Dynamics of small-scale deforestation in Indonesia: examining the effects of poverty and socio-economic development

R.S. Purnamasari

An empirical analysis suggests that the rate of deforestation is actually lower in poorer regions; it increases at first with wealth, but subsequently decreases after a certain wealth level is reached.

Ririn Salwa Purnamasari is an Economist in the World Bank office in Jakarta, Indonesia and is a Research Partner of the Poverty Environment Network (PEN) of the Center for International Forestry Research (CIFOR).

Forest-dense areas are frequently associated with high levels of poverty (Chomitz *et al.*, 2007). The areas are often remote from markets and services and lack infrastructure. Opportunity costs of labour are low. The population also often lacks the finance necessary for investments to maintain the quality of soil or increase yields on the existing cleared land. Deforestation, including clearing for agricultural activities, is often the only option available for the livelihoods of farmers living in forested areas (Angelsen, 1999).

Does this mean that poverty in the frontier areas is the driving factor of small-scale deforestation? Should areas of greater prosperity, with better infrastructure and market integration, be expected to be associated with lower deforestation? Previous studies of poverty and deforestation have given ambiguous results. On the one hand, regional development is expected to create new opportunities for local people and improve their livelihoods, while on the other hand, poverty alleviation and improvements in well-being could also ease capital constraints and facilitate more forest conversion. Better understanding is therefore needed of the impact of regional development on rural livelihoods and the well-being of people in forest areas and, in turn, the implications for the rate of small-scale deforestation.

As in other developing countries, deforestation in Indonesia is the result of complex socio-economic processes. Poverty is widely considered to be an important underlying cause of forest conversion by small-scale farmers. This article presents the findings of a study that examined the contribution of different regional-level socio-economic and physiogeographic factors (such as altitude and slope of land) to the dynamics of small-scale deforestation in three primary forest areas in Indonesia – Kalimantan, Sumatra and Sulawesi – which together constitute about 60 percent of Indonesia's total forest cover.

R.S. PURNAMASARI

Small-scale deforestation in East Kalimantan, Indonesia

The analysis was conducted at the district level. A temporal and spatial econometrics approach was used to investigate the extent to which various facets of poverty and regional development motivated people to clear forest land in 124 districts over an 18-year period (1985–2003). For the purpose of the study, deforestation refers to small-scale district-level deforestation, unless otherwise indicated.

CONCEPTUAL FRAMEWORK

The theoretical framework employed in this study is a dynamic optimization model of irreversible land-use change as in Kerr, Pfaff and Sanchez (2002) and Vance and Geoghegan (2002). The framework models the decision of an individual land user about whether or not to convert a patch of land from its forested state to agricultural use in response to changing economic conditions over space and time, given location-specific factors affecting returns from the land. The assumption about the irreversibility of land-use change is broadly consistent with the reality of tropical deforestation today, as most cleared land is not returned to its previous forested state (Kerr *et al.*, 2004; Vance and Geoghegan, 2002). The impact of expected returns from conversion to agriculture is seen clearly in the case of the impact of agricultural commodity prices on deforestation. Even when the increase in commodity price is only temporary, it tends to raise expectations about future prices, increasing the expected profitability from land clearance and conversion to agriculture (Angelsen, 1995; Sunderlin *et al.*, 2000). Thus, even if prices subsequently fall to a level insufficient to stimulate clearing, the price fall might not lead to abandonment and hence reforestation on recently cleared land.

This model provides some key insights into the process of irreversible land conversion. However, it leaves out some key factors that can influence the decision-making of farmers living on forest frontiers. In particular, the nature of property rights and changes in traditional community ownership systems produce incentives to induce earlier land conversion. Nevertheless, in Indonesia property rights over forest land are not well defined in practice, although most forest land is formally controlled by the State. In most frontier areas, forests are generally regarded by communities as an open access resource with free entry and no restrictions on land use. This means that, in general, an individual farmer can exercise control over the land-use options for any selected patch of forest land and decide whether to keep the land in its current forest state or convert it to agricultural production. Therefore, while the loss of property rights to a parcel of forested land is not directly measured and incorporated in the model, it can be considered and included as one of the potential costs of allowing land to remain in its traditional forested state.

POVERTY CONTEXT

Some have argued that poor people clear forests and cultivate new lands in order to maintain yields because they cannot finance the necessary investments to preserve soil quality of the existing cultivated land (Zwane, 2007). Poor people tend to be clustered in frontier areas with inadequate access to market institutions (which would limit transaction costs), transport infrastructure, means and services. In this situation, labour-intensive land clearing is more profitable than other activities for these poor people (Deininger and Minten, 1996; Vedeld *et al.*, 2004). In other cases, the expansion of cultivated areas for crop diversification is a coping strategy for poor people who are vulnerable to price volatility and other types of uncertainty (Sunderlin, et al., 2000). On the other hand, poverty may reduce deforestation because of the lack of capital necessary to clear land (Wibowo and Byron, 1999).

Individual farmers make land-use decisions taking into account expected costs and revenues associated with each alternative. The decision is also affected by farmers' resource constraints. Thus, other things being equal, one can expect that if expected returns from agriculture increase, then deforestation rates are likely to increase. If forest conversion is costly and/or there is a long gestation period for positive returns from agriculture, then poorer, liquidity-constrained farmers are less likely to shift to increased land-clearing activities.

Clearly, there is no simple theoretical expectation as to the impact of poverty on land-use activities. The signs and relative magnitudes of the different factors associated with poverty need to be investigated empirically.

EMPIRICAL ANALYSIS

A population-averaged panel model was used to estimate the annual deforestation rate (the dependent variable) as a function of relative returns from forest conversion to agriculture and factors affecting them, including poverty and development (the explanatory variables) (Table). Of 142 total districts in the study region, 18 were excluded from the analysis because they lacked either forest area or the data needed for the estimations.

The technical details are omitted from this article but are available from the author.

Dependent variable: deforestation rate

Data on forest area and forest area change were derived from geographic information system (GIS) analysis of satellite images of land cover observed at five points in time: 1985, 1990, 1996, 2000 and 2003. Since Indonesia does not have nationwide integrated data on land cover, forest cover data are derived from land cover maps from several sources: the Regional Physical Planning Programme for Transmigration (RePPProT) for 1985 maps, the National Forest Inventory project of the Ministry of Forestry for

Summary statistics of the variables

Variable	No. of observations	Mean	Standard deviation	Minimum	Maximum
Annual deforestation rate (%)[a]	496	0.0475	0.1145	0.0001	1.6198
1985–1990 (%)	124	0.0181	0.0441	0.0001	0.4294
1990–1996 (%)	124	0.0062	0.0186	0.0002	0.1927
1996–2000 (%)	124	0.0237	0.0622	0.0003	0.6464
2000–2003 (%)	124	0.1420	0.1856	0.0001	1.6198
Wealth index	496	25.1494	2.9920	18.0000	39.0000
1986	124	24.1925	2.9690	19.2553	39.0000
1990	124	24.4692	3.0081	19.9143	37.0000
1996	124	25.8967	2.7450	21.1596	34.1667
2000	124	26.0393	2.8067	18.0000	34.6667
Return proxies					
Industrial crops suitable (% forests at risk)	496	23.2635	28.2052	0.0000	100.0000
Arable suitable (% forests at risk)	496	13.2830	20.0333	0.0000	100.0000
Distance to province capital (km)	496	127.0543	105.4845	0.0000	752.4142
River density (km/km^2)	496	0.2887	0.1549	0.0356	0.6346
Proxies for regional developments					
Per capita regional GDP (million Rp)	496	1.4606	1.1043	0.4055	9.9305
Industrial workers – proportion of population (per 1 000 persons)	496	7.0948	12.4597	0.0000	141.2487
(Lagged) Population density (persons/km^2)	372	258.3463	682.2017	2.0130	5760.0470
(Lagged) Annual HPH deforestation rate	372	0.0687	0.1802	0.0000	1.0000
(Lagged) Cumulative deforestation (% total forests period 1)	372	0.1355	0.2866	0.0000	3.2651
Neighbouring district variables (average)					
Per capita regional GDP (million Rp)	496	1.2874	0.7547	0.0000	5.8792
Industrial workers – proportion of population (per 1 000 persons)	496	6.2611	6.5602	0.0000	42.9607

[a] For this table the deforestation rates are presented in % (the actual values and their standard deviations are multiplied by 100).

1990 maps, and the Planning Department of the Ministry of Forestry for 1996/1997, 2000 and 2003 maps, including maps of forests allocated for logging concession (referred to as *hak pengusahaan hutan* [HPH]) from 1980 to 2000. Although the data are the best available, they vary in terms of scale and precision and possibly contain inconsistencies, and they should be interpreted with caution (Chomitz *et al.*, 2007; FWI and GFW, 2002).

All series of the land cover maps were first regrouped into two broad categories – forests and non-forests – so they could be integrated across time. The forest and non-forest maps were then overlayed with HPH maps to exclude the large-scale concession areas from the forest area considered to be potentially clearable by small-scale farmers. Formally, most forests in Indonesia are State owned, although in practice they are open access. Nevertheless, small-scale deforestation activity normally only takes place in areas not designated for HPH, and for this reason the HPH areas are excluded from the forest areas that can potentially be cleared by small-scale farmers. The new maps were then overlaid with the 1996 district boundary maps to generate data sets on forest area by district for each point in time.

Small-scale deforestation is defined here as a cleared patch in the range of 0.05 to 10 ha. Dewi *et al.* (2002) assert, and are supported by some field observations, that small patches of deforestation are mostly associated with smallholders' activities in agriculture. The small-scale deforested area for the district level is obtained by aggregating all small-scale cleared patches in the whole district.

The dependent variable, the annual deforestation rate (in percentage), is defined as the area deforested between periods divided by the total forest area in the initial period of interest. The deforestation rates were generated for the periods 1985–1990, 1990–1996, 1996–2000 and 2000–2003. Because the time intervals are different across the periods, annual deforestation rates were used for the estimation, assuming that this annual rate was the same in each year within the period. Annual deforestation rates were calculated using the FAO formula for calculating the annual rate of forest change, based on compound interest principles (FAO, 1995).

Explanatory variables

To match with the dates of the dependent variable, the study used data dates of 1986, 1990, 1996 and 2000 for the explanatory variables.

Poverty measure. The use of poverty as an explanatory factor in a deforestation model can lead to an endogeneity problem, resulting from the possibility of reverse causality: poverty is normally defined as a lack of income, and that income is a function of deforestation activities. Therefore, per capita income is not used as a poverty measure in the estimation. Instead, poverty incidence was assessed using a wealth index based on infrastructure and facilities, natural resources and socio-economic conditions at the district level. A regional wealth index was generated from the National Village Potential Survey (PODES) data for 1986, 1990, 1996 and 2000 from Badan Pusat Statistik (Statistics Indonesia).

Proxies for returns to clearing. Since direct information on agricultural and forest-product returns which is consistent across different products and over time is difficult to find, proxies were used.

To capture unobserved agricultural productivity, two district land suitability measures, derived from RePPProT maps, were used: the proportion of the district forested area at the beginning of each period that was suitable for food crops (arable suitable) and for tree crops such as cocoa, palm oil, rubber and coffee (industrial crops suitable). The land suitability assessments, which were based on topography, climate, water and soil characteristics, indicate the most beneficial or productive use of the land. River density and distance between district and provincial capital cities were used as proxies for transport costs and access to markets.

Proxies for regional development. Although the effect of development is already indirectly taken into account through several factors in the wealth index measurement, the study also includes some direct measures for district development, to examine better the direct effect of the development process on relative returns and hence clearing patterns.

The first measure of district development is per capita non-oil regional gross domestic product (regional GDP) (Statistics Indonesia, 2007) . Since this measure is based on the market value of all final goods and services in the region over time, regional GDP represents regional economic and general development, including infrastructure and institutional development.

Industrialization is expected to improve the social and economic welfare condition of the regions and also to offer more economic opportunities to people – an important factor affecting deforestation rates (Angelsen, 1999; Godoy *et al.*, 1996; Shively and Pagiola, 2004). Thus, in addition to regional GDP, the proportion of the population engaged in the district's industries was included as a proxy for off-farm employment opportunities.

The impact of population density on deforestation has been a subject of controversy. Several studies of deforestation have included population density in the analysis, but no systematic relationship has been seen (e.g. Cropper, Griffiths and Mani, 1999; Pfaff, 1999; Uusivuori, Lehto and Palo, 2002). To investigate the impact of population on the pace of deforestation, population density was included in the study as one of the explanatory variables.

In Indonesia, HPH activities could stimulate local development in the surrounding areas, which in turn could either stimulate deforestation in the area (Angelsen, 1995) or stimulate off-farm economic activities which could cause a shift away from clearing (Levang, 2002). To capture these potential effects, the estimations include the annual HPH deforestation rate.

The study also included a district's cumulative deforestation as another proxy for local development.

Land-use patterns in a given district are possibly not only a function of variables for that district, but may also reflect the characteristics of neighbouring districts as a result of shared constraints and opportunities, networks or externalities. The study therefore included variables reflecting economic development, off-farm employment opportunities and population density in neighbouring districts.

RESULTS AND DISCUSSION

Poverty and deforestation

The estimation results show a significant impact of poverty on deforestation. The observed relationship between poverty and deforestation follows an inverted U-shape which implies that deforestation is lower in the poorest districts. One possible explanation is that people in severe poverty lack the means to convert land to agricultural cultivation and prefer to have income that can be generated quickly – in the form of cash or subsistence – such as that obtained from forest products extraction. This argument is consistent with a study by Wibowo and Byron (1999) showing that poverty conditions prevented deforestation in Kerinci-Seblat National Park, Indonesia. As the people in an area become wealthier, deforestation rates increase, possibly because the people now can afford to put more land into production. The increase in deforestation, however, is at a decreasing rate (i.e. the increment in the deforestation rate decreases as wealth increases), which suggests that after a certain wealth level, possibly when people have the required capital inputs for agricultural intensification or better access to other income-generating options, there is less demand for further agricultural expansion.

The estimated relationship between poverty and the deforestation rate could be graphed (Figure) with the predicted values of the deforestation rates estimated by varying the value of the district wealth index but keeping the values of the other variables constant at their mean values. As shown in the Figure, the deforestation rate reaches a maximum at about the ninetieth percentile of the

Inverted U-shaped relationship between poverty and deforestation

distribution of the wealth index, indicating that the deforestation rates of most districts are still increasing.

Since wealth reflects development, these results suggest that the impact of development on deforestation varies depending on the current state of wealth. In the study sites, from 1985 to 2000 the per capita regional GDP grew at an average rate of 3.7 percent per year. During this time, the district wealth index increased on average by 7.9 percent and the deforestation rate increased from 0.018 to 0.14 percent per year. The annual deforestation rate for 2000 to 2015, predicted using the same growth rate of the per capita regional GDP and the district wealth index from 1985 to 2000 while keeping the other variables constant, shows a decrease to 0.01 percent.

Returns and development proxies

In line with expectations, a higher proportion of available forest land suitable for tree crops leads to significantly higher deforestation. On average, a 1 percent increase in the proportion of the district forested area that is suitable for industrial or estate crops will increase the deforestation rate by 0.48 percent. However, the estimation showed the proportion of forest land suitable for wetland and dryland agriculture to be insignificant. This indicates that areas suitable for tree crops, instead of food crops, are of greater interest to small-scale farmers in frontier areas. This is consistent with a previous finding that tree-crop shifting cultivation, rather than staple-crop shifting cultivation, plays the largest role in small-scale deforestation in Indonesia (Chomitz and Griffiths, 1996). Sunderlin *et al.* (2000) noted that land clearing for tree crops increased as a result of the severe economic crisis that hit the country in 1997.

The significant coefficients of river density and distance confirm the important role of transportation costs and access to markets in the deforestation process. The negative coefficient of river density suggests that in the study regions the net impact of better transport facilities is to reduce deforestation. The positive sign of the distance variable suggests that greater distance to big cities increases deforestation. The estimate shows that the deforestation rate increases, on average, by 14.3 percent for each 100 km of distance from a provincial capital. However, the negative sign of this variable when it is interacted with a time variable suggests that this effect diminishes with time, perhaps because of improved transport infrastructure and vehicles over time. Overall, isolated areas with limited transportation facilities and poor access to markets experience higher deforestation.

The results show that the per capita regional GDP variable is not significant in the model. One explanation could be that within-region disparities are still a serious problem in Indonesia. That is, development processes and their impacts might not be equally experienced throughout the district and hence the district-level variables do not reflect conditions in frontier regions. Alternatively, it could be that there are offsetting effects between development factors that actually reduce small-scale deforestation rates (e.g. improved legal systems inducing productive investments in the existing cleared land) and factors that accelerate deforestation (e.g. new concessionaires' roads which stimulate land clearing for shifting cultivation).

Contrary to expectations, the variable reflecting the number of industrial workers was found to have a positive and significant correlation with deforestation. This may reflect limited opportunities for local people, who are generally involved in small-scale land clearing, to work in industry, as most of the new employment opportunities resulting from growth in industry or concessions are often taken by outsiders who migrate to the area. Limited skills and fears about the reliability of local workers are often given as the main reasons firms are reluctant to hire them (Levang, 2002). Further, new migrants in the area increase demand for food and other agricultural products which can induce the farmers at the forest frontier to increase their agricultural production by expanding agricultural land.

The insignificant effect of population density on deforestation is consistent with the argument that, at the regional level, population is potentially determined by other factors that influence economic activity, such as off-farm activities and infrastructure availability. Thus, population *per se* is unlikely to be the underlying cause of deforestation (Kaimowitz and Angelsen, 1998).

The insignificance of HPH activities may contradict the common expectation of a positive correlation between logging concessions and small-scale deforestation. However, previous studies on the impact of logging intensity on small-scale deforestation focused on small-scale farming in abandoned logging plots, rather than on farmers' new clearing of forested land (Geist and Lambin, 2001).

Results show that, when controlled for other influences, the percentage of total forest area cleared in the preceding period has statistically insignificant effects on the deforestation rate. This could be because the level of local development has already been controlled for by the variables representing the proportion of forest area suitable for farming and tree crops available for clearing in each period in the specifications. Alternatively, as was the case for the per capita regional GDP variable, it may be that these lagged variables are insignificant because they are at the district rather than local, frontier level.

The regional GDP and number of industrial workers in neighbouring areas appear to have insignificant effects on a district's deforestation, suggesting that spatial interactions are not very important.

SUMMARY AND CONCLUSIONS

Unlike most previous studies on the deforestation-poverty link, the empirical analysis in this study utilizes a data set combining spatial data on forest cover and physiogeographic factors from satellite imagery with socio-economic panel data from several national surveys. The poverty measure incorporates both human well-being and location welfare components, allowing for a comprehensive examination of poverty effects on the pace of deforestation. With data spanning more than 18 years – presented at five points in time – and 124 districts, the study is one of the most comprehensive examinations of deforestation by small-scale farmers undertaken for Indonesia.

The empirical results show an inverted U-shaped relationship between district wealth and deforestation where the rate of deforestation increases with wealth, but at a decreasing rate. Poorer districts – those with a higher percentage of poor people – tend to deforest less. Deforestation increases until a certain wealth level is reached and then declines. However, it starts to decrease only at the top decile of the current district wealth distribution.

In the Indonesian context it is the land that is most suitable for tree crops that is most vulnerable to deforestation. When the land is suitable for tree crops, the incentives are obviously higher for forests to be cleared for establishment of cash crops such as oil palm. This has been a factor driving a significant part of land conversion through deforestation in the past, and also has implications for the future.

The findings of this study suggest that the impact of development on deforestation depends on the current state of wealth and the level of development in the frontier regions. A worrying feature of these findings is that policies aimed at stimulating regional development may stimulate further deforestation. For most districts, increased wealth, other things being equal, will initially increase deforestation.

Counterbalancing this concern, however, is the finding that lower transport costs and better access to markets reduce deforestation. The study also found that greater off-farm employment opportunities were associated with less forest clearing. Thus, the challenge for districts will be to manage development in such a way as to ensure good and equitable access to labour markets and remunerative off-farm employment opportunities for rural people. ◆

Bibliography

Angelsen, A. 1995. Shifting cultivation and deforestation: a study from Indonesia. *World Development*, 23(10): 1713–1729.

Angelsen, A. 1999. Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights. *Journal of Development Economics*, 58: 185–218.

Chomitz, K.M., Buys, P., Luca, G.D., Thomas, T.S. & Wertz-Kanounnikoff, S. 2007. *At loggerheads? Agricultural expansion, poverty reduction, and environment in the tropical forests.* World Bank Policy Research Report. Washington, DC, USA, World Bank.

Chomitz, K.M. & Griffiths, C. 1996. *Deforestation, shifting cultivation, and tree crops in Indonesia: nationwide patterns of smallholder agriculture at the forest frontier*. Poverty, Environment, and Growth Working Paper No 4. Washington, DC, USA, World Bank.

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

Deininger, K.W. & Minten, B. 1996. *Poverty, policies, and deforestation: the case of Mexico*. Poverty, Environment, and Growth Working Paper No. 5. Washington, DC, USA, World Bank.

Dewi, S., Belcher, B., Puntodewo, A., Tarigan, J. & Widodo, M. 2002. Deforestation: Who does what? Paper presented to the International Symposium of Land Use, Nature Conservation and the Stability of Rainforest Margin in Southeast Asia, Bogor, Indonesia, 30 September – 2 October.

FAO. 1995. *Forest Resources Assessment 1990 – global synthesis*. FAO Forestry Paper No. 124. Rome.

FWI & GFW. 2002. *The state of the forest: Indonesia*. Bogor, Indonesia & Washington, DC, USA, Forest Watch Indonesia & Global Forest Watch.

Geist, H.J. & Lambin, E.F. 2001. *What drives tropical deforestation?* LUCC Report Series. Brussels, Belgium, Land-Use and Land-Cover Change (LUCC) International Project Office.

Godoy, R., Franks, J.R., Wilkie, D., Alvarado, M., Gray-Molina, G., Roca, R., Escobar, J. & Cardenas, M. 1996. *The effects of economics development on neotropical deforestation: household and village evidence from Amerindians in Bolivia.* Discussion Paper No. 540. Cambridge, Massachusetts, USA, Harvard Institute for International Development.

Kaimowitz, D. & Angelsen, A. 1998. *Economic models of tropical deforestation: a review*. Bogor, Indonesia, Center for International Forestry Research (CIFOR).

Kerr, S., Pfaff, A.S.P., Cavatassi, R., Davis, B., Lipper, L., Sanchez, A. & Timmins, J. 2004. *Effects of poverty on deforestation: distinguishing behaviour from location.* ESA Working Paper No. 04-19. Rome, FAO.

Kerr, S., Pfaff, A.S.P. & Sanchez, A. 2002. *The dynamic of deforestation: evidence from Costa Rica.* Wellington, New Zealand, Motu Economic and Public Policy Research. Available at: www.motu.org.nz/docs/publications/costa.rica.pdf

Levang, P. 2002. People's dependencies on forests. In *Technical report, Phase I 1997–2001. ITTO Project PD 12/97 Rev.1 (F) – Forest, science and sustainability: the Bulungan model forest*, pp. 109–130. Bogor, Indonesia, CIFOR.

Pfaff, A.S.P. 1999. What drives deforestation in the Brazilian Amazon? Evidence from satellite and socioeconomic data. *Journal of Environmental Economics and Management*, 37(1): 26–43.

Shively, G.E. & Pagiola, S. 2004. Agricultural intensification, local labor markets, and deforestation in the Philippines. *Environment and Development Economics*, 9(2): 241–266.

Statistics Indonesia. 2007. *Pendapatan Domestik Regional Bruto (PDRB) Propinsi-propinsi di Indonesia Menurut Lapangan Usaha 2002–2006*. Jakarta, Indonesia, Badan Pusat Statistik.

Sunderlin, W.D., Resosudarmo, I.A.P., Rianto, E. & Angelsen, A. 2000. *The effect of Indonesia's economic crisis on small farmers and natural forest cover in the outer islands*. CIFOR Occasional Paper No. 28(E). Bogor, Indonesia, CIFOR.

Uusivuori, J., Lehto, E. & Palo, M. 2002. Population, income and ecological conditions as determinants of forest area variation in the tropics. *Global Environmental Change*, 12(4): 313–323.

Vance, C. & Geoghegan, J. 2002. Temporal and spatial modelling of tropical deforestation: a survival analysis linking satelite and household survey data. *Agricultural Economics*, 27(3): 317–332.

Vedeld, P., Angelsen, A., Sjaastad, E. & Berg, G.K. 2004. *Counting on the environment: forest incomes and the rural poor.* Environment Department Paper No. 98. Washington, DC, USA, World Bank.

Wibowo, D.H. & Byron, R.N. 1999. Deforestation mechanisms: a survey. *International Journal of Social Economics*, 26(1/2/3): 455–474.

Zwane, A.P. 2007. Does poverty constrain deforestation? Econometric evidence from Peru. *Journal of Development Economics*, 84(1): 330–349. ◆