Impacts of Paving Roads for Development in the Democratic Republic of Congo: Deforestation and Biological Carbon Loss

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Selected Paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 18-24 August, 2012.

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Revised on June, 2012

Abstract. This paper develops an econometric model to explore the determinants of land use choices for the Democratic Republic of the Congo. The model is not just capable of representing land use choices using large aggregation categories, but it also allocates agricultural area to the country relevant crops by augmenting the dataset with low-cost, widely available, agricultural statistics about crop areas and production. This is important to decision makers who want to plan for economic growth while trying to minimize greenhouse gas emissions. An empirical application indicates that the implementation of an ongoing government's plan for road construction in the country would cause a reduction of about 2% of the existing standing forest stock, and a loss in biological carbon stock estimated to be 294 TgC. Encroachment of agriculture into forested land would contribute to the reduction in biological carbon stock by an estimated 112 TgC and would generate annual emissions estimated to be 21 thousand Mg CO_2e with low nitrogen application or 300 thousand Mg CO_2e from high nitrogen application.

Key words: Land use, deforestation, crop allocation, road construction, greenhouse gas emissions

JEL classification: Q15, Q24, Q54

1. Introduction

The Democratic Republic of the Congo (DRC) has 125 million hectares of tropical forest, the second largest in the world after the Amazon. The DRC forests play an important role in the cycling of the greenhouse gases (GHGs) acting as both sink and source of these gases (Houghton 2005). Gaston et al. (1998) estimated the carbon pool of the DRC's forests at 16.9 thousand Tg (1 Tg = 10^{12} gram) in 1980, of which 11% is in protected areas and 17% in current logging concessions. The amount is equivalent to 55% of the total forest carbon pool in Central Africa.

Despite the DRC's potential for agricultural production, with its vast land resources and favorable water supply, the DRC has experienced a severe economic depression lasting from the 1960s to 1990s—gross domestic product (GDP) decreased by more than 3% per year. Agriculture, the largest economic sector and population employer, has suffered even more:[1] agricultural exports declined from 40% of all exports in 1960 to only 10% in 2000. Approximately, two-thirds of the population lives on less than US$1.25 per day—the international poverty line (Ravallion et al. 2009).

The DRC government has pursued large scale farming projects and significant foreign investments in agriculture. These policies are affecting the economic viability of farming traditional and non-traditional crops and can, potentially, put at risk the forested areas of the country. Even though historically rates of deforestation in the DRC are low relative to those experienced in South America and Southeast Asia, ongoing and potential investments in agriculture development, coupled with the rapid population growth, are likely to result in deforestation and forest degradation (Cropper and Griffiths 1994; Lubowski et al. 2006; Stavins and Jaffe 1990).

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[1] Agricultural sector employs over three quarters of the population in the DRC according to some official statistics.

Of particular importance are the investments in transport infrastructure and energy made by the DRC government, with projects totaling 8.5 billion USD; a sum equivalent to DRC's entire GDP of 2006. Many of these roads and river rehabilitations cut through or near to the DRC's tropical forests, and will obviously significantly improve the economic viability of the logging industry and the profitability of agricultural activities. The need for economic growth and intense use of existing resources is occurring at a time when attention is devoted to the GHGs emission foot-print of the portfolio of development strategies available to a country.

Given that the use of forested land is intimately connected to other land uses, and given that the environmental impact of deforestation depends on factors such as the rate at which it occurs, its location, and its pattern (Rodrigues et al. 2009), a spatially explicit model of land use choices is of critical importance to correctly plan for the use of the forest resource and to develop sound agricultural and natural resource policies. The literature on the drivers of land use change and deforestation is extensive and, in general, the qualitative effects of the drivers are well understood (Chomitz and Gray 1996; Nelson and Hellerstein 1997; Deininger and Minten 2002; Chomitz and Thomas 2003) even in more complex dynamic settings (Schatzki 2003; De Pinto and Nelson 2009). However, the quantitative effects vary with the changing geophysical characteristics and each country political situation. Limited by the data, few studies have made efforts to obtain such knowledge for the DRC.

In this paper we develop an econometric model to identify the determinants of land use choices for the DRC. Most previous models, particularly those implemented in sparse data environments, treat agriculture as a single land use category. This paper demonstrates that by augmenting the data set with low-cost, widely available, statistics about crop areas and production, it is possible to model some of the more complex interactions that can lead to changes in landscape that cannot be captured with pervious approaches. We believe that, as the focus on GHG emissions and climate change mitigation activities increases, a deeper understanding of the implications of development and agricultural policies becomes necessary. The proposed approach represents a step in the direction of modeling, in a consistent framework, the effects of development policies on land use. To demonstrate its applications, we analyze existing plans for the expansion of the transportation network and the possibility of intensifying the use of nitrogen fertilizer on food-crop production.

The remainder of this paper is organized as follows: Section 2 develops an econometric land use model. Section 3 describes the data sources and handling method. Section 4 discusses the results. The final section offers our conclusions.

2. Econometric Land Use Model

Land tenure in the DRC is regulated by a law enacted in 1973 and amended in 1980, making the government the sole owner of land across the country. The law itself originates from traditional practices which require prior approval of the village chief before the Administrative Authority issues any land title. By law, perpetual land concessions are available only to indigenous population and the conversion of a regular lease to a perpetual concession is possible only for Congolese nationals. However, long term leases can be granted to foreigners for a period of 5–25 years renewable. Such concessions can be granted for free or against payment. Besides land managed by the government in the form concessions for agriculture, forestry and industrial as well as reserves, protected areas and land boundaries between urban and non-traditional (towns and cities), all other land areas are governed by traditional land tenure. In other words, in rural areas, except in capitals of territories, land policy falls under the authority of the traditional leader. In this system, individual endowment to land is based on her or his membership to the clan, tribe or village, and her or his ability to perform some social obligations to the community. Any person recognized as a member of the clan/tribe/village has therefore the right to use land to support her or his family. For people outside the community, a special arrangement is required to access land.

Consider land use decision on a 1×1 km^2 homogeneous land grid, indexed by n; $n = 1, \ldots, N$. Suppose the decision maker is a risk-neutral landowner, local governor, or the "nature"; she chooses land uses to maximize the present discounted value of the stream of the expected net benefits from the land. The land grid could be allocated to K alternative major uses, indexed by k; $k = 1, \ldots, K$. Among these uses, cropland and mosaic of cropland are two nests, within which the decision maker is allowed to make crop choices, indexed by j; $j = 1, \ldots, J_K$.[2] Mosaic of cropland is referred to as a mixed use of cropland and other nature vegetation (tree, shrub, herbaceous, etc.). Our data identify six major crops: beans, cassava, groundnuts, maize, plantain, and rice. Those unidentified crops are classified as a category named "others". The decision maker has no alternative options when the land plot is allocated to other major land uses.

Under these simplifying assumptions, the steady-state decision rule that emerges from the related dynamic optimization problem is to put a land parcel to the use generating the greatest present discounted value of net benefit (Lubowski et al. 2006). That is, allocate a parcel of land to use j if

$$U_{nkj} > U_{nk'j'}, \forall\, k' \text{ and } j \neq j' \text{ if } k = k', \tag{1}$$

where U_{nkj} the one-period expected net benefit from allocating land parcel to use j $(j \in k)$. The potential value of U_{nkj} depends on attributes of the parcel, such as land quality, weather conditions, locational characteristics, and economic conditions in the surrounding area, as well as attributes associated with alternative choice, such as price and yield.

A standard practice in the land use modeling literature is to decompose U_{nkj} into a deterministic component $\overline{U}_{nkj}$ and a random error term ε_{nkj}. $\overline{U}_{nkj}$ represents the expected average net benefit from allocating land use in a grid; ε_{nkj} represents the deviation from the average net benefit and is often assumed to follow a normal, logit, or type-I extreme value

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[2] In the remainder of this paper, we will use *nest* to represent major land use and use *crop* and *alternative* interchangeably to represent nested land use.

distribution. In the context of the present study, we further decompose $\overline{U}_{nkj}$ into two deterministic components:

$$\overline{U}_{nkj} = X_{nk} + Y_{nkj}. \tag{2}$$

X_{nk} depends on variables that describe the nest *k*; it differs over nests but not over alternatives within each nest. Y_{nkj} depends on variables that describe nested use *j* ($j \in k$); it varies over alternatives within the nest.

Under the assumption analogous to the nested logit model about ε_{nkj}, i.e., ε_{nkj} is correlated within nest *k* but uncorrelated across nests, the probability of grid *n* allocated to alternative *j* ($j \in k$) can be derived as follows (McFadden 1977):

$$P_{nkj} = \Pr\left(U_{nkj} > U_{nk'j'}\right) = \frac{e^{\overline{U}_{nkj}/\lambda}\left(\sum_{j' \in k} e^{\overline{U}_{nkj'}/\lambda}\right)^{\lambda-1}}{\sum_{k'=1}^{K}\left(\sum_{j' \in k'} e^{\overline{U}_{nk'j'}/\lambda}\right)^{\lambda}}, \tag{3}$$

where the parameter λ is a measure of the degree of independence in ε_{nkj} among the alternatives in each nest.[3] A higher value of λ implies less correlation and $\lambda = 1$ indicates complete independence. λ could be a fixed parameter or a random parameter, depending on the assumption of the covariance structure in random errors. In particular, a fixed parameter implies that land use decision on all locations has the same correlation among error terms. But in reality, the correlation may differ over land grids based on their observed attributes. For example, the unobserved factors affecting the revenues of crops might vary more in a sparsely populated region than a densely populated region, whereas those factors affecting the transportation costs of crops might vary less in an area far away from markets than an area close to markets. This leads to a reduced correlation among crops in a location characterized by sparse population or easy to access markets. To accommodate these differences, we assume λ is a random parameter and follow a standard logit distribution:

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[3] We assume λ is homogenous across nests because the alternatives within the two nests are exactly same.

$$\lambda_n = \frac{1}{1+e^{\mathbf{z}_n\boldsymbol{\alpha}}}, \tag{4}$$

where $\mathbf{z}_n$ is a vector of population density and transportation costs in grid *n* and $\boldsymbol{\alpha}$ is a vector of parameters to be estimated along with parameters that enter the net benefit. The specific functional form chosen is not very critical (Bhat 1997). Employing a logit transformation assures that λ is between zero and one.

Based on (2)–(4), the nested logit probability P_{nkj} can be derived as a product of two multinomial logit probabilities (Train 2003):

$$P_{nk} = \frac{e^{X_{nk}+\lambda_n I_{nk}}}{\sum_{k'=1}^{K} e^{X_{nk'}+\lambda_n I_{nk'}}}, \tag{5}$$

and

$$P_{nkj|k} = \frac{e^{Y_{nkj}/\lambda_n}}{\sum_{j'\in k} e^{Y_{nkj'}/\lambda_n}}, \tag{6}$$

where $I_{nk} = \ln\left(\sum_{j'\in k} e^{Y_{nkj'}/\lambda_n}\right)$, is called inclusive value of nest *k*. Specially, equation (5) defines marginal probability of choosing an alternative in nest *k* and equation (6) defines conditional probability of choosing alternative *j* given that an alternative in nest *k* is chosen. We refer to the marginal probability as an upper-level model and to the conditional probability as a lower-level model, reflecting their relative positions in the hierarchy structure. In equation (6), λ_n is treated as a scale parameter that scales coefficient parameters implicitly defined in Y_{nkj}.[4] For those nests where there are no alternatives inside, the conditional probability given in (6) equals one and the inclusive value is reduced to $I_{nk} = e^{Y_{nkj}/\lambda_n}$. Insert I_{nk} into (5), λ_n will be canceled. Probabilities (5) and (6) are fundamental equations in the nested logit model.

Based on the economic theories and previous studies (Hall 1966; Nelson and Hellerstein

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[4] Without dividing by λ in this equation would not substantially change the results. However, the division by λ is needed for the product of conditional and marginal probabilities to equal the nested logit probabilities given in equation (1) (See Train (2003) for more discussion).

1997; Pfaff 1999), the average expected net benefits from allocating every grid *n* to nest *k*, X_{nk}, is specified as $X_{nk} = \boldsymbol{x}_n \boldsymbol{\beta}_k$, where $\boldsymbol{x}_n$ is a vector of location-specific variables describing population density, transportation costs, topography, soil attributes, and weather conditions; $\boldsymbol{\beta}_k$ is vector of coefficients on $\boldsymbol{x}_n$. Given *k* is chosen, the average expected net benefits from allocating each location *n* to nested alternative j, Y_{nkj}, is specified as $Y_{nkj} = \boldsymbol{y}_{nkj} \boldsymbol{\gamma}_{kj}$, where $\boldsymbol{y}_{nkj}$ is a vector of crop-specific variables describing the price and the maximum attainable yield for each crop;[5] $\boldsymbol{\gamma}_{kj}$ is a vector of coefficients parameters specific to crop. Note that if the choice-specific variables perfectly captured the average expected net benefits for each crop at the level of the individual grid, then $\boldsymbol{\gamma}_{kj}$ should simply reflect the marginal net benefit and would not be expected to differ over crops. We allow this parameter varying across crops in our specification because both crop-specific variables are originally measured at relatively coarse resolutions and hence cannot perfectly capture the average expected net benefits for each crop at each location. To eliminate λ_n from the lower-level model, we introduce $\widetilde{\boldsymbol{\gamma}}_{kj}$ by dividing $\boldsymbol{\gamma}_{kj}$ by λ_n such that $\widetilde{\boldsymbol{\gamma}}_{kj} = \boldsymbol{\gamma}_{kj}/\lambda_n$. This scaling facilitates the estimation.

3. Data Sources and Handling

The upper-level model uses remotely sensed data, most of which are measured at a spatial resolution of approximately 1 km at the equator. Specifically, land cover was generated from Global Land Cover 2000 Project (GLC2000, JRC 2003). GLC2000 database defines 23 land cover classes globally, among which 10 classes are identified in the DRC. We grouped the 10 classes into 7 aggregated categories of land use, including tropical rainforest, deciduous forest, swamp, shrub and herbaceous, cropland, the mosaic of cropland, and other vegetation mosaic. Table 1 provides the classification details.

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[5] Hereafter we will use *suitability* and *yield potential* interchangeably to represent the maximum attainable yield.

Population density data were collected for 1995 and 2000 from Global Rural-Urban Mapping Project (CIESIN, Columbia University, IFPRI, The World Bank, and CIAT 2004). We use population density in 1995 to estimate the land use model to obviate a potential problem with endogeneity while population density in 2000 is used to conduct our simulations. Even though land use choices do not necessarily affect population levels (Pfaff 1999; Seto and Kaufmann 2003), the use of the lagged population value should help reducing the potential endogeneity.

Data on transportation costs, proxied by travel time to major cities, were provided by Ulimwengo et al. (2009). Topographical variables including terrain slope and elevation are derived from the GLOBE product (Hastings and Dunbar 1998); climate data, measured by mean precipitation and mean annual temperature, are generated from theWorldClim product developed by Hijmans et al. (2005).

In contrast to the upper-level model, the lower-level model combines local statistics with geo-referenced data. The DRC's first level administrative unit is province, at the second level district, and at the third level territory. There are 11 provinces, 26 districts, and 192 territories in the country. Harvested areas for six crops are available at the territory level. Ideally, we would collect data on crop yield and price at each location to determine the crop choice with highest profitability. But such data are unavailable. Lacking better data, we use geo-referenced biophysical suitability and spatially explicit price for each crop in their place.

Among possible methods to assess the biophysical suitability of a given location for crop production, the Agro-ecological Zones (AEZ) approach, developed by FAO and the International Institute for Applied Systems Analysis (IIASA), has been widely applied because of its capability of providing a standardized framework for the effects of climate, soil, terrain conditions, as well as socioeconomic factors relevant to agricultural production (Fischer et al. 2001). We use one of the production systems—low input/technology rainfed—in FAO/IIASA crop suitability datasets as a proxy for the maximum attainable yield in the DRC. The suitability data are originally available as an approximately 9 km at the equator and were disaggregated to 1 km in the present study.

Producer prices of six crop commodities are available for each province since 2000. Using the measure of provincial-level prices substantially reduced the concerns about endogeneity between territory-level crop choices and local producer prices. Further, some of the commodities, such as rice, sold on local markets are mostly imported from foreign market, which is exogenous to our model.

To generate spatially explicit prices, we follow the methods described below. Assume their producer prices can be observed at the major markets that are located in cities with population greater than 50,000. With this assumption, we map commodities producer prices (2000) as discrete points and generate a smooth surface of these prices using kriging interpolation technique. Then we estimate the spatially explicit prices, pp_{nj}, for each grid and each crop in the continuous space of price using a distance decay function

$$pp_{nj} = PP_{nj} e^{-d_{nc}/\max_{\{n',c'\}} d_{n'c'}}, \tag{7}$$

where PP_{nj} represents the producer price in the continuous space and d_{nc} is the Euclidean distance from each location n to the nearest major market c. The specific functional form of distance decay is arbitrary. This formula has desirable properties that the producer price decays at a moderate speed and the spatially explicit price is between $0.368PP_{nj}$ and PP_{nj}.

Therefore, this econometric method relies mostly on remotely sensed data and other relatively inexpensive ancillary data and can easily be applied to land use analyses constrained by lack of data (De Pinto and Nelson 2007). Given different spatial resolutions of geo-referenced data, we use GRASS GIS (Geographic Resources Analysis Support System) to adjust their resolutions to 1 km at the equator.

Spatial dependence is a common econometric concern when applying contiguous geographic data for empirical analysis. It may arise when land uses in nearby grids directly affect each other or are affected by the same unobserved factors. In a logit model, the cost of not correcting for spatial dependence is biased (or inconsistent) estimates if the issue induces heteroskedastic errors (Yatchew and Griliches 1985). To avoid the potential bias caused by spatial dependence, we divide the contiguous surface of the country into numerous 5×5 km^2 squares. Each square contains 25 grids of 1×1 km^2. Then we withdraw the grids that are located at the center of all squares and use them to construct a smaller sample for estimation. This coding scheme has been demonstrated effective at reducing or eliminating potential spatial correlation in the error terms (De Pinto 2010). Table 2 provides some summary statistics for the variables used in the analysis.

Maximum likelihood method is a common approach to the efficient parameterization of a nested logit model. However, we lack observations of crop choice at each grid, which makes it impractical to estimate the lower- and upper-level models simultaneously. Alternatively, a nested logit model can be estimated consistently but less efficiently in a sequential fashion, by beginning with the lower-level model and using the coefficient and inclusive value estimates as explanatory variables to enter the upper-level model. This approach exploits the fact that the choice probabilities can be decomposed into marginal and conditional probabilities that are logit functions. Lacking more disaggregated data on crop areas, we estimate the nested logit model using the second approach.

Specifically, we assume: 1) Crop area, A_{mj}, is a random variable and independent across territories; 2) In each territory, A_{mj} follows a multinomial distribution with parameters N_m and P_{mj}, where N_m is the number of grids located in territory m (m = 1, …, M) and P_{mj} is the average probability that crop j is chosen; 3) P_{mj} is parameterized as a weighted logit function, yielding

$$P_{mj} = \frac{1}{N_m}\sum_{n=1}^{N_m}\sum_{k=1}^{2} w_{mk}P_{nkj|k}, \tag{8}$$

where $P_{nkj|k}$ is the conditional probability defined in equation (6) and w_{mk} is the weight pre-assigned to balance the probability of choosing crop from cropland ($k = 1$) or from mosaic of cropland ($k = 2$); $w_{m1} + w_{m2} = 1$.[6] Note that essentially, P_{mj} is a function of variable $\boldsymbol{y}_{nkj}$ and parameter $\widetilde{\boldsymbol{\gamma}}_{kj}$

Using observed crop areas a_{mj}, parameters in the lower-level model can be estimated by maximizing the log-likelihood function (9) with respect to $\widetilde{\boldsymbol{\gamma}}_{kj}$:

$$LL(\boldsymbol{P};\boldsymbol{a}) = \sum_{m=1}^{M}\left[\ln(N_m!) - \sum_{j=1}^{J}\ln\left(a_{mj}!\right) + \sum_{j=1}^{J} a_{mj}\ln\left(P_{mj}\right)\right], \qquad (9)$$

where $\boldsymbol{P}$ and $\boldsymbol{a}$ represent the sets of probabilities P_{mj} and crop acreage a_{mj} for all *m*’s and *j*’s. Then inclusive values for cropland and mosaic of cropland can be obtained using the estimates $\hat{\widetilde{\boldsymbol{\gamma}}}_{kj}$ from the lower-level model, i.e., $\hat{I}_{nk} = \ln\left(\sum_{j'=1}^{J_k} e^{\boldsymbol{y}_{nkj}\hat{\widetilde{\boldsymbol{\gamma}}}_{kj}}\right)$. Inserting $\hat{I}_{nk}$ as an explanatory variable into the upper-level model, equation (5) becomes a mixed logit function with *K*-1 fixed coefficient vectors $\boldsymbol{\beta}_k$ (*k* = 1, …, *K*-1) and a random coefficient λ. Finally, we estimate the upper-level model using the maximum likelihood method (BHHH-2 (**B**erndt, **H**all, **H**all, and **H**ausman) procedure; see Train 2003, pp. 199–200).

4. Results

In this section we will first discuss the predictive power of the model, then report the estimation results, and finally generate a road-development scenario proposed by the DRC government and discuss its policy implications.

4.1 Predictive Power of the Model

The performance of land use models is often judged by their capability to reproducing the observed land use choices. This is usually done by assigning each pixel to the land use category with the highest probability (Nelson and Hellerstein 1997, Munroe et al. 2004, among many). We decide against following the winner-take-all assignment method as it would hide the complexities

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[6] We lack information about how many acreages of every crop are from cropland and how many are from mosaic of cropland.

of the landscape in the study area and would not allow us to evaluate the crop allocation portion of the model given that we only have provincial census data on crop shares. The typical output of a discrete choice model is a set of choice probabilities for each observation. We interpret these probabilities as land use shares and crop shares and base our assessment on the comparison between observed and predicted shares at the provincial level. Assessment results, reported in the appendix (Tables A1 and A2), indicate that across land use categories, the average discrepancies between predicted and observed land use categories range from 0.9% to 4.4%. Similarly, the differences between predicted and observed crop shares, is the highest for the “catch-all” other crops categories (6.6%) and the lowest for plantain (0.9%).These results indicate that the model is quite accurate in reproducing observed land use choices.

4.2 Estimation Results

Given that our main interest here is to identify the drivers of land use change, we report the estimated marginal effects for the upper-level model in Table 3 and the estimated elasticities for the lower-level model in Table 4. The coefficient estimates are presented in the appendix. Marginal effects and elasticities are evaluated at the means of the data.

Most of the marginal effects are statistically significant at the 1% level and their signs are consistent with expectations. Land, for instance, is more likely to be tropical rainforests and less likely to be farmed in areas with higher transportation costs. A common suggestion is that population growth may cause deforestation, which is confirmed here by the case of deciduous forest. In some applications such as tropical rainforests where the logging costs are pretty high, however, it is possible that deforestation is mainly driven by governmental and commercial projects rather than demographic factors. This is reflected in our results.

In Table 4, 13 out of 24 elasticity estimates are statistically significant. Their signs are generally as anticipated, with two notable exceptions: the effect of increasing soil suitability on the probability of choosing plantain and the effect of price changes on the decision of planting rice. We believe that these results are due to quality of the data available for these commodities. For instance, given that most of the rice sold on local markets is imported from the foreign market, the relationship between its price and land use choices is tenuous.

4.3 Road Development Scenario

As previously mentioned, one of the main investments in the DRC is in road infrastructure. We therefore investigate the effects of a change in the DRC transportation network proposed by the government (See Ulimwengo et al. (2009) for more details on road network development in the DRC). The government plan includes paving 8,500 km of roads and the construction and improvement of railways and it is schematically described in Table 5 and the location of road expansion can be observed in Figure 1.

Deforestation — Ulimwengo et al. (2009) generated maps of travel time to major cities under the current network scenario (baseline) and the government's plan scenario, respectively. These data in combination with the estimated βs from equation (5) are used here to assess the effects of road network development on land use choices. Land use conversions and total changes summarized in Table 6 and Table 7.

The simulation results indicate that forested area would be strongly affected by the expansion of the road network. New roads affect transportation costs and allow for a more efficient transportation of inputs and outputs. As a result, land that previously could not be profitably brought into agricultural production becomes viable for farming. The overall effect of this process is that agriculture encroaches into natural and forested areas. According to our results, agricultural land, defined as a combination of cropland and mosaic of cropland, would increase by some 2 million hectares and forested area, defined as a combination of tropical forest and deciduous forest, would decrease by 3.3 million hectares, about 2 percent. Figure 2 and Figure 3 present the spatial patterns of simulated changes in forest cover and agricultural land.

Forested areas do not only transition to agriculture but also to other land use categories like shrub-herbaceous and other vegetation mosaic. This seems to suggest that forest degradation would also result from the increase mobility that derives from road construction. We quantify the reduction in biological carbon stock induced by road expansion by considering changes in three pools: above- and below-ground biomass, and soil organic carbon (SOC). As a measure of the above-ground biomass, we use Baccini et al.'s (2008) biomass density map of tropical Africa. Estimates of the ratios of below-ground biomass to above-ground derived from IPCC (2006) and Jackson et al. (1996) are used to account for below-ground biomass changes. Estimates of SOC density for the top layer (0–30 cm) and the sub layer (30–100 cm) are generated by Hiederer and Köchy's (2012). Detailed information about the carbon stock in the three pools is available in the appendix (Table A3).

We calculate the mean values of biological carbon density for each land cover and each pool assuming that these values are a correct representation of biological carbon densities once they reached equilibrium. Carbon stock statistics are summarized in Table 7. Results indicate that the land use changes induced by road construction would cause a total reduction in carbon stock of about 294 TgC. The overwhelming majority of this loss is due to the decrease in forested area.

The Role of Agriculture — We now turn to agriculture and its contribution to GHG emissions by looking at the change in agricultural area as a whole but also at the changes in the area allocated to the most important crops. Every time that a new hectare of land is brought into agricultural production there is a change in biological carbon stock and a change in emissions.[7] Combining the changes in land area and carbon stock statistics (Table 6 and Table 7,

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[7] In our calculations we make the simplifying assumption that the change in emissions is only due to agricultural use of fertilizers.

respectively), we can compute changes in biological carbon stock for each land cover category [8] and the average change in total carbon stock caused by an additional hectare of farmed land (Table 8). Calculations suggest that agricultural expansion causes a total reduction in biological carbon stock of about 112 TgC ,[9] equivalent to an average loss of 7.8 MgC/ha (1 Mg = 10^6 gram).

To compute emissions, we employ the IPCC recommendations on emissions deriving from fertilizer applications and use the recommended rates of nitrogen fertilizer by crop and by province reported in the literature (Table 9) assuming that nitrogen is delivered through urea applications. Given the current economic conditions, farmers are using very little amounts of chemical fertilizers; we therefore assume that application rates are one tenth of the recommended low rates**.** Results of our analysis are reported in Table 10. Calculations indicate that there is an additional 118 thousand Mg of CO_2e per year that would be emitted from farming the six major food crops on the new agricultural area. .

We compare the consequences of deforestation with those of agricultural expansion. For this, we express all emissions in CO_2e and note that when one hectare of tropical forest transitions to other land uses, an average of 106 Mg CO_2e /ha of carbon stock is lost. Conversely, an additional hectare of agriculture returns a one-time loss of carbon stock of 29 Mg CO_2e /ha and yearly average emissions equivalent to 0.06 Mg of CO_2e/ha per year. This means that for one additional hectare of agricultural land to cause the same damage of one hectare of deforested land, once accounted for the difference in carbon stock loss, it would require more than one thousand years (1,253) of farming.

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[8] To calculate changes in biological carbon stock, we first generated transition matrices of carbon density in three pools based on their carbon stock statistics (Table 7), then added the values for the three matrices and multiplied the summation by land use conversions (Table 6).

[9] Note that the net one-time change in biological carbon stock of cropland is positive due the high country-average SOC density on cropland (181 MgC/ha.).

These results, the fact that emissions from agriculture are negligible compared to those caused by deforestation, are not surprising given the type of agriculture prevalent in the country which is mostly smallholders involved in subsistence farming.

Cost-Benefit Analysis and Agricultural Intensification — The concept of agricultural intensification as a mean to reduce tropical deforestation was originally put forward by Nye and Greenland (1960) and later by Borlaug (1983). The argument is that by increasing the production capacity of a given amount of land, the need to clear forest is reduced. The existing literature provides conflicting evidence whether this is what happens in reality (Angelsen 2010; Barbier and Burgess 1997; Burney et al. 2010; Humphries 1993; Rudel et al. 2009). The issue is to what extent an increase in agricultural emissions from intensification is capable of offsetting the reduction of emissions from avoided deforestation. The modeling technique proposed in this paper cannot address the questions whether agricultural intensification leads to reduced deforestation. For that, it would be necessary to have a system of supply and demand equations to determine the equilibrium prices for the various commodities after intensification is implemented. We explore however how intensification contributes to overall emissions, and how the benefits and costs from intensification compare to traditional agriculture.

We begin with an admittedly rough estimate of the costs and benefits that derive form the loss in carbon stock caused by road construction. Making the simplifying assumption that the totality of carbon stock loss is transformed into emissions, we use the available estimates for the social cost of the GHG emissions of one ton of carbon in the atmosphere. These vary greatly in the literature. By looking at the published estimates Yohe et al. (2007) derive an average value of US$43/MgC. We use this value together with the computed total loss in carbon stock of 294 TgC and an assumed discount rate of 5%, to calculate the annualized social cost of the loss in carbon stock which we compute to be 632.5 million USD.

Fuel wood and charcoal production are considered among the main driver for deforestation as it is considered to account for 95% the population's energy needs. However, a portion of forest products are exported and generate some benefits. Deforestation rates are reported to be constant at about 311 thousand hectares per year since 1990 (FAO 2011). FAO (2011) also reports the export value of forest product for the period 2005–2010 to be an average of 111 million USD per year. From this, we extrapolate the average benefit from one hectare of deforested land: 356 USD/ha.[10] Accounting for the 3.3 million hectares of deforested land, the annualized benefits deriving from deforestation are computed to be 59 million USD.

Let us assume that the new agricultural areas have the same characteristics of low-input usage of the already existing farmland. The total additional yearly emissions are 21 thousand Mg of CO_2e, equivalent to a yearly social cost of about 0.2 million USD (Table 10). Once we account for the total cost of using fertilizers (15.7 million USD), we use the average value of provincial-level crop prices over the period 2006–2010 to calculate the annual net benefits deriving from agricultural output produced on new agricultural land. Further details on price and yield data are provided in the appendix (Tables A4–A6). We estimate these to be 60.9 million USD. Hence the total benefits are some 120 million USD. Using this information and the total social annual costs of 648 million USD we compute a cost benefit-ratio equal to 5.4.

Let us assume now that fertilizers are made widely available to farmers and that they apply the recommended high of nitrogen (Table 9), we quantify cost and benefits that derive from this type of agricultural intensification. Total emissions from additional use of fertilizers amount to 300 thousand Mg of CO_2e, equivalent to a yearly social cost of about 3.5 million USD and total expenditures on nitrogen fertilizer amount to 228 million USD (Table 11). Total social annual costs of agricultural expansion (632.5 million USD from loss in carbon stock plus emissions and fertilizer expenditures) amount to 864 million USD and benefits from agricultural output are 672

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[10] We admittedly ignore the benefits deriving from using fuel wood to satisfy households' energy needs.

million USD. When these benefits are added to those deriving from selling forest products (59 million USD), they return a cost-benefit ratio of 1.2.[11]

5. Conclusions

In this paper we propose a modeling approach that not only is capable of representing land use choices using large aggregation categories, commonly found in the existing in the literature, but can also allocate agricultural area to the country relevant crops. Importantly, this approach is characterized by a relatively low data requirement and data that is generally publicly available. We believe that this could be an important tool for decision makers who want to plan for growth and development conscious of the effects on GHGs emission. As empirical application, we simulate the effects of implementing an existing plan for road construction in the DRC. Not surprisingly, such expansion would cause considerable deforestation, a reduction of about 2% of the existing standing forest stock, and a total reduction in carbon stock estimated to be 294 TgC. The encroachment of agriculture into forested land that follows road construction is one of the main causes behind the loss of forest and contributes to the total loss in carbon stock for an estimated 112 TgC and additional annual emissions equal to 21 thousand Mg CO_2e from nitrogen fertilizer applications. It appears evident that the damage caused by the loss of forest overwhelms that of agriculture. Given the amount of carbon that is stocked in the tropical forest and the low level of inputs used in subsistence agriculture, this results in not surprising.

More interesting, and deserving additional investigation, are the results obtained in the agricultural intensification scenario explored in this paper. We employed a cost-benefit analysis to compare low-input and high-input fertilizer usage and find that, *given the amount of*

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[11] By considering the average emissions per hectare that derive from high application of nitrogen fertilizer, we can calculate the number of years that would take for this type of agricultural intensification to equate the damage caused by the loss of one hectare of forested land. We calculate this to be 89 years. This is an important reduction from what was calculated for subsistence agriculture.

deforestation that has already occurred, the use of high-level recommended rates of nitrogen fertilizer mitigates the social damage that is caused by deforestation. The cost-benefit ratio decreases from about 5 to close to 1. There are obviously many details that we have omitted in this study and, given the scarcity of data available, we were forced to make important simplifying assumptions. As such, these results must be interpreted with caution. However, our calculations are strongly indicative of the importance of analyzing the forest-agriculture interface when policies that target GHG emission reduction are developed. Agriculture seems to pose a problem in the measure that it causes deforestation while, comparatively, little damage is caused by its emissions. Even when the recommended high rates of nitrogen fertilizers are employed, the damage caused by farming on hectare of land is equivalent to the damage of losing one hectare of forest after 89 years. This result is consistent with other studies (Burney et al. 2010; Gockowski and Sonwa 2011), which also find that the tradeoffs between emission flows and losses in carbon stock are suggestive of the important role that agricultural intensification could play in reducing deforestation. It is in light of these results and considerations, that the possibility of transitioning from low- to high-productivity agriculture as a tool to combat deforestation becomes a legitimate empirical question. In order to properly address this question a more complex model is necessary. The approach presented in this paper represents a step in that direction.

Grouped Footnotes:

[1] Agricultural sector employs over three quarters of the population in the DRC according to some official statistics.

[2] In the remainder of this paper, we will use *nest* to represent major land use and use *crop* and *alternative* interchangeably to represent nested land use.

[3] We assume λ is homogenous across nests because the alternatives within the two nests are exactly same.

[4] Without dividing by λ in this equation would not substantially change the results. However, the division by λ is needed for the product of conditional and marginal probabilities to equal the nested logit probabilities given in equation (1) (See Train (2003) for more discussion).

[5] Hereafter we will use *suitability* and *yield potential* interchangeably to represent the maximum attainable yield.

[6] We lack information about how many acreages of every crop are from cropland and how many are from mosaic of cropland.

[7] In our calculations we make the simplifying assumption that the change in emissions is only due to agricultural use of fertilizers.

[8] To calculate changes in biological carbon stock, we first generated transition matrices of carbon density in three pools based on their carbon stock statistics (Table 7), then added the values for the three matrices and multiplied the summation by land use conversions (Table 6).

[9] Note that the net one-time change in biological carbon stock of cropland is positive due the high country-average SOC density on cropland (181 MgC/ha.).

[10] We admittedly ignore the benefits deriving from using fuel wood to satisfy households' energy needs.

[11] By considering the average emissions per hectare that derive from high application of nitrogen fertilizer, we can calculate the number of years that would take for this type of agricultural

intensification to equate the damage caused by the loss of one hectare of forested land. We calculate this to be 89 years. This is an important reduction from what was calculated for subsistence agriculture.

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Figures

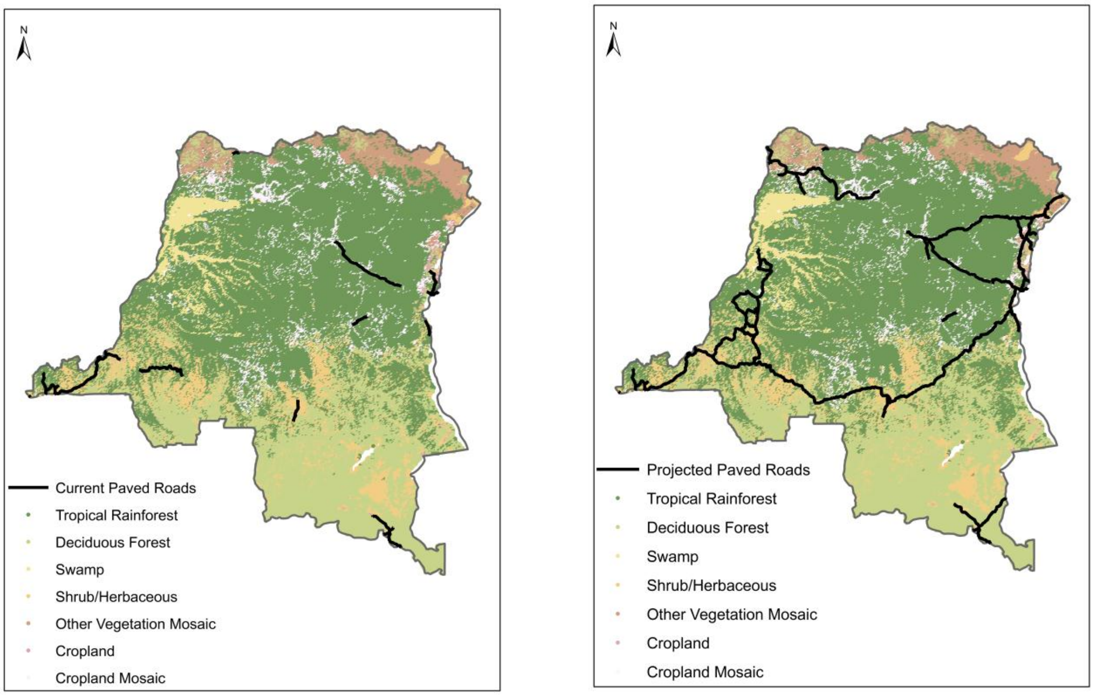

Figure 1: Existing road network and planned road expansion

Sources: 1) Ulimwengu et al. (2009); 2) Global Land Cover 2000 database. European Commission, Joint Research Centre, 2003. http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php (accessed September 28, 2010).

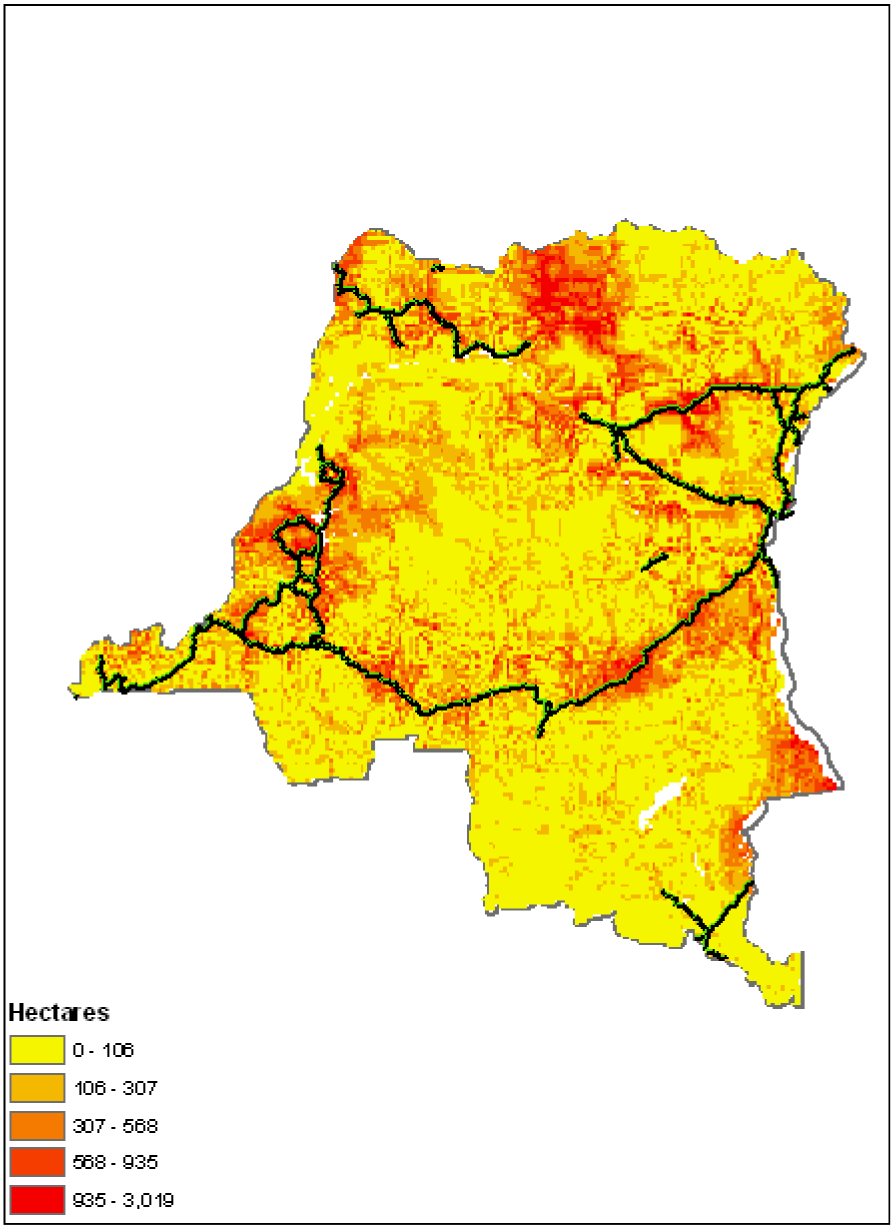

Figure 2: Simulated reduction in forest cover induced by road construction

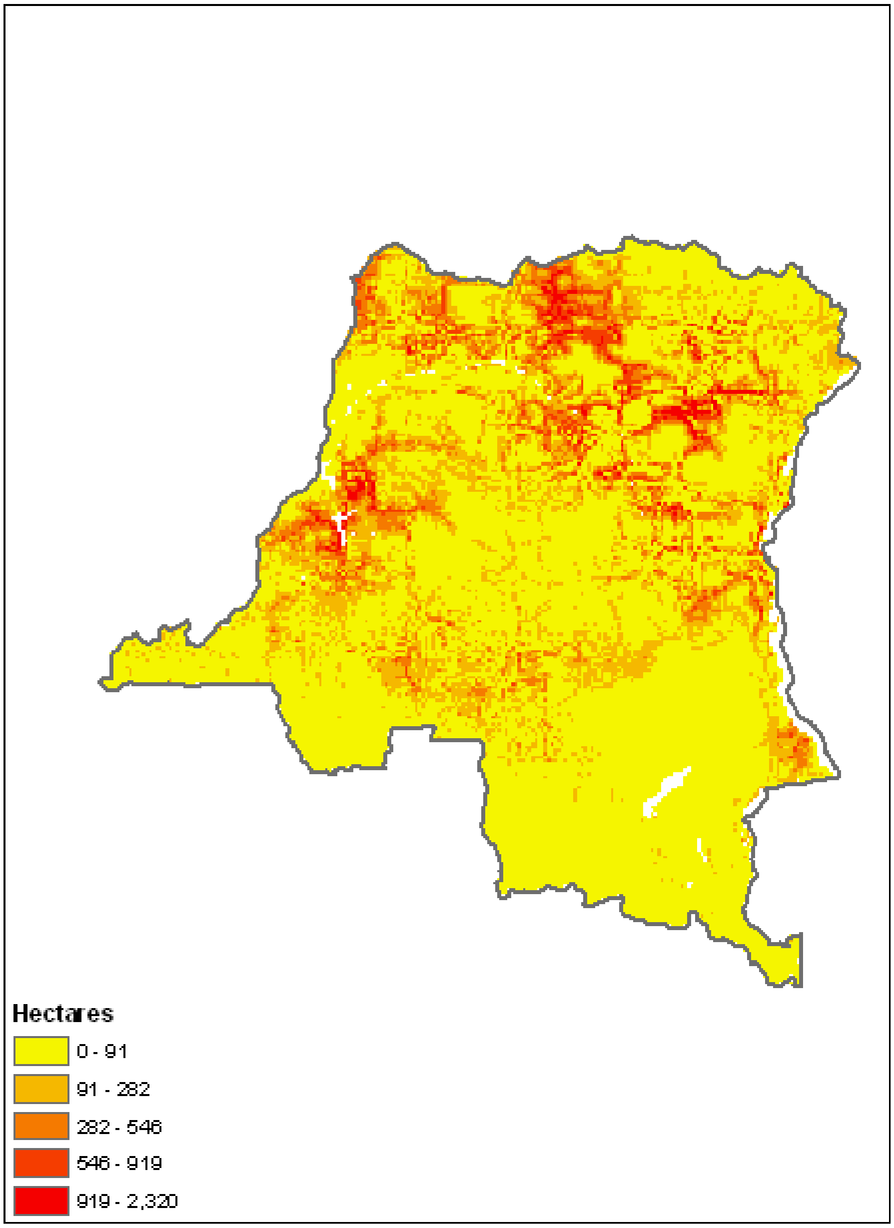

Figure 3: Simulated increase in cropland and mosaic of cropland induced by road construction

Tables

Table 1: Remotely Sensed Land Cover in the Democratic Republic of the Congo, 2000

Land Cover Category	Frequency	Percent
Tropical rainforests	48,231	52.59%
Tree cover, broadleaved, evergreen		
Deciduous forest	21,848	23.82%
Tree cover, broadleaved, deciduous, closed		
Tree cover, broadleaved, deciduous, open		
Swamp	3,204	3.49%
Tree cover, regularly flooded, fresh water		
Shrub/herbaceous	8,755	9.55%
Shrub cover, closed-open, deciduous		
Herbaceous cover, closed-open		
Other vegetation mosaic	4,773	5.20%
Mosaic: tree cover / other natural vegetation		
Cropland	285	0.31%
Cultivated and managed areas		
Mosaic of cropland	4,611	5.03%
Mosaic: cropland/tree cover/other natural vegetation		
Mosaic: cropland/shrub and/or grass cover		
Total	91,707	100.00%

Note: Land grid is approximately equivalent to 1 km^2 at the equator. Rows with italic fonts give the original category defined in GLC2000.
Source: Global Land Cover 2000 database. European Commission, Joint Research Centre, 2003. http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php (accessed September 28, 2010).

Table 2: Summary Statistics of Variables

Variable	Measurement Unit	Sample size	Mean	Standard Deviation	Minimum	Maximum
Lower level model						
Physical area of bean	10^3 ha.	110	0.8	3.3	0	19
Physical area of cassava	10^3 ha.	110	7.2	7.0	0	51
Physical area of groundnuts	10^3 ha.	110	1.2	1.4	0	8
Physical area of maize	10^3 ha.	110	5.5	7.6	0	45
Physical area of plantain	10^3 ha.	110	0.8	1.5	0	7
Physical area of rice	10^3 ha.	110	2.8	4.6	0	30
Physical area of other crops	10^3 ha.	110	19.3	28.1	0	188
Suitability of bean	kg/ha.	4896	2	18	0	342
Suitability of cassava	kg/ha.	4896	259	182	0	1003
Suitability of groundnuts	kg/ha.	4896	9	26	0	224
Suitability of maize	kg/ha.	4896	61	132	0	1468
Suitability of plantain	kg/ha.	4896	197	198	0	1626
Suitability of rice	kg/ha.	4896	583	409	0	2022
price of bean	2000 USD/kg	4896	0.42	0.16	0.16	1.14
price of cassava	2000 USD/kg	4896	0.10	0.08	0.01	0.52
price of groundnuts	2000 USD/kg	4896	0.21	0.17	0.04	1.06
price of maize	2000 USD/kg	4896	0.10	0.06	0.03	0.33
price of plantain	2000 USD/kg	4896	0.15	0.06	0.07	0.39
price of rice	2000 USD/kg	4896	0.19	0.16	0.05	2.06
Upper level model						
Population density, 1995	population/ha.	91707	0.18	1.26	0.00	118.01
Population density, 2000†	population/ha.	91707	0.20	0.91	0.01	79.54
Travel time to major cities	10^5 minutes	91707	0.10	0.06	0.00	0.45
Improved travel time to major cities†	10^5 minutes	91707	0.09	0.06	0.00	0.44
Terrain slope	degree	91707	0.68	1.17	0.00	24.95
Elevation	km	91707	0.69	0.34	0.00	3.21
Precipitation, 2000	10^3 mm	91707	1.59	0.28	0.79	2.17
Mean temperature, 2000	degree Celsius	91707	18.39	1.99	6.98	23.82
Soil silt content	n.a.	91707	20%	7%	3%	38%
Soil PH	n.a.	91707	5.20	0.29	4.79	7.60
Inclusive value of cropland	n.a.	91707	1.06	0.41	0.35	4.89
Inclusive value of cropland mosaic	n.a.	91707	1.28	1.37	0.32	21.84

Note: In the lower level model, physical area is measured at territory level, while suitability and price are measured at grid level; in the upper level model, all of the variables are measured at grid level.

† Data are used for generating baseline and policy scenario.

Table 3: Marginal Effects of Explanatory Variable on the Probabilities of Land Cover Choice

Indep. Variables	Tropical rainforest	Deciduous forest	Swamp	Shrub /herbaceous	Other vegetation mosaic	Cropland	Mosaic of cropland
Population density (×10)	8.552***	-10.593***	-0.001***	0.921***	0.631***	0.005***	0.485***
	(0.471)	(0.282)	(0.000)	(0.229)	(0.136)	(0.001)	(0.107)
Travel time	20.769***	-6.291***	0.000*	-7.641***	-0.341***	-0.078***	-6.418***
	(0.401)	(0.314)	(0.000)	(0.197)	(0.119)	(0.011)	(0.161)
Terrain slope	0.421***	-0.210***	-0.000***	-0.083***	-0.124***	-0.000**	-0.003
	(0.018)	(0.013)	(0.000)	(0.007)	(0.008)	(0.000)	(0.007)
Elevation	3.912***	-3.852***	-0.005***	-0.763***	0.522***	-0.000	0.186***
	(0.151)	(0.111)	(0.001)	(0.065)	(0.059)	(0.001)	(0.051)
Precipitation	10.277***	-7.991***	0.001***	-3.144***	-0.407***	-0.019***	1.282***
	(0.096)	(0.078)	(0.000)	(0.053)	(0.059)	(0.003)	(0.033)
Mean temperature	1.597***	-1.405***	0.000***	-0.290***	0.045***	-0.002***	0.054***
	(0.030)	(0.023)	(0.000)	(0.013)	(0.013)	(0.000)	(0.009)
Soil silt content	8.824***	-9.327***	0.003***	-5.545***	6.017***	0.007	0.021
	(0.377)	(0.305)	(0.001)	(0.161)	(0.132)	(0.005)	(0.083)
Soil PH	-0.346***	0.569***	-0.000	0.970***	-0.953***	0.003***	-0.243***
	(0.073)	(0.053)	(0.000)	(0.027)	(0.034)	(0.001)	(0.025)
Inclusive value	-0.160**	-0.040**	-0.000**	-0.018**	-0.010**	2.237**	-0.009**
(cropland)	(0.067)	(0.017)	(0.000)	(0.008)	(0.004)	(0.100)	(0.004)
Inclusive value	-17.970***	-4.486***	-0.001**	-2.045***	-1.167***	-0.009**	25.677***
(cropland mosaic)	(6.784)	(1.694)	(0.000)	(0.785)	(0.455)	(0.004)	(9.716)

Note: (1) *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. (2) Marginal effects are evaluated at the means of the data. (3) We enlarge the magnitude of marginal effects of inclusive values by 10^{11} times and enlarge the magnitude of marginal effects of other variables by 10 times.

Table 4: Own Elasticities of Crop Choice

Crop choice	Cropland		Cropland mosaic	
	Suitability	Price	Suitability	Price
Bean	0.093	-2.380	0.006***	1.109***
	(0.157)	(5.941)	(0.000)	(0.237)
Cassava	0.978**	0.457**	-0.278	0.584
	(0.478)	(0.207)	(2.322)	(2.263)
Groundnuts	0.350***	0.930*	0.123***	0.341*
	(0.044)	(0.513)	(0.021)	(0.197)
Maize	0.365	0.440*	-0.112	0.770
	(0.244)	(0.272)	(0.478)	(2.723)
Plantain	-1.805***	-0.142	0.111	-1.317***
	(0.104)	(0.128)	(0.205)	(0.227)
Rice	1.551***	-1.111***	0.307	0.899
	(0.277)	(0.076)	(6.976)	(1.451)

Note: (1) *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. (2) Elasticities are evaluated at the means of the data and are the percentage change in the probability of crop choice for 1% change in crop suitability and in crop price, respectively.

Table 5: A Comparison of Baseline and Simulated Scenario by Road Category

	Baseline: Current network (km)	Simulation: Government's plan (km)
Paved roads (80km/hr)	1,611	8,500
4WD roads (30km/hr)	26,500	25,875
Loose gravel (25km/hr)	59,500	53,236
Trails (3km/hr)	87,200	87,200
Ferry crossing (5km/hr)	239	239
Ferries, boats, etc. (10km/hr)	1,486	3,200
Estimated cost (US$ millions)	n/a	US$2,064

Source: Ulimwengu et al. 2009 (Table 11, page 32).

Table 6: Simulated Land Use Conversions Induced by Road Construction (Million ha.)

	After Road Construction							
Before Road Construction	Tropical rainforest	Deciduous forest	Swamp	Shrub/her baceous	Other vegetation mosaic	Cropland	Mosaic of cropland	***Total transition (from row category)***
Tropical rainforest	81.29	12.14	4.33	7.73	6.83	0.16	8.51	***120.98***
Deciduous forest	11.42	30.16	0.15	8.76	1.83	0.35	1.17	***53.84***
Swamp	4.20	0.16	2.37	0.18	0.57	0.00	0.48	***7.96***
Shrub/herbaceous	6.87	8.43	0.15	4.90	0.67	0.21	0.90	***22.13***
Other vegetation mosaic	6.50	1.88	0.56	0.74	1.47	0.04	0.81	***12.00***
Cropland	0.12	0.30	0.00	0.19	0.03	0.06	0.02	***0.72***
Mosaic of cropland	6.98	1.06	0.38	0.85	0.69	0.02	1.58	***11.55***
Total transition (to column category)	***117.39***	***54.12***	***7.95***	***23.35***	***12.09***	***0.83***	***13.46***	-

Table 7: Summarized Changes in Land Use Area and Biological Carbon Stock

Land Cover Category	Land area (million ha.) Before road construction	After road construction	Change	Average aboveground C stock (MgC/ha.)	Average belowground C stock (MgC/ha.)	Average SOC stock (MgC/ha.)	Total C stock before road construction (TgC)	Total C stock after road construction (TgC)	Total one-time change in C stock (TgC)
Tropical rainforest	121.0	117.4	-3.0%	110.6	40.3	87.7	28,855.4	27,998.9	-856.5
Deciduous forest	53.8	54.1	0.5%	37.0	10.2	75.0	6,577.0	6,611.3	34.3
Swamp	8.0	7.9	-0.2%	125.2	46.3	79.0	1,994.5	1,991.4	-3.1
Shrub/herbaceous	22.1	23.3	5.5%	18.1	5.8	76.1	2,213.6	2,335.1	121.5
Other vegetation mosaic	12.0	12.1	0.8%	34.3	12.4	88.8	1,626.1	1,638.5	12.4
Cropland	0.7	0.8	15.1%	17.4	4.9	181.1	146.9	169.1	22.3
Mosaic of cropland	11.6	13.5	16.5%	81.3	29.8	85.6	2,272.2	2,647.1	375.0
Total	*229.2*	*229.2*	-	-	-	-	*43,685.6*	*43,391.4*	*-294.2*

Table 8: Estimated Changes in Biological Carbon Stock (TgC) Induced by Road Construction

	After Road Construction							
Before road construction	Tropical rainforest	Deciduous forest	Swamp	Shrub/herbaceous	Other vegetation mosaic	Cropland	Mosaic of cropland	***Total transition (from row category)***
Tropical rainforest	-	-1412.3	51.9	-1070.7	-703.6	-5.5	-356.0	***-3496.2***
Deciduous forest	1329.2	-	19.7	-194.0	24.4	28.2	87.3	***1294.7***
Swamp	-50.4	-21.0	-	-26.7	-65.8	-0.03	-25.6	***-189.5***
Shrub/herbaceous	951.7	186.7	23.3	-	23.8	21.5	86.9	***1294.0***
Other vegetation mosaic	669.7	-25.1	64.8	-26.2	-	2.5	49.2	***735.0***
Cropland	4.3	-24.0	0.03	-20.0	-1.9	-	-0.13	***-41.6***
Mosaic of cropland	292.0	-78.6	20.4	-82.3	-42.2	0.14	-	***109.4***
Total transition (to column category)	***3196.5***	***-1374.2***	***180.2***	***-1419.8***	***-765.3***	***46.8***	***-158.3***	***-***
Carbon loss: Loss of 1 ha. of tropical rainforest (MgC)	***-28.9***	***Carbon loss: Increase of 1 ha. of agricultural land (MgC)***				***-7.80***		***-***

Table 9: Fertilizer Recommendation Rates in Provinces of the DRC

Crop	Province	NPK (N-P_2O_5-K_2O Kg/ ha)	
		Low	High
Cassava	All provinces	50-50-50	100-100-100
	Province Orientale, Kasai occidental	60-40-0	90-60-0
	Kasai Oriental, Equateur, Katanga, Bandundu, Bas-Congo	40-40-0	60-60-0
Groundnut	Bas-Congo, Province Orientale, Equateur, Katanga, Bandundu	0-45-0	20-45-0
	Province Orientale	20-45-0	20-45-0
	Kivu	18-46-0	18-46-50
Soybean	Bandundu	0-45-0	20-45-0
	Kasai Occidental, Kasai Oriental, Equateur	0-45-0	35-35-35
	Kivu	18-46-0	18-46-0
Rice rain-fed	Province Orientale, Equateur, Kasai Occidental	40-40-0	60-60-0
Rice irrigated	Bandundu, Kinshasa	85-35-0	120-80-80
	Bas Congo	85-35-0	115-70-0
	Kivu	46-0-0	76-30-30
Beans	Bas Congo	30-30-30	60-60-60
	Kivu, Province Orientale	18-46-0	60-90-30
Maize	Province Orientale, Kasai Oriental, Bandundu	90-60-0	
	Katanga	100-75-45	
	Kasai Occidental	50-50-10	
Banana/plantain	Bas Congo	150-30-300†	N: 200-60-400†

†Amounts applied in 4 to 6 applications per year.

Source:

Programme National Engrais. 1998. Synthèse agronomique des essais de fertilisation dans la République Démocratique du Congo. Projet AG: GCPF/ZAI/013/BEL. FAO. Rapport technique no 98/1.

INERA Mvuazi. 2009. Fruit and Banana Research Program. Ministère de l'Enseignement Supérieur, RDC.

Dombele, K. D. 2009. Utilisation, entreposage et gestion des engrais minéraux et organiques en riziculture de bas – fond. Atelier de formation. PROJET TCP/DRC/3201. Initiative contre la flambée des prix des denrées alimentaires.

Table 10: Estimated Changes in Crop Area Induced by Road Construction and the Resulting Nitrogen Emissions—Low-input Scenario

Crop	Changes in area due to road construction (Million ha.)	Nitrogen Fertilizer (kg Urea/ha.)	IPCC emission factor for Nitrogen fertilization (kg CO2e/kg N)	IPCC emissions factor from CO2 for urea applications (Kg CO2e/Kg Urea	Annual emissions per hectare (Mg CO$_2$e)	Total annual emissions due to road construction (MgCO$_2$e)	Annual costs from emissions (Million USD)	Cost of Fertilizer (Million USD)	Total Costs (Million USD)	Annual benefits from agriculture (Million USD)
Beans	0.020	7	2.98	0.73	0.0137	278.86	0.003	0.21	0.22	1.67
Cassava	0.204	11	2.98	0.73	0.0229	4,676.60	0.055	3.56	3.61	17.90
Groundnuts	0.036	0	2.98	0.73	0.0000	0.00	0.000	0.00	0.00	2.00
Maize	0.145	20	2.98	0.73	0.0412	5,974.60	0.070	4.54	4.61	5.20
Plantain	0.030	130	2.98	0.73	0.2745	8,242.91	0.097	6.27	6.36	0.93
Rice	0.079	9	2.98	0.73	0.0183	1,446.88	0.017	1.10	1.12	33.15
Total	0.51	-	-	-	-	20,619.85	*0.242*	15.68	15.92	*60.86*

Notes: (1) The price of carbon assumed is US$43/MgC with a consequent price of US$11.73/MgCO$_2$e; the price of urea, which contains 46.4% of nitrogen, is assumed to be US$1.6/kg. (2) Annual benefits from agriculture are calculated using the average value of provincial-level crop prices over 2006–2010.

Table 11: Estimated Changes in Crop Area Induced by Road Construction and the Resulting Nitrogen Emissions—High-input Scenario

Crop	Changes in area due to road construction (Million ha.)	Nitrogen Fertilizer (kg Urea/ha.)	IPCC emission factor for Nitrogen fertilization (kg CO2e/kg N)	IPCC emissions factor from CO2 for urea applications (Kg CO2e/Kg Urea	Annual emissions per hectare (Mg CO_2e)	Total annual emissions due to road construction (MgCO_2e)	Annual costs from emissions (Million USD)	Cost of Fertilizer (Million USD)	Total Costs (Million USD)	Annual benefits from agriculture (Million USD)
Beans	0.020	130	2.98	0.73	0.27	5,577.27	0.07	4.24	4.31	24.5
Cassava	0.204	217	2.98	0.73	0.46	93,531.92	1.10	71.12	72.22	292.3
Groundnuts	0.036	43	2.98	0.73	0.09	3,265.76	0.04	2.48	2.52	29.8
Maize	0.145	217	2.98	0.73	0.46	66,384.44	0.78	50.48	51.26	118.8
Plantain	0.030	1739	2.98	0.73	3.66	109,905.49	1.29	83.57	84.86	24.7
Rice	0.079	130	2.98	0.73	0.27	21,703.18	0.25	16.50	16.76	182.3
Total	0.51	-	-	-	-	300,368.06	*3.52*	228.40	231.92	672.2

Notes: (1) The price of carbon assumed is US$43/MgC with a consequent price of US$11.73/Mg$CO_2$e; the price of urea, which contains 46.4% of nitrogen, is assumed to be US$1.6/kg. (2) Annual benefits from agriculture are calculated using the average value of provincial-level crop prices over 2006–2010.

Appendix

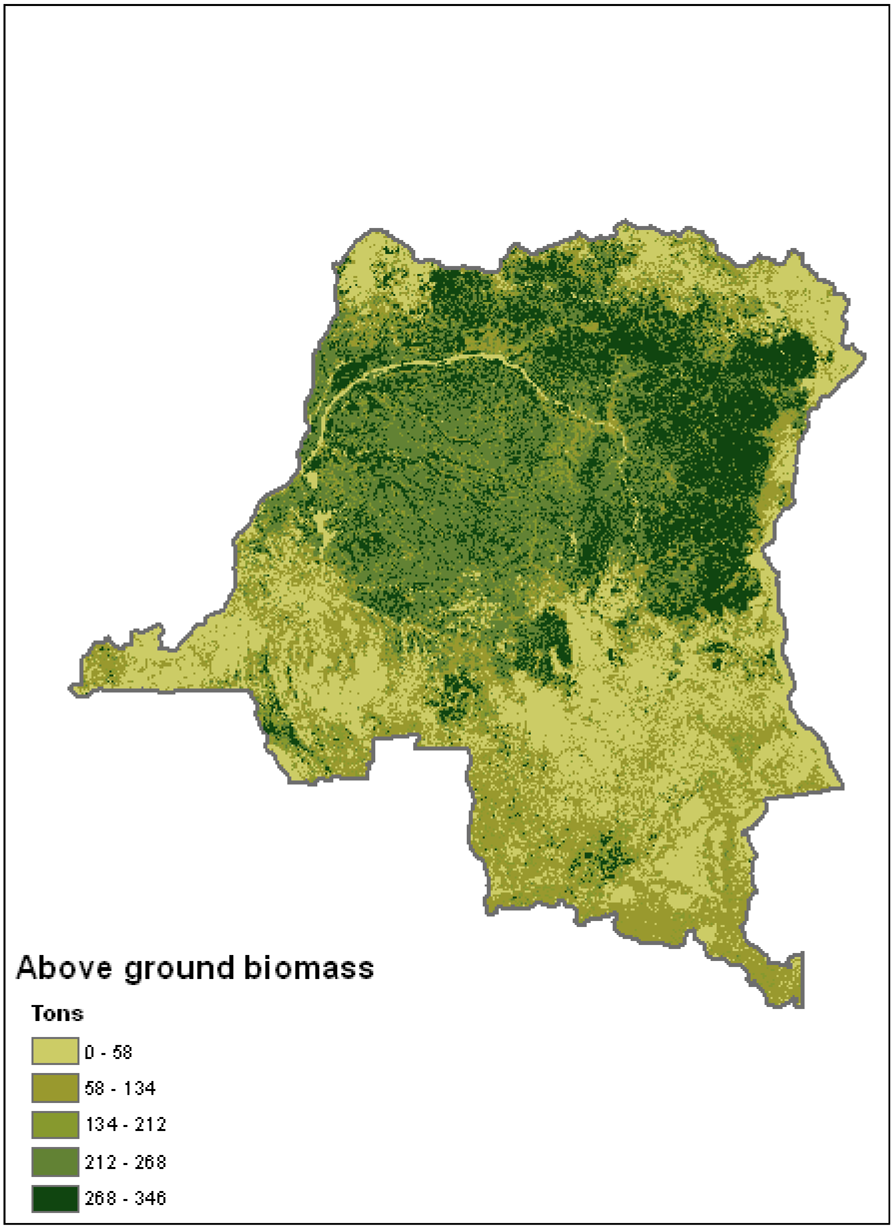

Figure A1: Above ground woody biomass in the DRC
Source: Baccini et al. (2008).

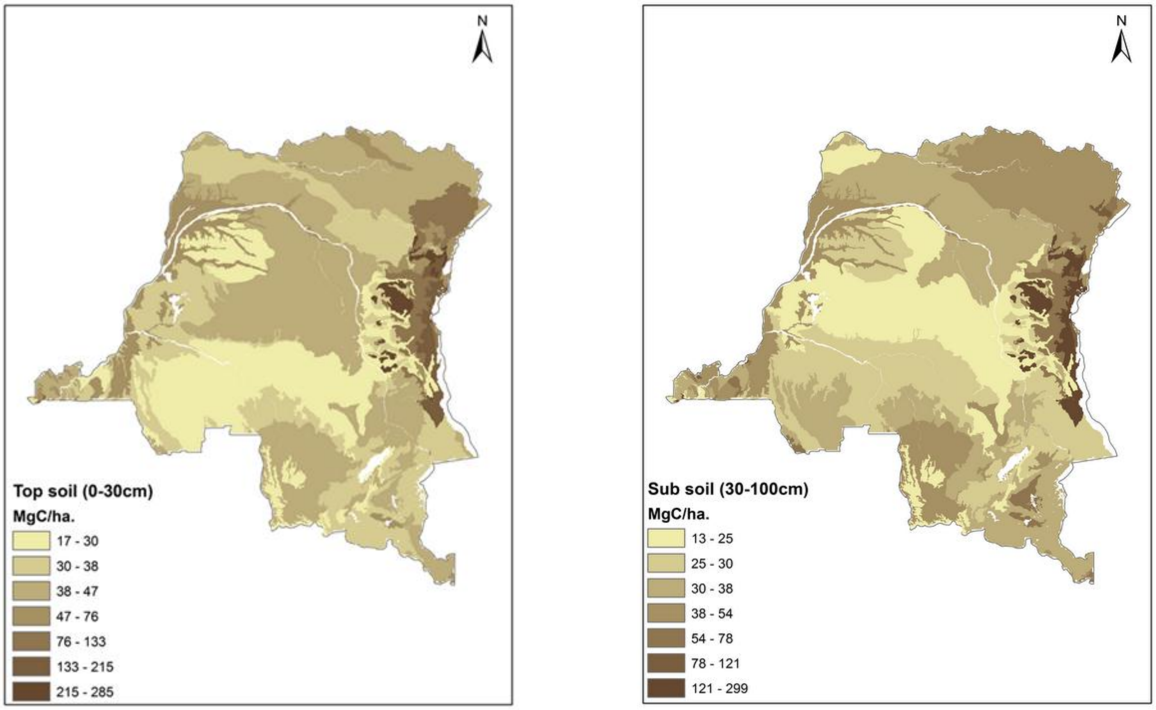

Figure A2: Soil organic carbon density in the DRC
Sources: Hiederer and Köchy's (2012).

Table A1: Assessment of the Predictive Power of the Upper-level Model by Province

	Total	Tropical rainforests			Deciduous forest			Swamp			Shrub/herbaceous			Other vegetation mosaic			Cropland			Mosaic of cropland		
Province	(million ha.)	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue	GLC2000	Estimation	Residue
Bandundu	16.9	33.0%	41.3%	-8.3%	38.6%	33.1%	5.4%	0.0%	0.5%	-0.5%	28.3%	19.5%	8.9%	0.0%	1.0%	-1.0%	0.1%	0.1%	0.0%	0.0%	4.4%	-4.4%
Bas-Congo	17.5	63.8%	57.2%	6.7%	11.6%	15.1%	-3.5%	7.7%	6.4%	1.2%	14.9%	15.4%	-0.5%	0.0%	1.5%	-1.5%	0.1%	0.1%	0.0%	1.9%	4.4%	-2.5%
Equateur	39.8	65.1%	67.4%	-2.3%	2.8%	2.9%	-0.1%	16.5%	15.1%	1.4%	0.2%	1.5%	-1.4%	6.8%	6.4%	0.4%	0.0%	0.0%	0.0%	8.5%	6.5%	2.0%
Kasai-Occid	15.5	56.2%	57.1%	-0.8%	23.1%	17.8%	5.2%	0.6%	0.4%	0.2%	11.2%	14.8%	-3.6%	0.0%	2.4%	-2.4%	8.8%	0.1%	8.7%	0.0%	7.4%	-7.4%
Kasai-Orien	27.9	35.7%	43.4%	-7.7%	42.9%	35.3%	7.6%	0.0%	0.1%	-0.1%	18.1%	14.7%	3.4%	0.1%	3.4%	-3.4%	3.2%	0.2%	3.0%	0.0%	2.8%	-2.8%
Katanga	36.0	13.3%	9.4%	3.9%	72.6%	71.7%	0.9%	0.0%	0.0%	0.0%	13.7%	14.1%	-0.4%	0.0%	3.7%	-3.7%	0.4%	0.6%	-0.3%	0.0%	0.4%	-0.4%
Kinshasa	1.1	12.9%	41.2%	-28.4%	23.3%	28.6%	-5.2%	0.0%	0.2%	-0.2%	56.7%	26.0%	30.7%	0.0%	0.7%	-0.7%	7.1%	0.2%	7.0%	0.0%	3.7%	-3.7%
Maniema	12.9	73.5%	71.5%	2.0%	11.6%	9.4%	2.2%	0.0%	0.3%	-0.3%	5.8%	6.3%	-0.4%	0.0%	5.1%	-5.1%	0.0%	0.1%	0.0%	9.1%	7.3%	1.8%
Nod-Kivu	5.7	73.3%	47.4%	25.8%	4.5%	23.6%	-19.1%	0.0%	0.0%	0.0%	1.2%	14.4%	-13.1%	4.8%	7.9%	-3.1%	5.9%	3.8%	2.2%	10.2%	2.9%	7.3%
Orientale	50.0	72.4%	72.6%	-0.2%	1.3%	6.0%	-4.7%	0.0%	1.3%	-1.3%	1.6%	2.8%	-1.2%	17.8%	9.5%	8.3%	0.1%	0.2%	0.0%	6.7%	7.7%	-1.0%
Sud-Kivu	5.8	74.5%	62.5%	12.0%	9.4%	15.3%	-5.9%	7.8%	0.0%	7.8%	0.4%	8.1%	-7.7%	0.4%	6.8%	-6.4%	7.4%	1.4%	5.9%	0.0%	5.8%	-5.8%
Average	-	-	-	4.4%	-	-	3.9%	-	-	0.9%	-	-	2.6%	-	-	3.8%	-	-	1.2%	-	-	2.4%

Note: Residue is calculated as the discrepancy between the predicted and observed proportions of land use; the last row reports the weighted mean of residues across provinces, where the weight is the proportion of land area of each province in the country.

Table A2: Assessment of the Predictive Power of the Lower-level Model by Province

	Total	Bean			Cassava			Groundnuts			Maize			Plantain			Rice			Other crops		
Province	(thousand ha.)	Observed	Estimation	Residue	Oberved	Estimation	Residue	Observed	Estimation	Residue	Oberved	Estimation	Residue	Observed	Estimation	Residue	Oberved	Estimation	Residue	Observed	Estimation	Residue
Bandundu	11	0.0%	18.6%	-18.6%	52.8%	19.7%	33.0%	16.4%	1.6%	14.9%	28.4%	10.1%	18.3%	0.4%	1.2%	-0.8%	2.1%	4.6%	-2.5%	0.0%	44.2%	-44.2%
Bas-Congo	112	2.0%	1.7%	0.3%	37.2%	21.2%	16.0%	3.8%	2.5%	1.3%	9.7%	16.2%	-6.4%	1.2%	0.5%	0.7%	5.0%	10.9%	-5.9%	41.0%	46.9%	-5.8%
Equateur	1,091	0.0%	0.3%	-0.3%	17.0%	14.1%	2.9%	2.6%	2.3%	0.3%	15.9%	12.1%	3.8%	0.7%	2.2%	-1.5%	2.2%	6.2%	-4.0%	61.6%	62.8%	-1.2%
Kasai-Occid	440	0.0%	0.5%	-0.5%	19.2%	17.5%	1.7%	5.2%	3.7%	1.6%	33.0%	20.3%	12.7%	0.4%	1.1%	-0.6%	3.5%	9.3%	-5.8%	38.6%	47.7%	-9.1%
Kasai-Orien	295	0.1%	0.3%	-0.2%	20.5%	21.5%	-1.1%	4.5%	2.5%	2.0%	29.8%	19.8%	10.0%	0.3%	0.9%	-0.6%	9.4%	6.6%	2.7%	35.5%	48.4%	-12.9%
Katanga	86	5.1%	5.2%	-0.1%	38.8%	39.1%	-0.3%	10.0%	10.9%	-0.9%	26.3%	24.9%	1.4%	0.9%	2.6%	-1.7%	0.6%	0.3%	0.3%	18.3%	16.8%	1.4%
Kinshasa	48	0.0%	2.9%	-2.9%	0.0%	18.3%	-18.2%	0.1%	1.8%	-1.7%	0.1%	11.5%	-11.4%	0.0%	0.9%	-0.9%	0.1%	0.3%	-0.3%	99.7%	64.3%	35.4%
Maniema	376	0.0%	0.3%	-0.3%	21.0%	19.8%	1.3%	4.1%	4.0%	0.1%	7.7%	17.4%	-9.7%	1.5%	1.0%	0.5%	16.1%	13.7%	2.5%	49.6%	43.9%	5.7%
Nod-Kivu	403	17.7%	12.9%	4.8%	21.5%	26.1%	-4.5%	1.8%	2.5%	-0.7%	14.4%	12.7%	1.7%	6.1%	4.5%	1.6%	4.3%	4.5%	-0.1%	34.1%	36.9%	-2.7%
Orientale	1,114	0.5%	0.8%	-0.3%	15.7%	19.6%	-3.9%	1.5%	3.0%	-1.5%	6.0%	12.0%	-5.9%	4.0%	2.4%	1.6%	10.6%	6.4%	4.2%	61.7%	56.0%	5.8%
Sud-Kivu	153	4.4%	1.6%	2.8%	23.7%	23.8%	-0.1%	6.1%	5.2%	0.9%	5.7%	18.8%	-13.1%	0.5%	1.2%	-0.7%	22.1%	16.9%	5.2%	37.5%	32.4%	5.1%
Average	-	-	-	0.9%	-	-	3.4%	-	-	1.0%	-	-	6.6%	-	-	1.2%	-	-	3.6%	-	-	5.5%

Note: Residue is calculated as the discrepancy between the predicted and observed proportions of crop choice; the last row reports the weighted mean of residues across provinces, where the weight is the proportion of crop area of each province in the country.

Table A3: Ratio of Belowground Biomass to Aboveground Biomass

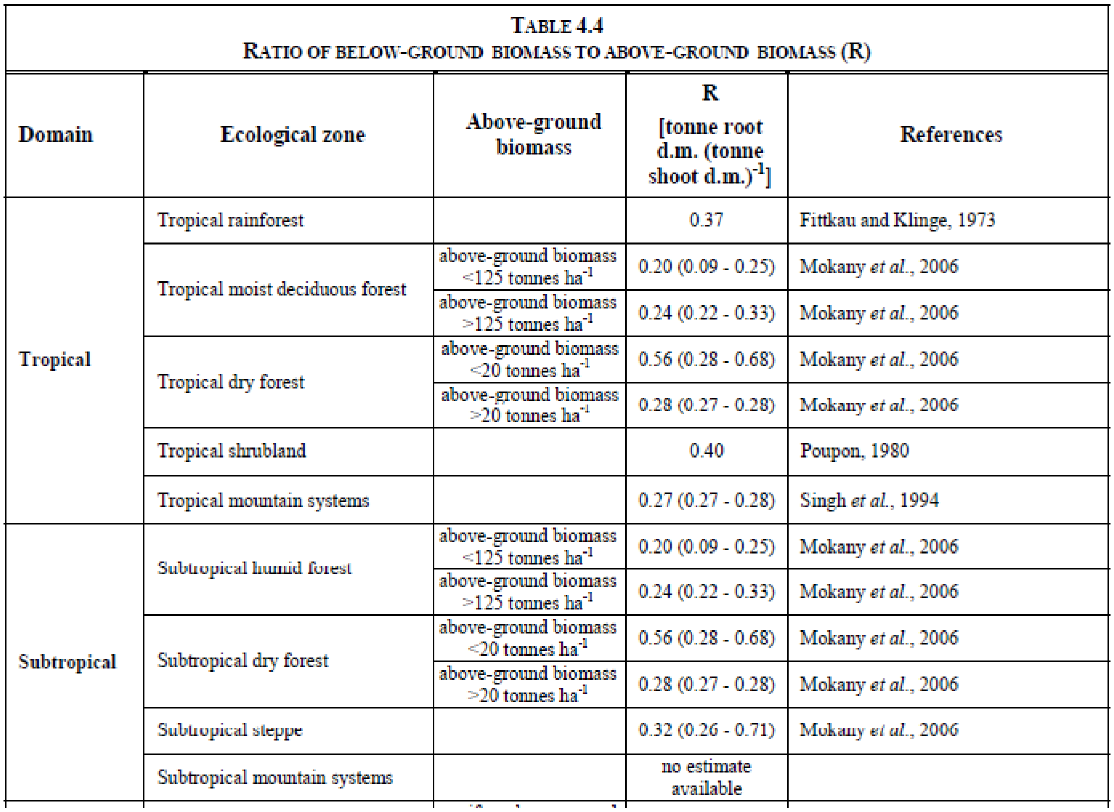

TABLE 4.4
RATIO OF BELOW-GROUND BIOMASS TO ABOVE-GROUND BIOMASS (R)

Domain	Ecological zone	Above-ground biomass	R [tonne root d.m. (tonne shoot d.m.)$^{-1}$]	References
Tropical	Tropical rainforest		0.37	Fittkau and Klinge, 1973
	Tropical moist deciduous forest	above-ground biomass <125 tonnes ha^{-1}	0.20 (0.09 - 0.25)	Mokany *et al.*, 2006
		above-ground biomass >125 tonnes ha^{-1}	0.24 (0.22 - 0.33)	Mokany *et al.*, 2006
	Tropical dry forest	above-ground biomass <20 tonnes ha^{-1}	0.56 (0.28 - 0.68)	Mokany *et al.*, 2006
		above-ground biomass >20 tonnes ha^{-1}	0.28 (0.27 - 0.28)	Mokany *et al.*, 2006
	Tropical shrubland		0.40	Poupon, 1980
	Tropical mountain systems		0.27 (0.27 - 0.28)	Singh *et al.*, 1994
Subtropical	Subtropical humid forest	above-ground biomass <125 tonnes ha^{-1}	0.20 (0.09 - 0.25)	Mokany *et al.*, 2006
		above-ground biomass >125 tonnes ha^{-1}	0.24 (0.22 - 0.33)	Mokany *et al.*, 2006
	Subtropical dry forest	above-ground biomass <20 tonnes ha^{-1}	0.56 (0.28 - 0.68)	Mokany *et al.*, 2006
		above-ground biomass >20 tonnes ha^{-1}	0.28 (0.27 - 0.28)	Mokany *et al.*, 2006
	Subtropical steppe		0.32 (0.26 - 0.71)	Mokany *et al.*, 2006
	Subtropical mountain systems		no estimate available	

Source: IPCC (2006).

Table A4: Average Crop Prices by Province (US$/Mg), 2006–2010

Province	Beans	Cassava	Groundnuts	Maize	Plantain	Rice
Bandundu	869	212	388	248	402	526
Bas-Congo	1338	441	740	553	588	484
Equateur	471	129	120	134	133	235
Kasai-Occid	516	159	246	230	255	246
Kasai-Orien	1232	209	508	322	266	526
Katanga	1615	502	1855	388	255	748
Kinshasa	2094	355	399	380	409	4163
Maniema	953	164	400	206	221	336
Nod-Kivu	541	346	487	282	331	515
Orientale	694	168	435	125	140	279
Sud-Kivu	725	458	1389	490	303	953

Table A5: Changes in Crop Production Induced by Road Construction—Low Nitrogen Application (1,000 Mg)

Province	Beans	Cassava	Groundnuts	Maize	Plantain	Rice
Bandundu	0.000	1.255	0.034	0.347	0.126	9.501
Bas-Congo	0.146	3.318	0.032	0.297	0.074	4.564
Equateur	0.000	6.417	0.033	0.675	1.376	8.844
Kasai-Occid	0.000	2.015	0.095	0.486	0.152	3.523
Kasai-Orien	0.025	1.586	0.074	0.524	0.053	4.361
Katanga	0.815	15.524	0.837	8.961	0.046	1.494
Kinshasa	0.000	0.011	0.000	0.000	0.001	2.405
Maniema	0.000	4.932	0.108	0.564	0.140	4.794
Nod-Kivu	0.004	1.575	0.003	0.269	0.063	0.857
Orientale	0.150	22.276	0.251	1.799	3.633	19.112
Sud-Kivu	0.037	3.926	0.137	1.405	0.110	2.310

Table A6: Changes in Crop Production Induced by Road Construction—High Nitrogen Application (1,000 Mg)

Province	Beans	Cassava	Groundnuts	Maize	Plantain	Rice
Bandundu	0.305	32.142	1.184	17.648	1.147	47.136
Bas-Congo	1.717	89.474	1.966	62.816	6.163	56.358
Equateur	0.203	153.294	2.723	71.196	41.500	54.706
Kasai-Occid	0.368	42.011	2.201	19.727	2.287	20.411
Kasai-Orien	0.590	42.184	1.834	22.968	2.344	26.527
Katanga	9.896	178.473	10.332	67.981	0.529	5.383
Kinshasa	0.001	0.243	0.003	0.059	0.012	10.904
Maniema	0.824	92.160	2.407	19.232	3.099	22.748
Nod-Kivu	0.168	20.746	0.269	9.587	1.461	4.015
Orientale	2.967	387.073	5.836	135.618	87.074	101.154
Sud-Kivu	2.715	73.657	2.344	16.822	1.430	11.574