurrence of these logging activities. In order to account and test for these possible lags, and to check for cross-country consistency of production changes over different periods, the two respective *proxies*, that is industrial roundwood production (note 11) and fuelwood/charcoal supply, were considered over the periods 1978-88 and 1980-90. Similarly, the observed presence of a sequential pattern in deforestation activities and the substantial time necessary to reconvert deforested land into permanent or temporary crops, or to develop transport infrastructure, suggested the use of two-year lags (relative to the reference period) for changes in land use (*arl* and *xcr* in the Appendix, defined in FAO, 1993, viii, and commented below)[12], and the introduction of a *lead* (1975-85) and a *lag* (1985-92) variable for length changes in domestic road networks (*road*).

FAO statistics on fuelwood and charcoal production do not allow a distinction between final uses. This variable can be better assessed by comparing the extent of open forest relative to total natural forest area, since private households' consumption of fuelwood and charcoal tends to affect open forest and shrubland, while industrial consumption for energetic use largely relies on plantations and, to some extent, closed forests (Amelung-Diehl, 1992:22-23). Another possible relevant factor, which can be regarded as a *proxy* for the extent of wood beneficiation, is the share of processed wood products in roundwood supply, with sawnwood being the main by-product of primary tropical wood (Amelung-Diehl, 1992:26). The impact of forestry policies, such as log export restrictions, can indirectly be tested by examining this variable in connection with a dummy which identifies highly timber export-dependent economies (*ddep*)[13].

As far as agricultural conversion is concerned, monocultural plantations and cash crops for export markets are considered to be adequately proxied by FAO data on land under permanent crops, while areas for livestock production are believed to be well approximated by data on permanent meadows and pastures. By contrast, *arable* land, basically defined as land under temporary crops, is not a good proxy for shifting cultivations, since these activities are frequently not registered officially (Amelung-Diehl, 1992:55) and the FAO statistical information excludes from this category the "abandoned land resulting from shifting cultivation" (FAO, 1993:viii). This constraint notwithstanding, the annual change in arable land was used here as an indicator of physical expansion of cultivations other than permanent crops. Data on permanent meadows and pastures were not included, because of the lack of reliability and updated estimates for numerous LDCs (WRI, 1994:289).

Similar problems are encountered in the selection of a variable for the mining sector. As considered in section 2, a dummy based on mineral export reliance can give only a limited insight into the issue. Besides this variable another dummy was added, so as to distinguish LDCs (not necessarily *mineral* economies in terms of the above definition) with a relatively high number of mining operations which are located in forest areas and are especially forest-intensive in nature (*dminfor*).

As an indicator of socio-political instability, the SPI index estimated by Alesina and Perotti (1996:1211) was used, covering 29 of the 48 LDCs. This index refers to 1960-1985 period averages, and is obtained as a composite function of proxies for domestic violence and political environment, including the political legitimacy of the government[14]. Although not updated to more recent years, results appear to be more realistic than those of an analogous index reporting annual estimates for 1948-1982 (Gupta, 1990). As a proxy for the degree of price inefficiency and potential misallocation of domestic resources, use was made of an index proposed and estimated by Dollar (1992), which is based on the distortions in the real exchange rate relative to a situation of free trade and after correcting for local endowments (*dist*).

3.2   Estimation results

3.2.1   *Preliminary data analysis and methodological remarks*

Simple correlation coefficients and scatter diagrams between the variables were analysed, so as to choose suitable regression models. These models would be expected to reflect some of the literature hypotheses earlier reviewed. The annual deforestation rates for the periods 1980-90 and 1980-85 (*defor* and *defor1*, respectively) appear to generally follow similar cross-country patterns, as revealed by a positive correlation coefficient between the two variables at a 10% significance level (r = 0.25, for 48 LDCs). This consistency in cross-country patterns between the two reference periods turns out to be highly significant, with a coefficient of 0.62, when the corresponding absolute changes are compared (*deforha* and *deforha1*): this implies that LDCs with relatively larger average annual deforested areas during the first half of the 1980s have tended to maintain this record throughout the entire decade.

Côte d'Ivoire, Nigeria, Colombia, Sri Lanka and Nepal emerge as LDCs affected by strikingly more severe deforestation in the first half of the decade, while the opposite extreme cases are represented by Jamaica, Bolivia, Venezuela, Bangladesh, Pakistan, Myanmar, Vietnam, Indonesia and the Philippines. On the whole, the highest deforestation rates are registered in the Central American

and Caribbean region, and, with an increasing intensity over the 1980s, in South East Asia (WRI, 1994:131). With few exceptions, a close cross-country overlap is obtained if the variables on percent changes of fuelwood and charcoal supply and industrial roundwood are compared for two selected periods with a two-year shift (subsection 3.1.2 and note 11). For the sake of brevity, for the other variables only regression results, reported in Table 2, will be discussed in detail, in subsection 3.2.2.

As pointed out in subsection 2.2, no clearcut distinction can be made in practical econometric modelling among different determinants of deforestation, since

(i)   a different conceptual coverage can provide, to some extent, different indications (e.g., various criteria defining *deforestation*, or alternative *proxies* for infrastructure development);

(ii)   in some cases, the same variable can indicate the relevance of more than one set of factors (e.g., fuelwood and charcoal supply; among the possible indirect determinants, inflation and socio-political instability interact with other factors); and

(iii)   an inter-temporal pattern is often observed, whereby different sets of factors are linked in a sequence.

Furthermore, as an aspect insufficiently considered in the literature concerned, some determinants may matter for some places, while being irrelevant for others. For these reasons, while possibly keeping the same *ceteris paribus* variable(s) across the equations, separate regression equations (except for equations [9] and [10]: Table 2) were run on specific groups of variables deemed to reflect relatively more each distinct set of factors: within-equation distinctions were made rather in terms of LDC subgroups.

In principle, this approach could be criticised on two grounds. Firstly, if correlated with any of the variables included in a regression equation, omitted relevant variables would cause contemporaneous correlation between explanatory variables and residuals, thus implying biased and inconsistent parameter estimates. This misspecification problem would be revealed by a positive or negative residual autocorrelation (Thomas 1993:140-142). However, in this case, the hypothesis of no serial correlation can not be rejected by the Durbin-Watson test, used as a misspecification test, in all equations reported in Table 2, and not only for the *encompassing* equation models [9] and [10]. One could also object that these more comprehensive models do not comply with the need for sufficient degrees of freedom, corresponding to the rule of thumb that

there should ideally be no more than one variable for every eight-to-ten observations (Rudel 1994: 105). Rather than reflecting competing theories, each of the partly *nested* models [1]-[4] and [7]-[8] in Table 2 (for equations [5] and [6], point (i) above applies) is an attempt at modelling largely overlapping or sequential

Table 2 - Estimation results

Main set of factors tested	Commercial logging				Fuelwood (+ shifting cultivation)	Temporary *vs.* permanent crop cultivation		Infrastructure and mining		Encompassing models	
Dependent variable	defor		lnprocwp	defor1	defor	deforha	deforha	defor	defor	defor	defor
Method	WML [1]	WML [2]	OLS	WML [3]	WML [4]	WML [5]	WML [6]	WML [7]	WML [8]	WML [9]	WML [10]
Constant	1.07 (3.65)	0.93 (2.67)	-12.6 (-6.32)	0.94 (1.53)''	-0.35 (-0.74)``	-109.3 (-8.16)	-105.2 (-7.54)	0.98 (5.02)	0.53 (6.6)	1.09 (4.28)	-0.001 (-0.002)``
arl							2.62 (11.6) [1.28]				
ddep		-0.45 (-1.36)''	9.08 (2.04)								
dist	-0.005 (-3.66) [-0.37]	-0.005 (-2.72) [-0.33]			-0.007 (-3.66) [-0.50]			-0.003 (-2.14) [-0.19]		-0.002 (-2.87) [-0.16]	-0.004 (-2.37) [-0.29]
dmin								-0.19 (-1.35)''			
dminfor									0.54 (2.19)	0.48 (3.55)	
dsr				0.066 (3.36) [0.49]							
dumroad								0.61 (4.08)	0.48 (2.96)	0.51 (4.85)	
fuelw					0.052 (3.66) [0.46]						0.031 (2.80) [0.42]
fuelwdum					-0.030 (-3.58)						-0.018 (-2.62)

Main set of factors tested	Commercial logging				Fuelwood (+ shifting cultivation)	Temporary *vs.* permanent crop cultivation		Infrastructure and mining		Encompassing models	
Dependent variable	defor		lnprocwp	defor1	defor	deforha	deforha	defor	defor	defor	defor
Method	WML [1]	WML [2]	OLS	WML [3]	WML [4]	WML [5]	WML [6]	WML [7]	WML [8]	WML [9]	WML [10]
haap						44.6 (11.4) [0.66]	45.8 (11.1) [0.68]				
humid^	0.008 (4.14) [0.49]	0.011 (4.96) [0.66]		-0.005 (-1.11)`* [-0.20]	0.007 (2.67) [0.46]			0.002 (1.32)''# [0.11]	0.003 (1.76)'# [0.15]	0.002 (0.78)``	0.006 (2.71) [0.33]
inst				-0.051 (-2.65) [-0.34]							
opentn					0.034 (2.60) [1.58]						0.023 (2.19) [1.22]
opentn^2					-0.00025 (-1.99)'						-0.0002 (1.97)'
procwperc	0.152 (2.92) [0.44]									0.07 (3.16) [0.32]	0.18 (3.87) [0.86]
procwdum	-0.185 (-3.61)									-0.06 (-3.01)	-0.20 (-4.74)
road								-0.025 (-2.21)# [-0.21]	-0.053 (-6.7)# [-0.45]		
roaddum								0.20 (5.37)	0.24 (6.53)	0.16 (7.89)	
tnarea				-0.019 (-1.37)'' [-0.23]		4.11 (5.98) [0.70]	3.79 (5.36) [0.65]			-0.01 (-3.12) [-0.20]	

Main set of factors tested	Commercial logging				Fuelwood (+ shifting cultivation)	Temporary *vs.* permanent crop cultivation		Infrastructure and mining		Encompassing models	
Dependent variable	defor		lnprocwp	defor1	defor	deforha	deforha	defor	defor	defor	defor
Method	WML [1]	WML [2]	OLS	WML [3]	WML [4]	WML [5]	WML [6]	WML [7]	WML [8]	WML [9]	WML [10]
xcr						17.37 (12.3) [1.33]					
lnypc			1.86 (6.34)								
lnypcdep			-1.13 (-1.78)′								
$F_{k-1,N-k}$	47.3 (4,35)	47.0 (3,36)	18.3 (3,35)	11.1 (4,21)	25.7 (6,24)	127.4 (3,38)	113.5 (3,38)	104.4 (6,33)	99.9 (5,34)	44.9 (8,31)	17.5 (8,22)
N	40	40	39	26	31	42	42	40	40	40	31
adj R²	0.83	0.78	0.58	0.62	0.83	0.90	0.89	0.94	0.93	0.90	0.81

Figures in parentheses: (under estimated parameters) t statistics, (under F statistics) degrees of freedom (N: number of observations)

Figures in square brackets: (under estimation method: third row) equation number, (under t statistics) standardised beta coefficients.

Level of significance: ′ 5-10%, ′′ 10-20%; ` 20-30%; `` more than 30% (in all other cases: 5% significance level or less)

^ variable used in WML estimations to correct for heteroscedasticity

* estimated parameter is sensitive to sample selection: it turns positive (0.019, t=2.68) if Niger is removed from the sample and the variable *humid* for PNG (missing value) is assumed to be 100

estimated parameter loses statistical significance if Niger is removed from the sample and the variable *humid* for PNG (missing value) is assumed to be 100 (see text)

Samples (Appendix): Jamaica and Pakistan are excluded from all equations except [5] and [6], for which the excluded observations regard Indonesia, Nigeria, Thailand and Vietnam

Sources: Alesina-Perotti (1996); Dollar (1992); FAO (1993); Summers-Heston (1988); WRI (1992, 1994); World Bank (1993; *SID* 1994 and computerised SID database; *WDR* 1995 and previous years)

determinants of tropical deforestation, by focusing, even if at an aggregate level, on inter-country variations.

Secondly, one could object against the simultaneous use in the same regression of explanatory variables at different levels, thus mixing direct (level 1) and underlying (level 2) factors of deforestation. This practice is common among econometric studies on the subject. As a consequence, some explanatory variables may be functions of others, and multicollinearity is likely to occur. In this study, besides level 1 variables, use was made of

(i)   level 2 variables which were uncorrelated to level 1 variables included in the same regression, and can be considered as proxies for unavailable level 1 variables (e.g., in equation [1], among others, *dist* is a proxy as defined in subsection 3.1.2), and

(ii)   *ceteris paribus* variables, which were supposed (following the discussion in section 2), and in some cases turned out to be, relevant for different aspects of deforestation, while being uncorrelated with other regressors in the same equation (e.g., in equations [3], [5], [6] and [9], the variable *tnarea*). When the above conditions were not satisfied, an estimate of a level 1 variable was obtained recursively (*procwperc/procwdum* in equations [1], [9] and [10]), from an auxiliary OLS regression equation with a level 2 variable as regressor[15].

Scattergrams relating deforestation rates (*defor*) with the explanatory variables identified Jamaica and Pakistan as clear outliers relative to the overall cluster of the observations. Once the selected explanatory variables are accounted for, country-specific features (unknown to this author) are likely to have determined the high rates of deforestation in these two LDCs relative to the average pattern across the sample. Jamaica is detected as an atypical case also in Rudel & Roper, (1997:60). The two countries were removed from all equations with the deforestation rate as the dependent variable. Their presence was found to be basically responsible for the expected positive relationship between deforestation and industrial roundwood production (note 11), and increases the risk of erroneously accepting spurious relationships (or inflating true relationships) for other variables as well. Similarly, the presence of a few outliers spuriously swells the positive correlation found between the extent of annual deforestation (*deforha*) and the annual expansion of arable land (Indonesia, Nigeria) or of permanent crops (Indonesia, Thailand, Vietnam). These four countries were left out of the regressions with *deforha* as the dependent variable[16].

Heteroscedasticity is likely to be common among cross-country studies on deforestation: in some cases it even appears to have been disregarded, with consequent negative implications on the reliability of parameter estimates[17]. Plots of studentised residuals of original OLS regressions against the predicted *deforestation* values, supplemented with Glejser tests, suggested the presence of some degree of heteroscedasticity and identified in the extent of humidity (*humid*, Appendix) a major determinant of this pattern. This variable was therefore used as a weighting factor in the equations, estimated with maximum likelihood (WML).

If the missing value in the variable *humid* for Papua New Guinea (PNG) is assumed to be 100 (as recorded by tropical LDCs in the same region), and if Niger is omitted (because of a suspiciously low deforestation rate, relative to the figure for 1980-85), parameter estimates prove to be remarkably stable (except for equation [3], which is based on a smaller sample), statistically significant, and with no change in sign (apart from the notes at Table 2).

The stability of linear relationships, as measured by simple correlation coefficients, over different sample sizes, was tested on group A countries (as the possibly most reliable forestry data set within the sample). This analysis was again complemented with scattergrams. While the extent of annual deforestation in the two periods (*deforha* and *deforha1*) maintains a fairly stable pattern (r = 0.49), unlike full-sample cross-country results no statistically significant relationship is apparent between the respective annual rates (*defor* and *defor1*, r = -0.1). Within the subsample, some LDCs with relatively lower deforestation rates in the early 1980s appear to experience a higher rate in the second half of the decade (Paraguay, Togo, Sierra Leone), whereas the opposite tendency seems to occur for others (particularly Côte d'Ivoire and Nepal).

Unlike for the complete sample, a strong positive relationship is found between the percentage increases of deforestation and industrial roundwood production (r = 0.51), especially if the outlier position of the Gambia is taken into account. Similarly to statistical results for the full sample, more severe absolute reductions in forest cover have tended to take place in LDCs with relatively larger portions of land occupied by forests, more involvement in wood processing activities, lower foreign trade distortions, and higher per capita income (r equal to 0.6, 0.88, -0.46 and 0.96, respectively). Moreover, in this case, larger forest losses appear to occur in LDCs with relatively lower urban population pressures (note 11).

3.2.2   Regression results and hypothesis testing

In order to test the relevance of commercial logging activities, among the possible explanatory variables three were found to explain a large amount of cross-country variation (see adjusted R^2 of equation [1], Table 2). LDCs with a relatively higher soil humidity, lesser real exchange rate distortions (overvaluation), and, except for a country subsample (considered below), a more relevant role of timber processing activities in overall wood production, have tended to undergo a faster rate of deforestation (equation [1]). In terms of standardised beta coefficients, foreign trade and pricing policy factors, as proxied by the distortion index, appear to be less relevant than climatic or, limited to the LDCs concerned, sector-related structural features.

In contrast with the general pattern, in sixteen LDCs in sub-Saharan Africa, South America and South East Asia, listed in the Appendix (those marked with the superscript *p*, henceforth indicated as group *p*), the deforestation rate appears to be unresponsive to the relative share of wood processing activities (the sum of the estimated parameters associated with the variables *procwperc* and *procwdum* in equation [1] is close to zero). In some country cases, the distinction between this group of LDCs and the remaining subsample appears to reflect the effects of different national experiences in timber industry and trade legislation, and different forest management policies, such as, typically, Indonesia *versus* the Philippines (subsection 2.2). However, a few LDCs with substantially different forestry policies appear to belong to the same clusters. For instance, despite their different policies for logging concessions (subsection 2.1), Côte d'Ivoire and Gabon are both part of group *p*, as suggested by an inspection of the scattergram; Mali and Niger could belong to both LDC groups, since they lie close to the intercept value (there was no need to introduce an intercept dummy, besides the slope dummy *procwdum*).

Except for Ghana, all LDCs which are highly dependent on timber exports (marked with the letter *d* in the Appendix, and henceforth referred to as group *d*) form part of group *p*. This can explain the negative parameter associated with the corresponding dummy (*ddep*) if this variable replaces the share of wood processing in roundwood supply and its slope dummy (*procwdum*) (equation [2], Table 2). In the auxiliary regression for the variable *procwperc* (OLS in Table 2), the share of processed wood activities was found to be quite income-elastic in most LDCs, with the interesting exception, once again, of timber export-dependent economies. Given the estimated parameters of the slope dummy variable for real per capita income relative to group *d*-economies (*ypcdep*), and of the variable *ypc* (with both variables in logarithms), the income elasticity for this LDC group is statistically close to 1. While this equation explains nearly 60% of

the variation, no outlier cases are identifiable according to a histogram of studentised residuals (du Toit *et al.*, 1986:205-206).

Although other explanatory variables possibly related to commercial logging (including those listed in note 11) were found to have no direct influence on the average rates of deforestation over the whole decade, some of them do contribute to explain the respective rates registered in the first half of the 1980s (equation [3]). Given the levels of soil humidity (*humid*) and the percentage shares of national forests in country area (*tnarea*), the relationship between foreign debt exposure, proxied by debt service ratios in 1985, and annual deforestation rates over the preceding five years seems to be relatively better modelled with a quadratic polynomial (rather than a linear) form tracing a U-pattern: deforestation rates would tend to decrease until levels of debt service ratios around 20-30%, then to increase. However, a relatively low statistical significance and goodness of fit, as revealed by t-statistics and R^2, are associated with these regression estimates (not reported in Table 2). Moreover, this pattern turns out to be linear, and following the general literature expectations (namely that difficulties in debt service repayments are likely to put pressures on logging activities), if socio-political instability is accounted for (*inst*).

From the regression results of equation [3], the presence of an unstable institutional and socio-economic environment seems to represent a disincentive for logging operations. In contrast to regressions on deforestation over the whole decade, soil humidity assumes an unexpected negative sign (of limited statistical reliability), and broadly defined macro policy-related variables were found to matter relatively more, in terms of beta coefficients (especially international indebtedness, but also socio-political instability). These results are consistent with those of an earlier study, which reveal how the interaction between tropical deforestation and its possible determinants varies following changes in the global economic environment (Capistrano 1994)[18]. As expected, LDCs with a larger share of forest cover tend to show smaller deforestation rates, while the opposite was found to occur for absolute forest losses during the whole decade (equations [5] and [6]).

With reference to other sets of factors affecting tropical deforestation, high rates of increase in supply (and hence domestic consumption: WRI 1994, 314) of fuelwood and charcoal tend to induce a quicker pace of depletion of forest resources, as expected. In view of the narrow FAO definition on which the dependent variable is based and the indications of simple correlation coefficients, this process can be modelled with a two-year lag, rather than being assumed as strictly simultaneous (equation [4])[19]. Furthermore, given certain levels of soil humidity, the relative size of open forests (as a share of total natural

forest areas: variable *opentn*), and the relative distortion of the real exchange rate, a comparison of the values of the estimated parameters associated with the variables *fuelw* and *fuelwdum* (Appendix) in this equation, reveals how the implications for forest resources of increasing fuelwood production have been more disruptive in countries in Asia and Latin America, which do not heavily depend on this supply as a source of energy consumption.

The contradiction of this finding with indications of other studies on deforestation is only apparent. This result could in fact be interpreted in two ways:

(i)   developing economies with a high reliance on traditional fuels, most typically in sub-Saharan Africa, have been experiencing severe firewood shortages in the 1980s (Seager, 1995:46-47); and/or

(ii)   non-commercial logging mainly associated with household uses in these economies has had a slower impact on deforestation, compared to countries where fuelwood is destined to a greater extent to industrial uses.

In this respect, an inverted U-pattern can be observed in deforestation rates relative to the extent of open forests, with African LDCs predominantly lying around the descending part of the hyperbolic curve, i.e. with values of this variable above 40% (the estimated parameter of *opentn²* in equation [4] is significant at a 6% level). According to beta coefficients, the extent of open forest area appears to be a more relevant explanatory factor than the other determinants included in this equation.

Countries with a dynamic expansion of land under temporary crops in the 1980s have, in several cases, experienced substantial enlargements in permanent crop cultivations, and vice versa for LDCs showing barely any change, if not even some contraction, in both types of crops (e.g., Indonesia and Colombia among the former group, as opposed to Ethiopia and Niger among the latter). The use of both variables in a regression modelling the average annual extent of deforestation would therefore lead to problems of multicollinearity. On similar grounds, while WML estimates with soil humidity as a "hidden" explanatory variable and weighting factor, yielded a better regression fit than OLS, multicollinearity between *humid* and agricultural population pressure on land (*haap*) prevented the use of both variables as regressors. The correlation coefficient between these variables over the whole sample is -0.43 (99% confidence level), and is almost unchanged in the subsample used for equations [5] and [6]: LDCs with very high demographic pressure in rural areas, generally

located in West Africa and South/South East Asia, are mostly characterised by high soil humidity.

Regression results of equations [5] and [6] show how the expansion of cultivated areas has negatively affected the capacity of an LDC to preserve its forest resources, particularly if these resources cover a large share of the national territory and, unexpectedly, in the presence of relatively high availability of per capita arable land in rural areas[20]. Changes in the crop surface (variables *arl* and *xcr*) have been the most important determinant of annual reductions in forest cover, relative to the other two regressors (beta coefficients). Within these changes, those concerning export crops and similar cultivations, such as coffee, cocoa, and fruit tree plantations, have had a relatively stronger impact on deforestation than equivalent size variations in temporary crops and meadows (possibly nearly six times higher, according to the relative sizes of the respective estimated parameters: *xcr* and *arl*, equations [5] and [6]).

As a fourth set of possible determinants of deforestation, the role of road and mining development was assessed through equations [7] and [8], among others. Also in this case, no homogeneous behaviour is evident across LDCs. Among the economies which widened their domestic road system (over a 10-year period with five years of lead time relative to the reference decade)[21], infrastructure development appears to have been associated with subsequent large losses in forest cover in several cases (especially in Central America), while being practically "neutral" in others. This is reflected by regression results, if an appropriate intercept and slope dummy is used to account for the former group of LDCs (identified with the superscript *r* in the Appendix), and once the level of soil humidity is considered. For the other half of the sample, road development does not influence deforestation rates, especially if the sensitivity of the parameter estimate to sample selection is taken into account. As in equations [1], [2] and [4], real exchange rate distortions prove to be an inhibiting factor for deforestation activities.

According to regression equation [7], moreover, a high reliance on mineral exports has apparently (at an 19% level of significance) allowed a group of countries to maintain a lower pace of deforestation during the 1980s, relative to non-mineral LDCs and given the above pattern of infrastructure development. The hypothesis that forest resources may be subject to more rapid exploitation in the presence of reduced foreign exchange inflows from mineral exports does not receive support from econometric results. To this end, the dummy (*dmin*) was restricted to mineral LDCs affected by declining and highly unstable international prices for their main mineral commodity over the period 1960-85 (as occurring for aluminium, copper and phosphate rock: Mainardi 1995, 165): the estimated parameter turns out to be even lower (-0.36), at a higher

confidence level (10% level of significance). For the alternative dummy (*dminfor*), geared to identify more accurately LDCs whose forest wealth might have partly been threatened by mining operations, a statistically significant positive parameter is estimated in [8], thus substantiating the complementary role of mining relative to other industrial logging activities in these five developing economies.

General models trying to simultaneously encompass all relevant aspects, provided shaky regression results, due to multicollinearity. At a less general level, two *encompassing* models yielded statistically significant estimates, and can be useful to check the stability of parameter estimates in previous equations. Equation [9] tests factors mainly related to infrastructure/mining development and commercial logging, whereas the latter, along with fuelwood gathering activities, are re-assessed in equation [10]. The signs of estimated parameters are unchanged. In regression [10], the overall goodness of fit is even slightly reduced, compared to the *nested* equations [1] and [4]. Relative to equations [1] and [8], equation [9] yields lower parameter estimates in absolute value for *procwperc/procwdum* and *roaddum*. Notwithstanding the remarks in subsection 3.2.1, this may indicate some minor bias in the earlier estimates.

Similarly to previous results, both equations [9] and [10] highlight how the relative importance of each determinant can remarkably vary across LDC groups. For instance, the parameter estimates of the dummy variables for road infrastructure accounting for half of the sample (*dumroad* and *roaddum*) show the importance of this factor for deforestation, while the opposite seems to apply to the rest of the countries, given the statistical insignificance of the parameter for the variable *road* (excluded from equation [9]). Similarly to results of equation [8], this problem appears to be of particular concern for Ghana, Thailand, and the Philippines: given the parameter values of the dummies *dminfor* and *dumroad*, and the constant term in equation [9], other explanatory variables tend to start exercising some influence on deforestation rates in these three economies when these rates are already close to a theoretical level of 2% p.a.. A particularly high beta coefficient is associated to the variable *opentn*: open forests are scattered across agricultural and other land uses, and are therefore more subject to (partly non-commercial) logging activities. As in equation [4], however, this relationship appear to be non-linear.

4.   CONCLUSIONS

Lack of reliability and accuracy of several LDCs' forestry data have discouraged, until recently, the application of econometric techniques in order to assess different determinants of deforestation. Improvements in remote sensing and

satellite imagery have allowed to better systematise the statistical information, although substantial differences in the quality of these data persist across LDCs. This study has focused on a selected group of LDCs, almost entirely based on a relatively more favourable assessment of their forestry data by the FAO. Relative to alternative sources, FAO is considered to provide more accurate and comparable cross-country estimates in this research field (Barraclough-Ghimire, 1995:9).

The econometric analysis has underlined the importance of distinguishing the use of different *proxies* for the phenomenon to be explained (*defor, deforha*), and of relating each of them to suitable explanatory variables (e.g., *deforha* and *xcr*). The results show how specific factors (relative extension of forest areas; population pressures on land) even interact in opposite ways with the two dependent variables. The analysis also points to the need to go beyond the use of simple correlation and general regression models in order to test the relevance of determinants of deforestation (e.g., Reis and Marguilis, quoted by Burgess, 1993:140, note 27), since this can provide misleading results by hiding substantially different patterns across LDCs.

Possible direct and indirect factors affecting tropical and subtropical deforestation were tested. The *rate* of deforestation is on an average higher in tropical than subtropical regions: *ceteris paribus*, a 10% increase in soil humidity tends to be accompanied by an increase in average annual deforestation rates ranging between 0.06 and 0.1 percentage points (except for the nearly neutral impact implied by equations [7]-[9]). However, LDCs with predominantly arid or semi-arid land (marked with an asterisk in the Appendix) have a relatively smaller stock of forest resources. The median value of the percent share of natural forests in the total national area in 1980 was nearly 21 for these six countries (with forests mainly of an *open* type, except for Pakistan), whereas it amounted to 36 for all other LDCs of the sample.

In forest resource-dependent LDCs, a relatively larger presence of timber processing activities tends to be less related to the level of development and has not generally had, as yet, severe implications on the rate of forest exploitation. By contrast, in most other LDCs the development of a processed wood industry, and, indirectly, the level of development, did have an influence on deforestation in the 1980s. In the latter countries it may have been more difficult to implement efficient forest management policies, aimed at restraining the pace of forest depletion while striving for a higher value-added domestic wood industry. Similarly to forest resource-dependent LDCs, mineral economies appear to have been able to better 'spare' their forest resources, other things being equal,

although this result does not hold for LDCs with alluvial and openpit deposits concentrated in forest regions.

Increased fuelwood production and consumption has also been a factor of high deforestation. This has especially concerned some Asian and Latin American countries, often characterised by intermediate extensions of open forests as a share of the total natural forest cover (30-70%). In some of these countries, especially in Central America, the deforestation process has been fostered by an expansion of the internal road infrastructure. A relatively larger endowment of natural forest resources and lesser exposure to foreign debt obligations appear to have allowed some LDCs to undertake a lower deforestation in the early 1980s, but these factors seem to have gradually lost such a role over the decade. With reference to controversial results of the literature, exchange rate misalignments and socio-political instability were found to have been a deterrent for logging activities, in spite of the arguments considered in section 2.

Unlike a study by Barbier *et al.* (1994: 30-32), an increasing supply of industrial wood was not found to affect deforestation, if two outliers (Jamaica and Pakistan) are excluded, and abstracting from the correlation analysis on a small subsample (group A), nor does a poorer performance in average cereal yields play a negative role[22]. Desertification in the Sahel could not be captured as a factor influencing deforestation in that area, possibly due to its slow effects. Cross-country disparities in inflationary pressures are not a relevant explanatory factor for either *rates*, or, with the possible exception of hyperinflation-ridden economies (Bolivia and Peru), *extent* of tropical deforestation in the 1980s. No clear relationship was also found between the deforestation process and macroeconomic features such as GDP growth, ODA inflows, and urban population growth. Although this aspect was not examined in detail, the statistical results did not lend support to an *environmental Kuznets* curve hypothesis, referred to in section 2.2. Other factors examined with panel data (time series cross-province) on individual LDCs (Panayotou-Ashton, 1995:269-270), namely agricultural crop and log prices, could not be included in this analysis.

At this level of aggregation, no distinction could be drawn with regard to territories within individual countries, individual crops, or soil conditions other than the degree of aridity/humidity. In countries characterised by substantial regional differences, such as Indonesia or Malaysia, such a distinction could confirm the hypotheses on different prevailing factors of deforestation, and their different order of importance: agro-conversion in relatively more developed areas; fuelwood gathering in highly populated poorer regions; and shifting cultivation and logging in more sparsely settled territories (Gillis 1988 and

1988a). Similarly, it has been argued that varying agricultural export crops can be expected to entail different extents of deforestation (Amelung-Diehl 1992:54; Barraclough-Ghimire, 1995:187): whereas cotton, maize, rice and banana require the clearing of large forest areas, plantations of cocoa, coffee, tea and oil palms have less destructive effects. Apart from these limitations, on the whole the econometric results confirm how increasing demand for agricultural land, especially that for permanent crop plantations, has had a definite impact on the *extent* of deforestation.

Despite low timber rents (due to the widespread downward bias in local governments' stumpage valuation of forests) and substantial forest resources, some LDCs (Congo, Gabon, PNG) seem to have so far succeeded in limiting the pace of domestic deforestation. However, this relative success has largely been facilitated by the presence of relevant alternative sources of tax revenues, and the inaccessibility of wide forest areas. By contrast, governments in most LDCs have seen forests as a policy instrument for provisorily addressing structural problems, particularly demographic pressures, poverty and unemployment, and foreign exchange shortage. This is likely to have been prompted by the wish to avoid or postpone more controversial policy decisions, such as reforms in the agricultural and domestic credit sectors.

Notes

1.   The term *subtropical* forest is henceforth replaced in the text by the more accurate terms of tropical deciduous and tropical dry forests, as distinguished from tropical rainforests (the most prevalent form of forests in the tropical regions). These three forms of tropical forests represent slightly over half of the world's forest cover. A small number of LDCs have mostly temperate forests, with their territory fully or mainly located in temperate regions (Chile, Argentina, North and South Korea); a few other LDCs, despite belonging to subtropical regions, have also extensive temperate forests (e.g., Nepal, which is included in this analysis). On the whole, forests in temperate regions are estimated to have even increased their cover, especially in the upper northern latitudes, partly as an effect of global warming and the removal from production of agricultural land, which has subsequently been afforested. However, opposing views have been expressed with regard to the extent of the environmental degradation affecting these forests (Le Hir 1996). Global warming is thought in turn to have been determined to a large extent (by one fifth up to one fourth) by carbon emissions due to tropical deforestation (Pearce-Brown 1994).

2.   Panayotou and Ashton (1995: 270) argue that "there have been remarkably few attempts to statistically quantify and rank the major causes of tropical deforestation".

3.   The FAO Forest Resources Assessment distinguishes among four forest ecosystems, namely rain, moist deciduous, dry (subdivided into dry, very dry and desert areas), and *mixed* alpine type (*hill and montane*:above 800 m) (WRI 1994: Table 19.2). In spite of its usefulness as an initial attempt of classification in this respect, the preliminary nature and limited reliability of forestry data at this level of disaggregation would probably cause distortions to econometric results. This information was not therefore included in the analysis. Data on forest plantations (established for afforestation or reforestation purposes) and protected forests were also not included, because of insufficient homogeneity across countries (WRI 1994:312). The inclusion of the latter estimates would substantially reduce the annual rates of total deforestation in the 1980s (by at least 0.6 percentage points) only for three LDCs in the sample (Burundi, Bangladesh and Vietnam) (WRI 1996: Table 9.2).

4.   A review of these studies is offered by Barbier *et al.* (1994: ch. 3), while four studies on individual South East Asian countries are reviewed by Panayotou and Ashton (1995: 267-270). According to the World Bank, new agricultural settlements account for 60% of tropical deforestation (quoted by Barraclough and Ghimire 1995:13).

5.   The FAO defines *deforestation* as "the change of land use or depletion of crown cover to less than 10%" (Barbier *et al.* 1994: 7). This change is the result of "permanent clearing of forest lands for use in shifting cultivation, permanent agriculture, or settlements". As such, it does not account for selective logging activities (WRI 1990: 296), or forests which have been logged and left to regenerate (WRI 1996:203).

6.   For instance, Barbier *et al.* (1994:29) stress the need to distinguish between *production* and *conversion* forests. Production forests are used solely for the extraction and processing of industrial wood. As such, they are more subject to logging regulations which take into account the regeneration times of timber, and to extensive tree replanting programmes. According to the above authors, should log production be especially associated with conversion forests, then timber extraction activities would mainly be a precursor or by-product of agricultural conversion. Even if the statistical information is not always reliable and exempt from national discrepancies, FAO deforestation estimates do actually focus on conversion forests (see notes 3, 5, 8 and 10).

7.   These effects do not always work in the same direction. Trypanosomiasis is a disincentive for cattle ranching, and therefore does not encourage deforestation in the affected African countries (Gillis, 1988b:345).

8.   Some studies consider only changes in closed forest areas as a proxy for tropical deforestation (Barbier *et al.*, 1994:31). The FAO definition of closed forests is "land where trees cover a high proportion of the ground and where grass does not form a continuous layer on the forest floor". As a threshold criterion for remote sensing, in these forests the crown coverage makes up 40% or more of the area. By contrast, open forests are constituted by "mixed [broad-leafed] forest/grasslands, with at least 10% tree cover and a continuous grass layer" (WRI, 1990:296). Barraclough and Ghimire (1995: 9-10) argue that, in practice, this distinction, far from being unambiguous, leaves wide scope to the observer's judgement.

9.   A different opinion is expressed by Amelung & Diehl (1992:37), for whom tropical "wood is predominantly harvested in the form of selective logging". However, no empirical evidence is provided to support this view, which contrasts with results of a survey by the ITTO (International Tropical Timber Organisation) (WRI 1990: 106). This survey shows that sustainable timber production in the 18 ITTO producer-members constitutes less than 1% of the exploitable tropical forests. Both studies do agree about the frequent permanent loss of regenerative capacity by forests affected by logging activities in LDCs.

10.   A more recent assessment by the FAO has reclassified a few countries: for instance, Mali and Rwanda, which did not stand out favourably in the 1988 survey, have been included in the high-reliability category, whereas several other African LDCs have been downgraded. On an average, relatively more accurate primary data on national forest resources are found in Asia (WRI, 1994:312). The 1996 WRI report, which was unavailable at the time of this research, provides the same FAO forest resource estimates as the 1994 report (with deforestation rates reported at the second decimal: Table 9.2), with no updated estimates for the 1990s. Alternative FAO forest data, used by Cropper and Griffiths (1994:252), assume a broad definition of forest land, including, besides natural forests, plantations and woodland which has been cleared, but is expected to be reforested in the foreseeable future (FAO 1993: Table 1). Besides being mainly based on unofficial figures or estimates for LDCs, the use of the latter data is subject to the drawbacks expressed in subsection 2.2. Rudel & Roper (1997) follow a radically different approach: while questioning the reliability of FAO deforestation data for most LDCs, their analysis is mainly based on a dichotomous qualitative variable which distinguishes between high and low rates of deforestation, with a cutoff point being set at 1% per year.

11.   The discarded variables included: (i) the percent change in industrial roundwood production (1978-88 and 1980-90); (ii) the relative importance of ODA inflows (as a percentage of GNP, 1985/90 average); (iii) the average annual growth rate of GDP, inflation, and urban population (1980-90); (iv) a dummy variable for 11 LCDs in or close to the Sahel region; and (v) another

dummy, partly overlapping with the former, for 10 LDCs, accounting for the particularly low levels and weak performance of average yields of cereals (less than 1 t/ha in 1989 and a percent change over 1979-89 not exceeding 20%, or, with the only case being the Gambia, an end-of-period average yield slightly higher than 1 t/ha, but with no improvement over the decade). The dichotomous distinction implied by (v) was preferred to the original data, in view of the likely scarce comparability of countries with relatively high and medium average yields, while attention was focused on LDCs with a particularly low productivity in agriculture. Given the high variability of the ODA share in GNP over the late 1980s for some African LDCs, the ODA/GNP variable was averaged between the mid-period year and the final year, instead of solely relying on 1985 data.

12.   For LDCs, most annual time series figures of these variables are estimated by the FAO, and otherwise obtained from official and unofficial information of individual countries. For this reason, a statistical analysis aimed at identifying the most suitable time lag, although desirable, is not likely to yield robust estimates.

13.   An alternative dummy, based on a share of exports in domestic production of tropical hardwood exceeding 30% in 1988 (Amelung-Diehl, 1992: Table A2), would just remove four countries (Cameroon, CAR, Côte d'Ivoire and Indonesia) from the group identified by *ddep*. As such, this alternative criterion is not expected to produce substantially different results than those obtained with the chosen dummy variable.

14.   At a similar level of political unrest, a democratic government is expected to be politically more stable than a non-democratic one (Gupta, 1990:197; Alesina-Perotti, 1996:1208). A second reason, adduced by the latter authors, lies in the offsetting effect of this dummy with regard to indicators of socio-political unrest (deaths in domestic disturbances, unsuccessful coups), which are likely to be under-reported in authoritarian regimes.

15.   The distinction between level 1 and level 2 variables is to some extent arbitrary, depending on the assumptions of a model. A *frontier* model emphasising the role of logging companies, farmers and road infrastructure will tend to see demographic pressures as a possible underlying factor. By contrast, this variable can be hypothesised to have a greater direct impact on deforestation within an *immiserisation* model, focused on shifting cultivation and agricultural migrants (Rudel-Roper, 1997:55-56). However, one can still distinguish variables related to predominantly direct as opposed to underlying causes, especially by considering that alternative assumptions are often applicable to the same location in a sequential manner (e.g., the frontier model in phases of economic expansion, and the immiserisation model during periods of severe decline in non-farm job opportunities) (*ibidem* : 62-63).

16. The distorting presence of outliers can cause serious estimation problems when using absolute deforestation figures, and other absolute changes in land use. While the median value of the sample for the variable *deforha* is 88 (thousand ha), the respective figure for Indonesia is 1212. An even stronger skewness characterises the sample distribution of the variables *arl* and *xcr*.

17. A symptomatic example is represented by the scattergram and linear fit of the rate of deforestation on percent cropland expansion across Asian LDCs (1964-84), presented by Panayotou & Ashton (1995:259, Fig. 14.1). Despite the opinion of its authors ("The statistical model ...is fairly robust given the complexity of the problem being analysed, ...", *ibidem*, 31), an OLS regression model by Barbier *et al.* (1994: Table 3.3) can also be called into question as to its overall statistical robustness, since it yields an R^2 of 0.27 while relying on a 53 tropical LDC sample and six explanatory variables (including a dummy). One should however notice that, while retaining the properties of consistency and asymptotic efficiency, the weighted maximum likelihood (WML) method suffers from a slight downward bias in the estimated standard error of regression in small samples. This bias is bound to increase the probability of type I error (larger t statistics for the estimated parameters).

18. These results are not fully comparable, since equations [1] and [2] refer to nearly all observations of the sample, while equation [3] to 26 observations, mainly due to the limited availability of cross-country information on socio-political instability (*inst*). The real exchange rate distortion index (*dist*) was found to be unrelated to annual deforestation in the first half of the 1980s. However, relative to the 29 LDCs with estimates for both *inst* and *dist*, these variables are highly correlated (r = 0.36, with a 5% significance level). LDCs experiencing low levels of socio-political instability during the period 1960-85 often fared better also in terms of a free trade-related real exchange rate over the last part of that period (e.g., Costa Rica and Malaysia), and vice versa for economies affected by a high socio-political unrest (Bolivia, Congo, Nigeria). The variable *inst* can therefore be related to some extent to the macroeconomic policy environment.

19. The correlation coefficients of deforestation rates vis-à-vis percentage changes in fuelwood and charcoal supply with (*fuelw* in the Appendix) and without a two year lag are 0.41 and 0.34, respectively. However, if the simultaneous, instead of the lagged, values are used for the variables *fuelw* and *fuelwdum* in equation [4], regression results are substantially equivalent, in terms of size and statistical significance of estimated parameters (see also remarks in subsection 3.2.1, second paragraph).

20. It should be added that, consistently with results of another study relying on a similar variable (Cropper-Griffiths, 1994), a negative sign would be obtained for the variable *haap*, if used as a regressor for *defor*, instead of *deforha*. As

mentioned in the text, multicollinearity problems with the soil humidity variable led to exclude this variable from the other regressions. This example highlights the need to test alternative hypotheses on tropical deforestation by clearly identifying the purpose of the deforestation proxy (e.g., rates *versus* absolute figures). For instance, Capistrano (1994:77) argues that "the smaller the ratio [of arable land to agricultural population], presumably, the greater the constraint on cultivable land, and the greater the likelihood that forests would be cleared for agriculture". However, in regressions on 45 LDCs, she uses a dependent variable similar to *deforha*, and her results report the same unexpected sign for *haap* as equations [5] and [6]. Relative to equation [5], the variable *dist* may be seen as a proxy for price-related factors influencing agricultural land expansion related to cultivation of export crops (*xcr*). For the regression sample, the correlation between the two variables is statistically insignificant (r = -0.15), even if with the expected sign.

21.   The few LDCs which register no improvements in road length, such as Burkina Faso and Mozambique, present low rates of deforestation. In contrast with the *lead* variable *road*, the respective *lag* variable (subsection 3.1.2) is uncorrelated to the dependent variable, thus implying that road infrastructure development may be a relevant factor of deforestation at an early stage.

22.   Surprisingly, Barbier *et al.* use *level* variables, namely industrial roundwood production per capita and agricultural yield in 1980, respectively, regressed on five year changes in closed forest area (note 17). For this analysis, see note 11.

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Appendix - LDC sample and variables

List of countries

Group A (11 LDCs): Benin^r, Cameroon^{dmp}, Colombia^p, Côte d'Ivoire^{dpr}, Gambia, Malaysia^{dpr}, Nepal, Paraguay^r, Sierra Leone^m, Togo^{mr}, Venezuela^{mpr};

Group B (27 LDCs): Bangladesh^r, Bolivia^{mpr}, Burkina Faso, Burundi, Congo^{dmp}, Costa Rica^r, Dominican Republic^r, El Salvador^r, Guatemala^r, Guinea^{mr}, Guinea Bissau, Honduras^r, Jamaica^m, Laos, Madagascar^p, Mozambique, Myanmar^r, Namibia*^{m}, Nigeria^{mp}, Panama^r, Papua New Guinea^{dmp}, Peru^{mp}, Philippines^r, Senegal, Sri Lanka^r, Thailand^r, Vietnam;

Group C (10 LDCs): Botswana*^{m}, Central African Republic^{dp}, Chad*, Gabon^{dmp}, Ghana^{dr}, Ethiopia, Indonesia^{dmp}, Mali*^{p}, Niger*^{mp}, Pakistan*.

- * 75% or more of total land area is arid or semi-arid (WRI 1992: Table 18.6)
- *d* high reliance on timber product exports (>5% of total exports) (Barbier *et al.*1994: Table 2.6)
- *m* high reliance (40% or more) of export revenues on mineral commodity exports (World Bank 1992: Table 1.3; *WDR* 1994: Table 15)
- *p* low incidence of deforestation relative to importance of domestic timber processing
- *r* high incidence of deforestation relative to domestic road infrastructure development

List of variables

<u>dependent variables</u>

defor	average annual deforestation rate (natural forest, %, 1980-90).
defor1	average annual deforestation rate (natural forest, %, 1980-85).
deforha	average annual extent of deforestation (natural forest, 000 ha, 1980-90).
lnprocwp	natural logarithm of *procwperc* (*procwperc* is defined below: the antilogarithm of the fitted values of *lnprocwp* was used as a regressor in other equations).

<u>explanatory variables</u> (for other reference periods/variables: see text)

arl	average annual change in arable land (000 ha, 1982-92).

ddep	dummy *timber export dependency* (1 for 9 LDCs indicated with *d* above, 0 otherwise).
dist	real exchange rate distortion index (1976-85; Dollar 1992: Table A1).
dmin	dummy *mineral economies* (1 for 16 LDCs indicated with *m* above, 0 otherwise).
dminfor	dummy *large openpit mines and/or alluvial deposits located in forest areas* (1990: 1 for PNG, Philippines, Thailand, Ghana, Indonesia, 0 otherwise; Amelung-Diehl 1992: Table 25).
dsr	debt service ratio (% debt service/exports of goods and services, 1985).
dumroad	dummy *apparent forest-disrupting road development* (1 for 20 LDCs indicated with *r* above, 0 otherwise).
fuelw	percent change in fuelwood and charcoal production (1978-88).
fuelwdum	fuelw multiplied by 1 for LDCs with high dependence of domestic energy consumption on fuelwood and charcoal (sub-Saharan African LDCs, Dominican Republic, Laos, Nepal), 0 otherwise (Seager 1995: Table 16).
haap	arable land (1982)/agricultural population (1985).
humid	% humid soil in total land area (WRI 1992: Table 18.6).
inst	socio-political instability index (1960-1985; Alesina-Perotti 1996: Table 2).
lnypc	natural logarithm of *ypc* (*lnypcdep*: *lnypc* multiplied by *ddep*)
opentn	open/total natural (open+closed) forest (%, 1980).
procwperc	processed wood (sawnwood+panels)/roundwood production (%, 1988).
procwdum	*procwperc* multiplied by 1 for 16 LDCs indicated with *p* above, 0 otherwise.
road	average annual compound rate of change in total road length (main [paved and unpaved] roads and unclassified lower standard roads, 1975-85).
roaddum	*road* multiplied by *dumroad*.
tnarea	total natural forest/country area (%, 1980).
xcr	average annual change in land under permanent crops (000 ha, 1982-92).
ypc	(constant 1980 US$) PPP-converted per capita income (1985; RGDP2 in Summers-Heston 1988).