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Households livelihoods and deforestation in the Tridom Transboundary Conservation : A spatial analysis

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Abstract

This paper aims to examine the determinants of household' deforestation in the Tridom tansboundary conservation landscape (Tridom-TCL). It investigates the role of households' livelihoods strategies. It also tests the effects of crop damage caused by elephants (human-elephant conflict) on the households' decision of deforestation, using a unique dataset gathered with 1035 households in the Tridom-TCL. The results of the spatial autoregressive model show that: (1) households tend to imitate deforestation decisions of their neighbors. (2) When accounting cash crops as part of a diversification livelihoods' strategy, households' deforestation increases significantly with a significant indirect impact on neighboring households' deforestation. In fact, a one-unit increase in the income of households that include cash crops in their portfolio, leads to six to seven times increases in households' deforestation compared to the effect of income increase in households choosing other livelihoods' strategies. Also, (3) the indirect effects of these choices on neighboring households' deforestation have almost the same magnitude as the direct impact resulting from other strategies. (4) We find no substitutability between leisure and work in land use choices. Indeed, the Pygmies, who constitute the pincipale labour with low cost, are employed in activities related to larger deforestation, while household labour duration does not significantly drive households' deforestation. The share of households' self-consumption is associated with a low deforestation, therefore, a bigger integration of the market can lead to increased deforestation, if practices remained unchanged.
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1. Introduction

In most developing world, rural households rely on both small scale farming and forest-based activities to develop their survival strategies. Small scale agriculture is known as a source of livelihoods for about 86 percent of the three billion people living in rural areas (Burch et al., 2007), while forests-based activities are widely recognized to provide safety nets to mitigate agricultural risk (Pattanayak and Sills, 2001) and contributes between 22.2% to 27% of total households income (Angelsen et al., 2014; Vedeld et al., 2007). As pointed-out by the literature on sustainable livelihoods' strategies by Ellis (2000); Scoones (1998), rural households switch between specialisation and diversification to optimize their livelihoods provisioning. In the Dja-Odzala-Minkébé trinational tansboundary conservation landscape (Tridom-TCL), Ngouhouo Poufoun and Delacote (2016) investigates the variables determining the household choice to specialize or diversify its activities. The authors have also shown that choosing a livelihoods' strategy in the Tridom-TCL can be seen as strategic choice between forest-based and non-forest-based portfolios including small-scale farming and/or cash cropping (cocoa and rubber). Yet, depending on the orientation between land-converting activities and forest resource extraction, effort allocation by households might either increase deforestation, increase forest degradation, or enhance both (Delacote and Angelsen, 2015). Indeed, agriculture is estimated to be the proximate driver for around 80% of deforestation worldwide, contributing for 10 to 12% of the total global annual anthropogenic emissions of GHGs (Verchot, 2014), while poaching and non-sustainable harvesting of non-timber forest products (NTFPs) can have significant adverse impacts on forest ecosystems and lead to forest degradation (Angelsen, 2009; Belcher and Schreckenberg, 2007; Hosonuma et al., 2012; Kissinger et al., 2012), reducing the capacity of forest to regenerate and to produce ecosystem services.

Our recent household survey at the Tridom landscape-scale provides some evidence that about 85,45% of households are responsible for changing forest cover to other uses regardless of their livelihoods' strategies.

There is a low population density (less than 7 $inh./km^2$) and local households are less likely to practice optimal crop rotation. As there is no binding regime[1] of land acquisition in the non-permanent forest estate[2] that is seen as common access resources, they can clear relatively large area of land at low cost. In almost all cases, land conversion is done without revival of forest neither artificially nor naturally. Indeed, rural households do not apply any agroforestry system and they are not involved in the reforestation activities, while primary or secondary forest is progressively replaced by corkwood, whose carbon storage potential is very low. In many case, extensive and unsustainable household farming based on slash-and-burn cultivation accentuates small-scale deforestation and forest degradation. After removal or selling the softwood lumber in surrounding forests, all the remaining plants and material in the forest are burnt and land is used for extensive agricultural and cash-crop production. Soil fertility and crop yields are continuously declining (Boahene et al., 1998) and could cause a food crop production loss of at least \$2.4billion to \$5 billion to across the Congo Basin (Ernst et al., 2010). Without an optimal fallow system, local people are experiencing poor yields per hectare regarding cash-cropping and crop production. Indeed, at least 75% cocoa and plantain yield observed are less than 0,338t/ha and 3.59t/ha respectively with an average of 0.236t/ha and 3,09t/ha. This average yield is below the average performance given limited farm means of production that is 0.5t/ha and 16.5 t/ha, respectively. The potential yield of Cocoa is 0.73t/ha and 1.22t/ha when cocoa plantations are associated with timber shade and leguminous tree species and when there is a good use of the litter fall resoectively. The maximum yield can reach 2.4t/ha (Somarriba and Beer, 1998, 2006). Regarding plantains, the potential yield can reach 30t/ha/year (MINCOMMERCE, 2010). The diminishing returns due to the unsustainable practices contribute to the perpetration of poverty (Alemagi et al., 2014). Hence, the high level of forest dependence may not necessarily correspond to a high and sustainable potential to reduce poverty (Angelsen and Wunder, 2003). Rather, this may lead to over-exploitation of common access resources and constitute poverty trap when rural households face a large need of insurance (Delacote, 2007).

In light of the above considerations, analyzing the full set of potential drivers of households' deforestation, prioritizing or distinguishing among them in order to inform policy makers and facilitate appropriate

[1] A binding regime or more secure property rights motivates efficient resources management by landowners (Angelsen and Kaimowitz, 2001).

[2] The forest sector in Congo Basin Countries is divided into (i) 'Permanent Forest Estate', that includes logging concessions, ought to remain forest and mandated to maintain the biological diversity, and (ii) 'Non-Permanent Forest Estate', that can be turned to alternative use including sustainable agriculture.

political decision process to curb deforestation in the medium and long term perspectives is of crucial interest (Pfaff, 1999; Tegegne et al., 2016). Our paper contributes to the literature, and seeks to answer the following questions : How and how much do the different livelihoods' strategies developed by households, given wildlife constrains such as human-wildlife conflict impact small-scale deforestation ?

The following sections develop the literature review and our contribution (section 2), Objectives and hypothesis (section 3), a simple microeconomic model (section 4). The spatial economic procedure in presented in section 5, the results in section (6) and discussion and conclusion in section (7).

2. Literature Review and contribution

2.1. Literature review

The substantial academic research on the causes of tropical deforestation includes (1) conceptual framework for analyzing deforestation, (2) macro-level empirical studies including regional and national levels, (3) micro-level empirical studies and (4) spatially explicit analyses.

2.1.1. Conceptual Framework related studies

The first analysis that combined the results of multiple studies to frame the causes of tropical deforestation was realized by Angelsen and Kaimowitz (1999). The authors have synthesized the results of more than 140 economic models using five types of variables[3] to build a helpful framework for both understanding deforestation processes and classifying modeling approaches. According to the authors, the agent or the source of deforestation (plantation companies, small farmers, etc.) has to be identified. Further, agents' decisions have to be considered, accounting for (1) their characteristics, including their preferences, their background (seniority of a households head), labour allocation as well as their initial resource and for (2) their decision parameters such as property regime, agricultural price, timber prices and income. These variables represent immediate or proximate causes. Finally, underlying variables, i.e., broader forces like macroeconomic variables or policy instruments that influence the source or agents and indirectly drive deforestation have to be taken into account. Proximate drivers stand for human-induced factors

[3] The five types of variables used in the 140 models of deforestation are : (1) The magnitude and location of deforestation; (2) the agents of deforestation, namely, individuals, households, or companies involved in land use change and their characteristics; (3) the choice variables (decisions about land allocation that determine the overall level of deforestation for the particular agent or group of agents); (4) Agents' decision parameters and (5) macroeconomic variables and policy instruments affecting forest clearing indirectly through their influence on the decision parameters Angelsen and Kaimowitz (1999).

that influence directly households' deforestation, while underlying driving forces are fundamental social processes, that underpin the proximate causes and either operate at the local level or have an indirect impact from the national level (Geist and Lambin, 2002; Kissinger et al., 2012). From their meta-analysis, Angelsen and Kaimowitz (1999) derived two categories of models. Microeconomic models should focus on immediate causes, while macroeconomic models tend to deal with underlying causes. The authors also suggest distinguishing between models based on perfect markets and models assuming imperfect markets.

Geist and Lambin (2002) have contributed to the building of this conceptual framework via a meta-analysis of 152 case studies taken from 95 articles published in 40 scientific journals. The authors' main contribution was the breakdown of numerous factors found in the existing literature into (1) three aggregate proximate causes that are agricultural expansion, wood extraction and expansion of infrastructure; into (2) five broad categories of underlying driving forces which are demographic, economic, technological, policy/institutional, cultural or socio-political factors; and a group of "other variables" associated with deforestation, comprising land characteristics, biophysical drivers and social trigger events (economic crises, war, etc.).

More recently, Combes et al. (2015) have contributed to the conceptual framework with a theoretical model that emphasize a substitution effect between seigniorage and deforestation income. This contribution complies with the framework presented above. Indeed, Combes et al. (2015) considered the triple Environment-Economic-Social crises, which Geist and Lambin (2002) refer to as social trigger event, and proposed a link or a trade-off between macroeconomic and environmental outcomes, using an explicit model. This contribution is valuable to the traditional framework developed by Angelsen and Kaimowitz (1999). It presents a very feasible transmission channel between broad underlying drivers and deforestation. For instance, international transfers, public debt and saving can be used by the government to optimize inter-temporal allocation of natural resources and spending (Combes et al., 2015).

2.1.2. Macro-level empirical studies

A broad existing literature addresses causes of tropical deforestation at national, regional, and global scales using macro-level data in developing countries, considering many type of forests, macroeconomic variables, institutional and policy factors (Barbier and Burgess, 2001; Bhattarai and Hammig, 2001; Combes et al., 2015; Culas, 2007; Damette and Delacote, 2012; Geist and Lambin, 2002; Kaimowitz and Angelsen, 1998;

Nguyen Van and Azomahou, 2007; Palo, 1999; Pfaff, 1999; Tegegne et al., 2016; Wolfersberger et al., 2015). Major conclusions from a meta-analysis using results of 150 deforestation models by Kaimowitz and Angelsen (1998) in Brazil, Cameroon, Costa Rica, Indonesia, Mexico, Thailand, Ecuador, the Philippines and Tanzania are that deforestation tends to be greater when economic liberalization and adjustment policy reforms increases; when forested lands are more accessible; when agricultural and timber prices are higher; when rural wages are lower and there are more opportunities for long distance trade. Nguyen Van and Azomahou (2007) use a panel dataset of 59 developing countries over the 1972–1994 period to study the deforestation process. They found no evidence of an Environmental Kuznets Curve and they pointed out political institution failures as factor that can worsen the deforestation process in developing countries. More generally, the evidence supporting the existence of an EKC for deforestation is contrasted (Choumert et al., 2013).

Hosonuma et al. (2012) derive deforestation and degradation drivers using empirical data synthesized from existing reports on national REDD+ readiness activities. They assessed the relative importance as well as the drivers of variability by continent reflecting approximately the period 2000–2010. They used the forest transition model, considering deforestation rate and remaining forest cover in 100 subtropical non-Annex I countries[4]. They found that, similarly to Asia, the importance of deforestation drivers in Africa varies with different forest transition phases and with different areas. The impact of commercial agriculture on deforestation rises until the late-transition phase and the relative importance of subsistence agriculture remains fairly stable throughout the different phases.

2.1.3. Micro-level empirical studies relating to agent livelihoods decision

There is strong evidence that forests have an important role in insuring livelihood over time and in some cases, contribute to poverty alleviation (Sunderlin et al., 2005). Yet, few studies have investigated the relation between agent livelihoods decision and tropical deforestation at household's level.

Babigumira et al. (2014) use the CIFOR-PEN dataset, comprising of 7172 households from 24 developing countries to analyze which household and contextual characteristics affect land use decision in the developing world. The authors consider the sustainable livelihoods framework and assess the role of various asset types on households' deforestation. The authors found out that 27% of rural household have

[4]Annex I countries parties to the Convention includes the OECD countries and economies in transition that accepted to returning individually or jointly to their 1990 levels of greenhouse gas emissions by the year 2000. The other countries are referred to as Non-Annex I countries.

cleared forest for agricultural based livelihoods. They also found out that asset poverty does not drive deforestation. Indeed, households with medium to high asset holdings and higher market orientation were more likely to clear forest than the poorest and market-isolated households. They found out that households that cleared forests were closer to the forest and came from villages with higher forest cover. Relying on a rich panel dataset collected from the Tsimane' communities in Bolivia, Perge and McKay (2016) analyze the relationship between forest households' livelihoods strategies, and forest clearing, and the relationship of both to welfare. The authors identify four livelihoods' strategies based on households' reported sources of cash earnings, namely, sale, wage, diversified and subsistence strategy. They find that forest clearing is positively linked to welfare especially for households whose income results from combining agricultural sales and wage activities compared to households adopting other strategies. Households with subsistence strategy are not able to accumulate assets in the long run. As one of the main conclusions, the authors state that households clear only small areas of forest with a positive effect on welfare, enabling accumulation of assets.

Pacheco (2009) define a typology of smallholders that accounts for both livelihoods, farming systems and wealth to analyze smallholders' deforestation in Uruará and Redenção in the Brazilian Amazon. The author use households survey data from 136 interviews in Uruará and 82 interviews in Redenção area, and find that cattle ranching is associated to greater impact than cash cropping or subsistence agriculture. Contrary to Perge and McKay (2016), a strong correlation between deforestation and the wealth of the farmers is found.

2.1.4. Spatially patterns studies

Spatially explicit econometric studies of drivers of deforestation have taken more importance in the last few years (Ferretti-Gallon and Busch, 2014). According to these studies, most deforestation tends to be located outside the reserve and mountainous area and deforestation occurred primarily within the more accessible Eastern counties and at areas near deforested areas. This illustrates the spread effect of deforestation in the Brazilian Amazon (Mertens et al., 2002). In the same vein, Pfaff et al. (2007) find evidence of spatial spillovers from roads in the Brazilian Amazon's deforestation. Considering local administrative entity, Amin et al. (2014) found that deforestation activities of neighboring municipalities are correlated with some leakage. As a point of fact, protected areas may shift deforestation to neighboring municipalities.

Using a general spatial two stage least squares model to analyze the determinants of deforestation in 24 Sub-Saharan African countries during the period spanning 1990 to 2004, Boubacar (2012) found that deforestation in one country is positively correlated to deforestation in neighboring countries and that determinants of forest clearing are region specific.

2.2. Contribution

More often, data on tropical deforestation including household scale-level have been debatable and notoriously unreliable or non-available (Geist and Lambin, 2002; Palo, 1999). Furthermore, there is a very poor level of econometric studies on the drivers of deforestation in tropical Africa including Congo Basin countries (Gbetnkom, 2009). While, unlike Southeast Asia and the Amazon regions, where large-scale agricultural operations play an important role, most deforestation in the Congo basin can be attributed to small-scale farmers using extensive slash-and-burn techniques (Kotto-Same et al., 2002; Weise and Ngobo, 2004). In the same vein, a meta-analysis by Ferretti-Gallon and Busch (2014) reveals a geographical lag of spatially explicit studies of tropical deforestation in peer-reviewed academic journals as regard to Africa from 1996-2013, underlined the availability of data as the main constraint.

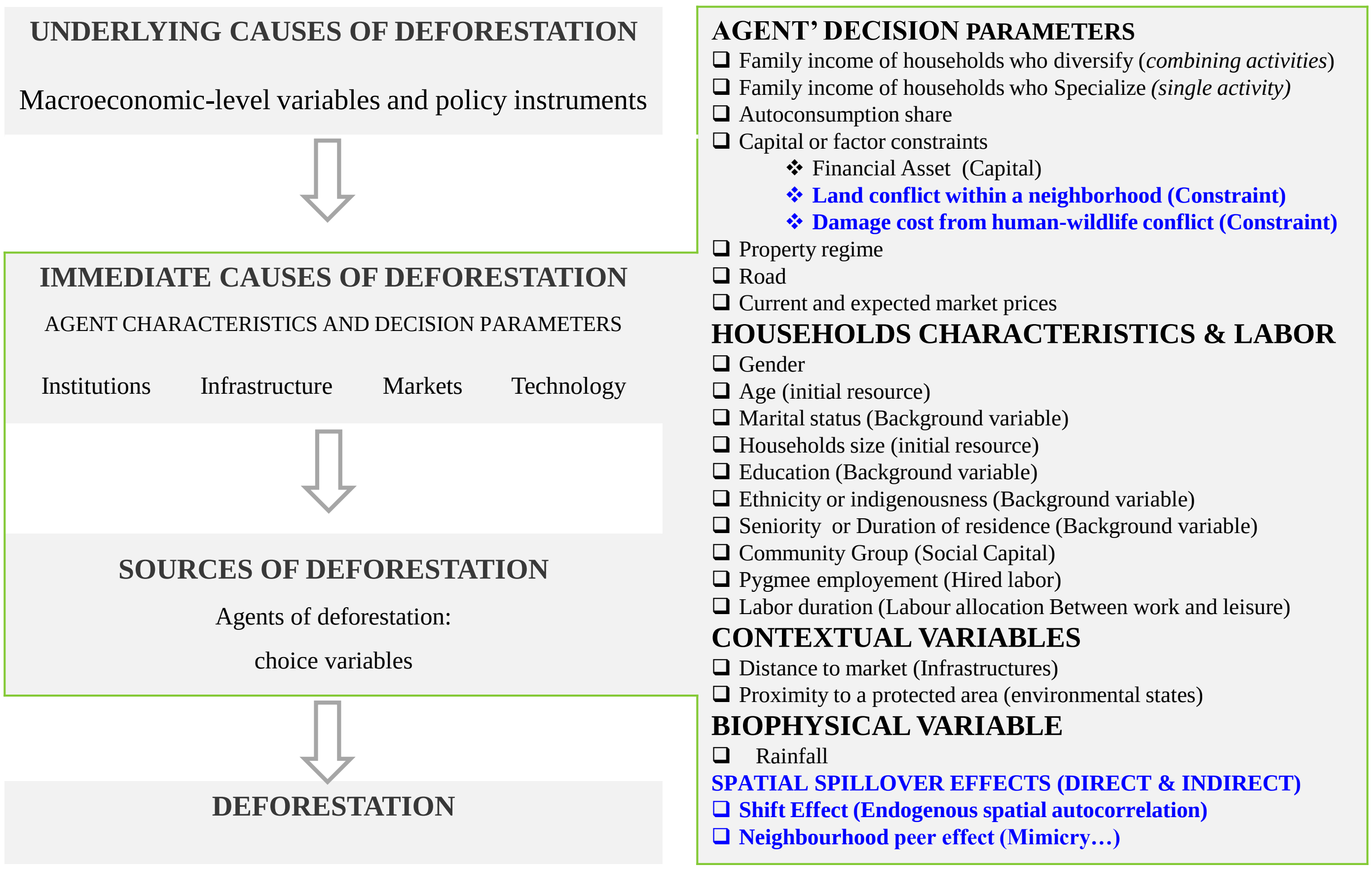
In this context, our contribution is multiple:

- We assess the impact of livelihood choices on deforestation. This research is among the pioneering studies that investigate the factors that govern households' deforestation in the Congo basin using a household-level survey. Indeed, west and central Africa account among regions that lag in econometric analysis of deforestation (Ferretti-Gallon and Busch, 2014; Geist and Lambin, 2002). At the same time, the factors affecting deforestation are more complex and vary significantly from one location or continent to another (Babigumira et al., 2014; Murali and Hedge, 1997; Rudel and Roper, 1997; VanWey et al., 2005).

- We refer to the standard protocol of analyzing deforestation. This is crucial as it allows for improved comparisons in future research (Geist and Lambin, 2002). Our research considers and tests the influence of (1) agents' decision parameters such as family income and factor constraints (2) agents' characteristics and (3) other contextual variables such as choice and biophysical variables on the agent' deforestation. Further, our research used a microeconomic model, therefore, we focus on immediate causes as suggested by (Angelsen and Kaimowitz, 1999). The figure 1 shows the adaptation of our research to the conceptual framework for analyzing households' deforestation.

- We consider the landscape approach and test the impact of human wildlife conflicts on households' deforestation. In the same vein, we consider testing the impact of land conflict among households on households' deforestation.

- The influence of spatial spillovers is investigated. Beside direct effects on households' characteristics, we consider endogenous and exogenous interactions among households and test the possible resulting spillover effect on households' deforestation within their neighborhood.



Source: Authors, Adapted from Angelsen and Kaimowitz (1999). Elements in blue color represent our contribution to the framework.

Figure 1: Adaptation of deforestation framework to Tridom-TCL case study

3. Objective and Hypothesis

This paper investigates the factors that drive households' deforestation in the Tridom-TCL, with a particular interest in the impact of households' choice of livelihoods' strategies. More precisely, we test the following hypothesis:

Decision variables influence deforestation.. (1) The impact of family income on small-scale deforestation is closely related to the households' livelihoods' strategies. This hypothesis will allow comparing the incremental change on households' deforestation resulting from a one-unit increase in income given their livelihoods portfolio and strategies. (2) Following Caldas et al. (2007); Fontes and Palmer (2016); Pfaff (1999), distance to market influences deforestation. Distance to market is considered here as an indicator of transaction cost regarding land location. (3) Financial asset (Walker et al., 2000, 2002) and factor constraints such as both Human-Human and Human-Wildlife conflicts drive households' deforestation. (4) Environmental state and policy, captured by the distance to the nearest protected area, rank among households' deforestation drivers. Due to their legal status, protected areas are supposed to be associated to lower deforestation (Ferretti-Gallon and Busch, 2014; Pfaff et al., 2015). Yet they may also have an impact on surrounding deforestation, for instance through leakage (Amin et al., 2014).

Households' characteristics influence deforestation.. Gender, households' head age and education, marital status, the household's size, ethnicity as well as duration of residence (seniority) account for the drivers of small-scale deforestation.

Households' Choice variables influence deforestation.. Following Pichón (1997); Walker et al. (2000, 2002), labour allocation between work and leisure and hired labour (especially Pygmies employment with very low cost in our case) increases forest clearing. (2) Social capital, like belonging to a group of interest, has an impact on households' deforestation. (3) Finally, following Chowdhury (2006a,b) we test that biophysical variables namely, rainfall have a strong impact on small-scale deforestation.

Spatial patterns influence deforestation.. This paper tests the presence of endogenous interaction of households' deforestation. Indeed, proximity among households in the Tridom-TCL implies the existence of cultural and social interaction that could yield spatial spillover effect leading to similarities in deforestation decision. Further, it was shown that, households' deforestation as a social and cultural phenomenon is likely to be characterized by spatial autocorrelation (Amin et al., 2014; Anselin, 2002; Boubacar, 2012; Brueckner, 2003; Mertens et al., 2002; Pfaff et al., 2007). The observations we did during the 8 months fieldwork in Cameroon and Gabon reveal some competition about land holding among household heads. This observation calls for testing the existence of spatial effects within a household's neighborhood.

4. A simple microeconomic model of deforestation choices

Consider household i choosing his/her level of deforestation D_i to maximize its utility:

$$\max_{D_i} U_i(D_i, L_i, X_i, D_j) \tag{1}$$

L_i is the livelihoods' strategy selected by the household, as defined in citeNgouhouoPoufoun2016lvlhd. 6 different household strategies are considered: agriculture (A), cash crop production (C), forest-based activities (F), and combinations of cash crops/forest-based (CF), agriculture/forest-based (AF) and agriculture/cash crops/forest-based (ACF); such that $L_i = [A, C, F, CF, AF, ACF]$.

X_i is a vector of household i socio-economic variables susceptible to influence deforestation. Household i's utility function may encompass income, but also other non-observable outcomes such as household's vulnerability. Thus, the household characteristics X_i may influence not only the household economic return, but also other household matters of interest. Furthermore, we also consider that household i's utility may be influenced by its neighbors. D_j is the level of deforestation chosen by household i's neighbors, that is likely to influence its decision. This type of strategic interactions is close to the resource-flow model presented by Brueckner (2003) and Anselin (2002).

The first-order condition implicitly gives the optimal level of deforestation $D_i^*(L_i, X_i, D_j^*)$ for household i:

$$U'_{D_i} = \frac{\partial U_i(D_i^*, L_i, X_i, D_j^*)}{\partial D_i^*} = 0 \tag{2}$$

Optimal deforestation strongly depends on the livelihoods' strategies chosen by the households:

$$D_i^*(L_i, X_i, D_j^*) \neq D_i^*(L_i', X_i, D_j^*),\ \forall L_i \neq L_i'. \tag{3}$$

Moreover, one can then infer the impact of livelihoods' strategies, other variables and neighbors deforestation on household i deforestation level:

$$\frac{\partial D_i^*(L_i, X_i, D_j^*)}{\partial X_i} = -\frac{\frac{\partial U'_{D_i}}{\partial X_i}}{\frac{\partial U'_{D_i}}{\partial D_i}} \tag{4}$$

$$\frac{\partial D_i^*(L_i, X_i, D_j^*)}{\partial D_j} = -\frac{\frac{\partial U'_{D_i}}{\partial D_j}}{\frac{\partial U'_{D_i}}{\partial D_i}} \tag{5}$$

In the next section, we will investigate the impact of livelihood choices on deforestation levels (sign of equation (3)), the impact of other control variables (sign of equation (4)) and the nature of spatial spillovers (sign of equation (5)).

5. Spatial Econometric Procedure

The common observation that individuals belonging to the same group tend to behave similarly can de explained by three hypotheses of the standard linear model (SLM) that are the endogenous effects, the exogenous effects, and the correlated effects (Manski, 1993). The endogenous and the exogenous effects express distinct ways that persons might be influenced by their social environments. The first assumes that, all else equal, individual behavior (deforestation (D_i) tends to vary with the average behavior (deforestation of the group or neighbor (D_{-i})). The second effect assumes that individual behavior is in some way influenced by the characteristics of the group or neighbors (Z_{-i}). The correlated effects express nonsocial phenomena. According to these similarities in individuals' behavior may results from spatially dependent omitted variables, interaction among error terms (ϵ) or environmental similarities (Anselin, 1988b; Brueckner, 2003; Elhorst, 2014; Manski, 1993). In the following, we present a short description of various cross-sectional spatial econometric models (5.1). Then, we present the selection procedure we used (5.2).

5.1. Cross-sectional spatial econometric models

The matrix form of the generalized nested spatial model that accounts for all the three effects was defined by Manski (1993) in equations (6-7). This model is also called the Manski model.

$$D = \alpha * I_N + \rho W D + Z\beta + W Z\theta + \epsilon, \tag{6}$$

$$\epsilon = \lambda W\epsilon + \mu \tag{7}$$

.

In this expression, I_N is a n by n identity matrix. WD denotes the endogenous effects, representing the average deforestation of neighboring individuals (D_{-i}). The ρ parameter measures the strength of spatial dependence. W is a row-standardized weights matrix such that the elements (w_{ij}) in each row (i) sum to one and the diagonal elements set to zero, each element (w_{ij}) measures the intensity of interaction among household's (i) and its relevant neighbors (Anselin, 1995). WZ stands for the exogenous effects representing the average value of neighboring households' characteristics, scaled by the parameter θ. The parameter β captures the direct impact of independent variables. $W\epsilon$ denotes the interaction among the disturbance terms. λ measures the spatial autocorrelation intensity among error terms. After testing the equations (6-7), Manski (1993) found that data on equilibrium outcomes cannot distinguish both endogenous and exogenous interactions from contextual effects based on testing the model (6-7). Further, LeSage (1997) suggested specifying a model that accounts for both endogenous and exogenous spatial effects among individuals. Equation (8) is the resulting model, called the Spatial Durbin Model (SDM) by Anselin (1988b). This model is equivalent to the component (6) of the Manski model, with $\lambda = 0$ in (7). Following (LeSage, 2008), The SDM will allow deforestation of each household to vary with respect to both own characteristics and the mean characteristics within his/her neighborhood.

$$D = \alpha * I_N + \rho WD + Z\beta + WZ\theta + \epsilon \tag{8}$$

A year later, Kelejian and Prucha (1998) suggested to include both endogenous interaction effects and correlated effects among the error terms. This model is equivalent to the Manski equation with $\theta = 0$ in the component (6). This model is called the Kelejian-Prucha Model or the Spatial Autoregressive model with Autoregressive disturbances (SARAR). This allows spatial autocorrelation in both non-observed pattern and households' deforestation, without spillover effects neither from the neighborhood characteristics, nor from own characteristics on neighboring households.

$$D = \alpha * I_N + \rho WD + Z\beta + \epsilon \tag{9}$$

$$\epsilon = \lambda W\epsilon + \mu \tag{10}$$

.

The Spatial Autoregressive Model (SAR) was proposed by Anselin (1988b) to test only the endogenous interaction, using the lag value of the dependent variable. The SAR model allows only spatial autocorrelation of households' deforestation, without spillover effects neither from the neighborhood, nor from own behavior on neighboring households.

$$D = \alpha * I_N + \rho W D + Z\beta + \epsilon \tag{11}$$

Among other models, (1) the Spatial Error Model (SEM) was developed by Anselin (1988b) to account only for the correlated effects. This assumes that $\rho = 0$ in the SDM model. (2) The Spatial Durbin Error Model (SDEM) includes spatial lags of independents varables ($\theta \neq 0$) and the spatially lagged error term ($\lambda \neq 0$) in equation (6-7). (3) The Spatial Lag of the explanatory variable (SLX), ($\rho = 0$), ($\theta \neq 0$) and ($\lambda = 0$) in equation (6-7)

5.2. Selection procedure

The consideration of spatial effects in econometric models require some specific processes to avoid model misspecification (Le Gallo, 2002).

The usual standard approach is to start with a specific SLM. Further, test if the error terms and/or the dependent variable are spatially correlated, to specify the spatial model that is consistent with the data generation process. This is called the specific-to-general approach. The second approach is to start with the Mansky model and test progressively the existence of various spatial effects (Elhorst, 2014). In this study, we started with the standard approach that is most common in spatial analyses, following Anselin (1988a). After estimating a SLM, we first tested for the existence of spatial autocorrelation using the Moran i statistic on the residual of the linear model. Further, we proceeded to the Lagrange Multiplier test that helps to find the type of spatial effects that fit with our data generation process. Tables 2 and **??** in the subsection 6.2 display our procedure of model specification.

An issue that arises in applied econometrics is the need to compare models (LeSage, 2008). Indeed, a universal criticism of spatial regression models is the sensitivity of the estimates and inferences to the form of spatial weight matrix (LeSage and Pace, 2014). After specifying our econometric model, we use four types of weight matrix namely, the Gabriel graph weight matrix, the five nearest neighbors (5NN), the ten nearest neighbors (10NN) and the distance based weight matrix to account for this criticism. These weight matrices are presented in detail in Ngouhouo Poufoun and Delacote (2016).

6. Results

6.1. Variables and Descriptive statistics

Dependent variable :. our measure of deforestation followed two steps. We first asked the households to fill the information about their land-holding in a table. After that, we randomly chose one plot among the total plots declared by the household to visit. The visited plot was tracked using a Global Positioning System (GPS) to have the real area. A total of 3338 plots of land were declared by overall sample that is on average 3.2 plots held by each household. A total of 526 plots were tracked with a GPS. The data declared were adjusted using the tracked data to obtain the value used in this study. On average, household heads declared clearing 4.75 ha of forest. We found after statistical adjustment that the average land clearing of each household stands at 4.41 ha.

Independent variables :. we distinguish our independent variables in three categories.
First, we consider the household income, depending on the livelihoods' strategy chosen. In our case study, like many contexts in rural areas of developing countries, access to land can be considered open. Second, diverse households' characteristics can have a part in explaining deforestation. We consider here several potential constraints to deforestation. Credit constraints are approached through credit and money transfer received by the household. Finally, land-use conflict is a proxy for constraints on land access, while the damage costs from wildlife conflicts represent environmental damages.
Third we consider a set of contextual variables, such as distance to markets, as a proxy for transaction costs. Proximity to protected areas represents constraints brought by environmental policies. Table 1 displays the variables' definition and descriptive statistics.

6.2. Spatial dependence diagnostic

Table 2 below displays the Moran coefficient index computed after running the SLM. This statistic tests the existence of the spatial autocorrelation. Except for the Gabriel Graph weight structure, the index value is positive and statistically greater than 0. It appears a positive spatial clustering of deforestation among nearby households in the Tridom-TCL.
The Lagrange multiplier test presented in table 3 is used to diagnose the type of spatial dependence that governs our data generation process among the endogenous effects, i.e. spatial lag of the dependent variable ($\rho \neq 0$) and the correlated effects or the spatial autocorrelation of the disturbance term ($\lambda \neq 0$).

Table 1: Variables and descriptive statistics (N=986 households)

Variable	Definition of variables	Mean	Std. Dev.
AGENT'S DECISION PARAMETERS			
Income of households adopting diversification livelihoods' strategies (FCFA10^3)			
FamilyIncome_ACF_$households$	Income of households mixing Agriculture &Cashcrop & Forest	38.96	117.06
FamilyIncome_AF_$households$	Income of households mixing Agriculture & Forest	54.97	126.6
FamilyIncome_CF_$CashcropForest$	Income of households mixing Cashcrop & Forest	21.28	73.34
Income of households adopting specialisation livelihoods' strategies (FCFA10^3)			
FamilyIncome_F_$Forestbased$	Income of households specializing in Forest-based activities	70.18	372.79
FamilyIncome_A_$Agriculture$	Income of households specializing in Agricultural	12.39	121.41
FamilyIncome_C_$Cashcrop$	Income of households specializing in Cashcrop	8.85	67.93
Other decision variables			
Autocons_Share (% of total value)	Autoconsumption share in the total income	0.26	0.19
Capital & factor constraints			
Finance_asset	Credit and money transfer (CFAF/month)	8.67	33.55
Human_Wildlife (FCFA10^3)	Damage cost of wildlife conflict (CFA/month)	0.62	1.45
Landconflict Dummy (1=yes)	Land use conflict, Dummy (1=yes)	0.18	0.38
HOUSEHOLDS CHARACTERISTICS			
Gender	Gender, Dummy (1=Male)	0.77	0.42
Age	Household head age (continuous, in years)	48.44	14.61
Ages_thr	Age centered and squared	213.34	246.72
Marit_single	Matrimonial status, Dummy (1=Maried)	0.7	0.46
Hsize	Household size (continuous)	6.5	4.01
Schoolcycl_2	Education level, Dummy (1=secondary school)	0.56	0.5
Autochbaka	Indegenouesness, Dummy (1=Pygmy. 0=Bantou)	0.05	0.22
Seniority	Seniority in the village (continuous, in years)	27.01	20.71
CommunityGroup	Community Interest Companies, Dummy (1=yes)	0.28	0.45
Pygmy_employmt	Pygmies employment (continuous)	1.87	2.96
Labourduration	Working hour per day	5.49	4.39
CONTEXTUAL VARIABLES			
Country	Country, Dummy (1=Cameroon, 0=Gabon)	0.73	0.44
Distmarket	Distance to market (in Km)	65.06	58.69
Distance to P. Area	Distance to the nearest Protected Area (in Km)	29.3	22.58
Biophysical factor			
Rainfall	The per annum amount of rain that falls (mm)	1638.30	113.66

This test suggests rejecting all the specifications that allow spatial autocorrelation in the disturbance term. Therefore, we avoid estimating the SARAR, the SEM and the generalized nested Manski spatial model. In the following, we estimate the SAR as it fits with our data generation process. We avoid displaying the results of the SDM as it yielded counter-intuitive findings.

Overall, following the findings in tables 2 and 3, we cannot reject our hypothesis of a spatial effects, giving rise to a presumption of the existence of a positive relation between households' deforestation and the average deforestation of neighboring households. In section 6.3 below will confirm or reject this presumption via the ρ parameter and present the drivers of households' deforestation.

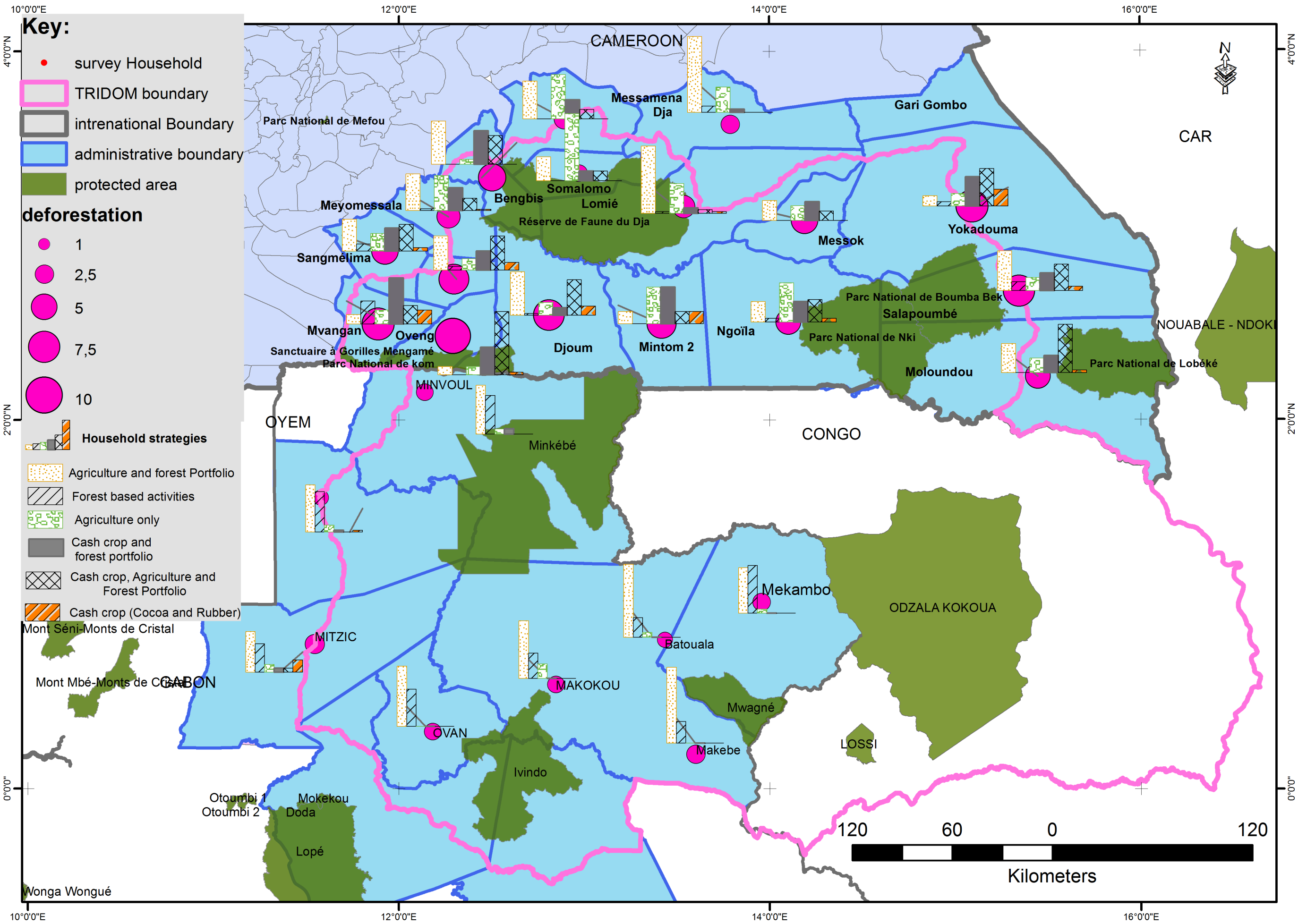


Figure 2: Livelihoods and Mean deforestation in the landscape

Table 2: Spatial autocorrelation test

	Global Moran I				Moran I test under randomisation			
	Moran I	E(I)	z(I)	**P-value**	Moran I	E(I)	z(I)	**P-value**
gabhsld.w	0.0171	-0.0032	0.7060	**0.2401**	0.1191	-0.0010	4.2133	**0.0000**
3NN weight matrix	0.0377	-0.0032	1.7138	**0.0433**	0.1461	-0.0010	6.2109	**0.0000**
4NN weight matrix	0.0339	-0.0032	1.7903	**0.0367**	0.1396	-0.0010	6.8335	**0.0000**
5NN weight matrix	0.0336	-0.0032	1.9876	**0.0234**	0.1301	-0.0010	7.1017	**0.0000**
10NN weight matrix	0.0363	-0.0030	2.9635	**0.0015**	0.1352	-0.0010	10.2690	**0.0000**
17NN weight matrix	0.0217	-0.0028	2.4270	**0.0076**	0.1218	-0.0010	12.0470	**0.0000**
Distance based weight matrix	0.0171	-0.0025	3.1368	**0.0009**	0.0993	-0.0010	15.4710	**0.0000**

6.3. What are the immediate causes of households' deforestation in the Tridom-TCL?

6.3.1. Robustness check and spatial dependence

Table 4 displays the estimates' results based on the SLM and four variants of SAR model considering four different types of weight matrix. This result considers only the factors that significantly drive households' deforestation. The table in AppendixB.1 displays the results from the model with overall

Table 3: Lagrange Multiplier Diagnostic of Spatial dependence

	LM Test for Spatial Error Components				LM Test for Spatial lag model				
	Ordinary LMerr		**Robust LMerr** ($\rho = 0$)		Ordinary LMlag		**Robust LMlag** ($\lambda = 0$)		
	Stat.	P-value	Stat.	P-value	Stat.	P-value	Stat.	P-value	
Gabhsldweight matrix	0.3512	0.5535	0.1233	**0.7254**	0.6565	0.4178	0.4286	**0.5127**	
3NN weight matrix	2.4699	0.1160	0.5971	**0.4397**	4.4385	0.0351	2.5657	**0.0992**	*
4NN weight matrix	2.6354	0.1045	0.6091	**0.4351**	4.9138	0.0266	2.8875	**0.0893**	*
5NN weight matrix	3.2194	0.0728	0.1058	**0.7449**	4.9313	0.0264	1.8178	**0.0976**	*
10NN weight matrix	7.2122	0.0072	0.8022	**0.3704**	13.0090	0.0003	6.5990	**0.0102**	**
17NN weight matrix	4.3451	0.0371	2.0311	**0.1541**	12.2670	0.0005	9.9533	**0.0016**	***
Distance based weight matrix	6.4858	0.0109	0.0442	**0.8335**	12.0590	0.0005	5.6177	**0.0178**	**

variables presented in the subsection 6.1 above. Insignificant variables were removed progressively until we got the reduced set of significant variables. The post estimation test (Akaike Information Criterion (AIC), Wald and LR tests) confirm the reduced model as best-suited compared to the full model.

The SAR models show a significant spatial dependence between deforestation of each household and the average deforestation of neighboring households. This suggests some similarities in the deforestation decision of households located nearby. The expected deforestation of each household in the Tridom-TCL is determined by both own characteristics and a linear combination of neighboring households' deforestation scaled by ρ. The SLM estimates have larger size compare to the SAR models considering all types of weight matrice. It attributes the variabilities in households' deforestation only to the independent variables. Also, the SAR model suggests that the variability of deforestation across households is partially explained by neighbors' deforestation behaviour. Further, the spatial lag of households' deforestation is treated as an endogenous variable and the error term is influence by the same process. As a result, although the Q-Q plot in the figure in AppendixA.1 reveals normal distribution of households' deforestation, the SLM is biased and yields inconsistent estimates due to simultaneity bias. In these conditions, the SAR is a proper specification to account for this endogeneity (Anselin, 2001). Following Anselin (1988b, 2001) our spatial lag model of deforestation was estimated using the maximum likelihood technique.

As shown in table 4, the strength of spatial dependence (ρ) varies along with the type of the weight matrix. The scale of the ρ parameter varies increasingly from 0.027 for the the Gabriel graph weight matrix to 0.235 for the distance-based weight matrix. It equals 0.089 for the 5NN and 0.179 for the 10NN weight matrices. Further, the estimates vary decreasingly from the from the Gabriel graph matrix to the distance-based matrix. The warning in LeSage and Pace (2014) regarding the sensitivity of the estimates and inferences to the type of matrix is confirmed. Among these four candidate models, the

10NN base model, displayed in the third column with bold characters, performs better as it minimizes the information loss. This model has the maximum log likelihood with the minimum Akaike Information Criterion (AIC) compared to others. The goodness-of-fit test confirms that the SAR model based on the 10NN weight matrix is the best to fit the households' deforestation. Indeed, combining the Wald test (W), the the Log-likelihood Ratio test (LR) and the Lagrange Multiplier test (LM) as suggested by Anselin (1988b), we found that the inequality $W \geq LR \geq LM$ is verified only for the 10NN based model that is $(W = 10.399) \geq (LR = 10.16) \geq (LM = 1.014)$. In the following, estimates from the SAR model based on 10NN weight matrix are used to derive the drivers of households' deforestation.

The β coefficient of the SAR model cannot be interpreted as partial derivatives of households' deforestation in the Tridom-TCL with respect to a one-unit change of various independent variables as in conventional linear regression model (Pace and LeSage, 2006). The subsection 6.3.2 below presents the impact of the various independent variables on the households' deforestation.

Table 4: Spatial Autoregressive Model

	SLM			GabGraph			5NN Weight matrix			**10NN Weight Matrix**			Distance based		
	Coef.	SD		Coef.	SD		Coef.	SD		**Coef.**	**SD**		Coef.	SD	
(Intercept)	-3.5941	1.1117	***	-1.1331	0.7166		-1.2545	0.7185	*	**-1.4842**	**0.7173**	**	-1.7664	0.7390	**
AGENT'S DECISION PARAMETERS															
Income of households adopting diversification livelihoods' strategies (FCFA10^3)															
FamilyIncome_*ACF_households*	0.0109	0.0013	***	0.0108	0.0013	***	0.0106	0.0013	***	**0.0102**	**0.0013**	***	0.0102	0.0013	***
FamilyIncome_*AF_households*	0.0026	0.0012	**	0.0026	0.0012	**	0.0025	0.0011	**	**0.0025**	**0.0011**	**	0.0025	0.0011	**
FamilyIncome_*CF_CashcropForest*	0.0120	0.0021	***	0.0119	0.0020	***	0.0116	0.0020	***	**0.0112**	**0.0020**	***	0.0113	0.0020	***
Income of households adopting specialisation livelihoods' strategies (FCFA10^3)															
FamilyIncome_*A_Agriculture*	0.0029	0.0012	**	0.0029	0.0012	**	0.0029	0.0012	**	**0.0029**	**0.0012**	**	0.0028	0.0012	**
FamilyIncome_*C_Cashcrop*	0.0186	0.0021	***	0.0185	0.0021	***	0.0183	0.0021	***	**0.0180**	**0.0021**	***	0.0179	0.0021	***
Autocons_Share (% of total value)	-2.1269	0.7737	***	-2.1210	0.7667	***	-2.1518	0.7649	***	**-2.0922**	**0.7620**	***	-2.1346	0.7633	***
Capital & factor constraints															
Finance_asset (FCFA10^3)	0.0106	0.0043	**	0.0106	0.0042	**	0.0104	0.0042	**	**0.0102**	**0.0042**	**	0.0099	0.0042	**
Human_Wildlife (FCFA10^3)	-0.2135	0.0979	**	-0.2125	0.0970	**	-0.2143	0.0968	**	**-0.2179**	**0.0965**	**	-0.2183	0.0966	**
HOUSEHOLDS CHARACTERISTICS															
Gender (1=Male)	0.6200	0.3450	*	0.6127	0.3419	*	0.5928	0.3411	*	**0.5816**	**0.3398**	*	0.6210	0.3404	*
Age (continuous. in years)	0.0293	0.0115	**	0.0293	0.0114	**	0.0291	0.0114	**	**0.0301**	**0.0113**	***	0.0303	0.0114	***
Ages_thr	-0.0013	0.0006	**	-0.0013	0.0006	**	-0.0013	0.0006	**	**-0.0013**	**0.0006**	**	-0.0013	0.0006	**
Hsize (continuous)	0.1692	0.0379	***	0.1677	0.0376	***	0.1669	0.0375	***	**0.1650**	**0.0374**	***	0.1675	0.0374	***
Seniority (continuous. in years)	0.0401	0.0080	***	0.0402	0.0079	***	0.0404	0.0079	***	**0.0399**	**0.0078**	***	0.0390	0.0079	***
CommunityGroup Dummy (1=yes)	0.5566	0.3263	*	0.5605	0.3233	*	0.5777	0.3226	*	**0.5718**	**0.3214**	*	0.5922	0.3220	*
Pygmy_employmt (coutinuous)	0.1428	0.0507	***	0.1462	0.0503	**	0.1522	0.0502	***	**0.1584**	**0.0500**	***	0.1539	0.0501	***
CONTEXTUAL VARIABLE															
Country (1=Cameroun. 0=Gabon)	1.3424	0.3556	***	1.2738	0.3617	***	1.0840	0.3722	***	**0.8565**	**0.3826**	**	0.8475	0.4080	**
R-squared:	0.32														
F-statistic: (16; 969)	28.38	*													
Rho (ρ)				0.0274			0.0892	**		**0.1799**	***		0.2354	***	
Log Likelihood				-2856			-2855			**-2852**			-2853		
ML residual σ				4.39			4.38			4.36			4.3667		
AIC Criterion	5750			5751			5748			**5742**			5744		
Wald Statistic				0.737			3.996	**		**10.399**	***		7.848	***	
LR test value				0.694			4.207			**10.165**			8.010		
LM for Residual autocorrelation				0.122			0.262			**1.014**			0.128		
Observations	986			986			986			986			986		

*, ** and *** = significance level at 1% 5% 10% respectively

6.3.2. *Direct, Indirect and Total effects*

Table 5 displays the factors that proximately drive households' deforestation in the Tridom-TCL. These factors are regrouped into (1) Livelihoods' Strategies; (2) households characteristics and (3) contextual variables. Variables with insignificant coefficients are displayed in the full model in table in AppendixB.1.

Livelihoods' Strategies:. The direct effects for household income are all positive and significant regardless of the livelihoods' strategy, except for the income of households who practice forest-based activities. Diversification strategies and specialization strategies have comparable impacts on deforestation. Strategies that encompass cash crops production have the highest impact. On the other hand, family income of households specializing in forest-based activities unsurprisingly do not tend to impact deforestation. Further, the indirect effects of these incomes are positive and significant except for households who adopt a diversified portfolio comprised of agriculture and forest-based activities. More precisely:

- **ACF**: A one-unit increase in the monthly income of a household's head, who diversifies choosing agriculture, cash-crop and forest-based activities (ACF), leads to increasing own deforestation by 0.0102 ha; with a positive spillover effect of 0.0023 ha within his/her neighborhood. The resulting total effect is 0.0125 ha. Translating into dollars, using the 2014 exchange rate [5], this approximately equates to an incremental increase of own deforestation by 4.9 ha with a spillover effect of 1.1 ha within the neighborhood, resulting from per annum $1000 increase in the household income. That is a total effect of 6ha.

- **CF**: Likewise, a one-unit increase in the monthly income, of a household's head who chooses cash crop and forest (CF), leads to increasing own deforestation by 0.0113 ha; with a positive spillover effect of 0.0025 ha within his/her neighborhood. This approximately equates to an incremental increase of own deforestation by 5.4 ha with a spillover effect of 1.2 ha within the neighborhood, resulting from per annum $1000 increase in the household income. The total effect is of 6.6 ha.

- **AF**: A one-unit increase in the monthly income, of a household's head choosing agriculture and forest, leads to increasing own deforestation by 0.0025 ha; This approximately equates to an incremental increase of own deforestation by 1.2 ha resulting from per annum $1000 increase in the

[5] In 2014, year of the field work, $ $CFAF1 = \$0,0021$)

household income. Households' heads choosing (AF) portfolio do not exert any significant spillover effect within their neighborhood.

- **A**: The direct effect of increasing of households specializing in agriculture (A) is a significant increase by 0.0030 ha of own deforestation. The resulting significant and positive spillover effect within the neighborhood is 0.0007 ha. The resulting total effect is 0.0037 ha. This approximately equates to an incremental increase of own deforestation by 1.43 ha with a spillover effect of 0.33 ha within the neighborhood, resulting from per annum $1000 increase in the household income. That is a total effect of 1.76 ha.

- **C**: The incremental change of deforestation resulting from a one-unit increase in the monthly income of households choosing cash crop (C) is an increase of 0.0180 ha. This leads to increasing deforestation of households sharing the same neighborhood by 0.0040 ha. The resulting total effect is 0.022 ha. This approximately equates to an incremental increase of own deforestation by 8.6 ha with a spillover effect of 1.9 ha within the neighborhood, resulting from per annum $1000 increase in the household income. The total effect is of 10.5 ha.

As regard the capital and factor constraint decision's variables, financial asset as well as "the damage cost from human-elephants conflict have both significant direct and indirect effects (table 5). Yet,the existence of land conflicts among households (Human-Human conflict) were insignificant (see table in AppendixB.1).

An additional unit of loan contracted (or transfer received) by a household's head leads to a marginal increase of own deforestation of 0.0102 ha with a positive spillover effect within his/her neighborhood of 0.0043 ha. That is a total effect of 0.0145 ha. This equates to an increase of own deforestation by 6.9 ha with a spillover effect of 2.04 ha within the neighborhood, resulting from per annum $1000 increase in the financial asset. That is a total effect of 8.94 ha. This indicates that increasing money transfer in favor of households living in the landscape may foster engagement in forest clearing by households.

Unlike the financial asset, monthly cost of crops damage by elephants exert a negative and significant direct and indirect effect on the households' deforestation. Indeed, additional unit of damage cost reduces both own and neighboring deforestation by 0.217 ha and 0.048 ha. The resulting total effect is 0.265 ha. This approximately equates to an incremental decrease of 103 ha and 22.8 ha respectively, resulting from per annum $1000 increase in damage cost. This result translates into two complementary effects. Firstly, a business discouragement effect that could lead to the abandonment of spaces nearby the promenade area of elephants; on the other hand, it may cause a switch from activities relating to land use to forest extraction activities that seem least risky with a possibility of increasing forest degradation.

The existence of land conflict among households (Human-Human conflict) were insignificant (see table in AppendixB.1). The third result gives the insight that there is little constraint on land access in our case study: deforestation and agricultural expansion is not impacted by neighbor conflicts.

Households characteristics:. Among the socioeconomic variables, education, the marital status and the ethnicity do not influence households' deforestation as shown in table in AppendixB.1. Those with significant effects include gender, age, households' size and the residence duration or seniority.

Table 5 shows that men are associated with 0.58 ha more deforestation than women without spillover effects within the neighborhood.

Deforestation increases slowly and significantly with the household's head age with some threshold effect. For every year they get older, deforestation increases by 0.03 ha, with a negligible spillover effect. Larger household's size induces more deforestation. Indeed, an additional member in a family increases own deforestation by 0.16 ha with a spillover effect of 0.034 ha. As pointed out by Kaimowitz and Angelsen (1998), the residence duration is positively associated to forest clearing with the same level as age.

When it comes to labour, it is interesting to note that Pygmy employment is related to larger deforestation, while household labour duration has no influence (see table in AppendixB.1). Thus both types of labour do not seem to be substitutes for households' labour. Pygmy labour appears to be more land-intensive practices, while household labour seems not to be related to land-use choices, i.e. more related to labour-intensive practices.

Contextual variables:. Among contextual variables presented in table 1, "distance to market", "distance to the nearest protected area" and the first result suggest that distance to markets has no direct effect on deforestation. However, as shown by citeNgouhouoPoufoun2016lvlhd, distance to markets influences the livelihoods' strategies: thus the effect of distance apparently passes through the livelihoods' strategies transmission channel. The second result indicates that public policies such as protected areas do not bring constraints on land use decision. Moreover, we do not find evidence of leakage between protected areas and neighboring households.

Finally, both the direct and the indirect effects of country are positive and significant. Indeed, households living in Cameroon are associated with 0.85 ha more deforestation compare to those living in Gabon, with a spillover effect of 0.178 ha on proximate households in Gabon. This result suggests paying additional attention in the Cameroonian segment of the landscape.

Table 5: Directs, Indirects and Total Effects

	Coeff.	Direct Effects			Indirect effects			Total effects		
		Mean	SD		Mean	SD		Mean	SD	
AGENT'S DECISION PARAMETERS										
Income of households adopting diversification livelihoods' strategies (FCFA10^3)										
FamilyIncome_*ACF_households*	0.0102	0.0102	0.0012	***	0.0023	0.0009	***	0.0125	0.0017	***
FamilyIncome_*AF_households*	0.0025	0.0025	0.0012	**	0.0006	0.0003		0.0030	0.0014	**
FamilyIncome_*CF_CashcropForest*	0.0112	0.0113	0.0020	***	0.0025	0.0010	**	0.0138	0.0025	***
Income of households adopting specialisation livelihoods' strategies (FCFA10^3)										
FamilyIncome_*A_Agriculture*	0.0029	0.0030	0.0012	**	0.0007	0.0004	*	0.0036	0.0015	**
FamilyIncome_*C_Cashcrop*	0.0180	0.0180	0.0021	***	0.0040	0.0016	***	0.0220	0.0029	***
Autocons_Share (% of total value)	-2.0922	-2.1099	0.7635	***	-0.4726	0.2496	*	-2.5825	0.9487	***
Capital & factor constraints										
Finance_asset (FCFA10^3)	0.0102	0.0102	0.0043	**	0.0023	0.0013	*	0.0125	0.0053	**
Human_Wildlife (FCFA10^3)	-0.2179	-0.2172	0.0975	**	-0.0488	0.0297	*	-0.2660	0.1213	**
HOUSEHOLDS CHARACTERISTICS										
Gender (1=Male)	0.5816	0.5802	0.3326	*	0.1300	0.0944		0.7102	0.4122	*
Age (continuous, in years)	0.0301	0.0301	0.0113	***	0.0067	0.0037	*	0.0368	0.0140	***
Ages_thr	-0.0013	-0.0013	0.0006	**	-0.0003	0.0002		-0.0017	0.0008	**
Hsize (continuous)	0.1650	0.1649	0.0369	***	0.0369	0.0164	**	0.2018	0.0475	***
Seniority (continuous, in years)	0.0399	0.0403	0.0080	***	0.0090	0.0039	**	0.0494	0.0105	***
CommunityGroup Dummy (1=yes)	0.5718	0.5729	0.3161	*	0.1281	0.0896		0.7010	0.3914	*
Pygmy_employement (coutinuous)	0.1584	0.1592	0.0495	***	0.0356	0.0177	**	0.1948	0.0622	***
CONTEXTUAL VARIABLE										
Country (1=Cameroun. 0=Gabon)	0.8565	0.8515	0.3778	**	0.1786	0.0921	*	1.0300	0.4406	**

*, ** and *** = significance level at 1% 5% 10% respectively

7. Discussion and conclusion

The aim of this study is to better understand how livelihoods' strategies have an impact on deforestation. To that matter, this paper is a natural extension of citeNgouhouoPoufoun2016lvlhd, which determines the variables influencing livelihoods' strategies. We also develop a spatial approach in order to take into account spatial interactions between agents. Our analysis relies on an original household survey collected in the Tridom-TCL.

Our results are multiple. First, when it comes to livelihoods, diversification and specialization strategies roughly seem to have the same impacts. Yet, we show that strategies incorporating agricultural activities tend to have an impact on deforestation. The corollary to this result is that only agents specializing in forest-based activities do not influence deforestation. More precisely, households integrating cash-crops in their activity portfolio are those getting the largest impact on deforestation. Further, spillover effects from strategies with cash-crop (C, CF, ACF) have almost the same scale than the direct effect of the remaining strategies (AF, A). Cash-crop as a specialization strategy has the highest influence on forest cover compared to the other strategies, with a spillover effect that is almost twice as large as the direct effect caused by households mixing agriculture and forest. These results bring the insight that, if development leads to households switching from small-scale agriculture to cash-cropping as a main activity, this would result to a major increase in deforestation. As an example, one extra dollar earned in cash-crops appears to have about a 7-times larger effect on deforestation than an extra dollar in agriculture. In the same vein, we show that the share of auto-consumption is negatively related to deforestation. Here again, if economic development brings a better market access and lower auto-consumption shares, this may positively influence deforestation.

Second, we show that land conflicts and distance to protected areas do not seem to influence deforestation. This result brings the insight that competing land-uses is not really a matter of constraints for households, nor does it represent a source of leakage. In contrast, land-wildlife conflicts do seem to have a negative impact on deforestation. Therefore, if policies are set with the aim to protect wildlife in rural areas and decrease human-wildlife interactions at the same time (Ngouhouo Poufoun et al., 2016), it is a crucial matter to monitor and to involve local populations in order to avoid a bump in deforestation.

Third, our paper underlines the importance of assessing deforestation factors in a spatial context, using a landscape approach. Indeed, spatial spillovers tend to be of large magnitude: indirect effects may reach up to 20% of the direct effects. This result is important, as it shows that micro-economic analysis of deforestation factors should take into account those spatial interactions, in order to have an accurate understanding of the mechanisms in place. This statement also holds for the choice of livelihoods' strategies (Ngouhouo Poufoun and Delacote, 2016).

Fourth, labour allocation is important. While the household labour duration does not seem to impact deforestation, employing Pygmy labour tend to increase it. Therefore, both types of labour cannot be considered as substitutes, especially when it comes to land use. Household labour appears to be allocated to labour-intensive activities, while Pygmy labour seems to be allocated to activities requiring more land and thus more deforestation. If we consider a Chayanovian approach (Kaimowitz and Angelsen, 1998), it seems that the trade-off between household labour and leisure does not influence deforestation.

Overall, our paper brings some reflexion on how development may influence deforestation in such a landscape. Three transmission channels are to be distinguished: an *income channel*, an *activity portfolio* *channel* and a *market integration channel*. First, economic development comes with larger income. We show that, except for households specializing in forest-based activities, an increase in income is related to more deforestation. Second, the portfolio of activities is likely to change with economic development, with an increased importance of cash-cropping. This would also result in larger deforestation rates. Finally, when households have a better access to markets, they tend to decrease their share of auto-consumption, which can also have an tendency to increase deforestation. It is important for development projects and policies to take those three channels into account, when dealing with possible environmental adverse effects.

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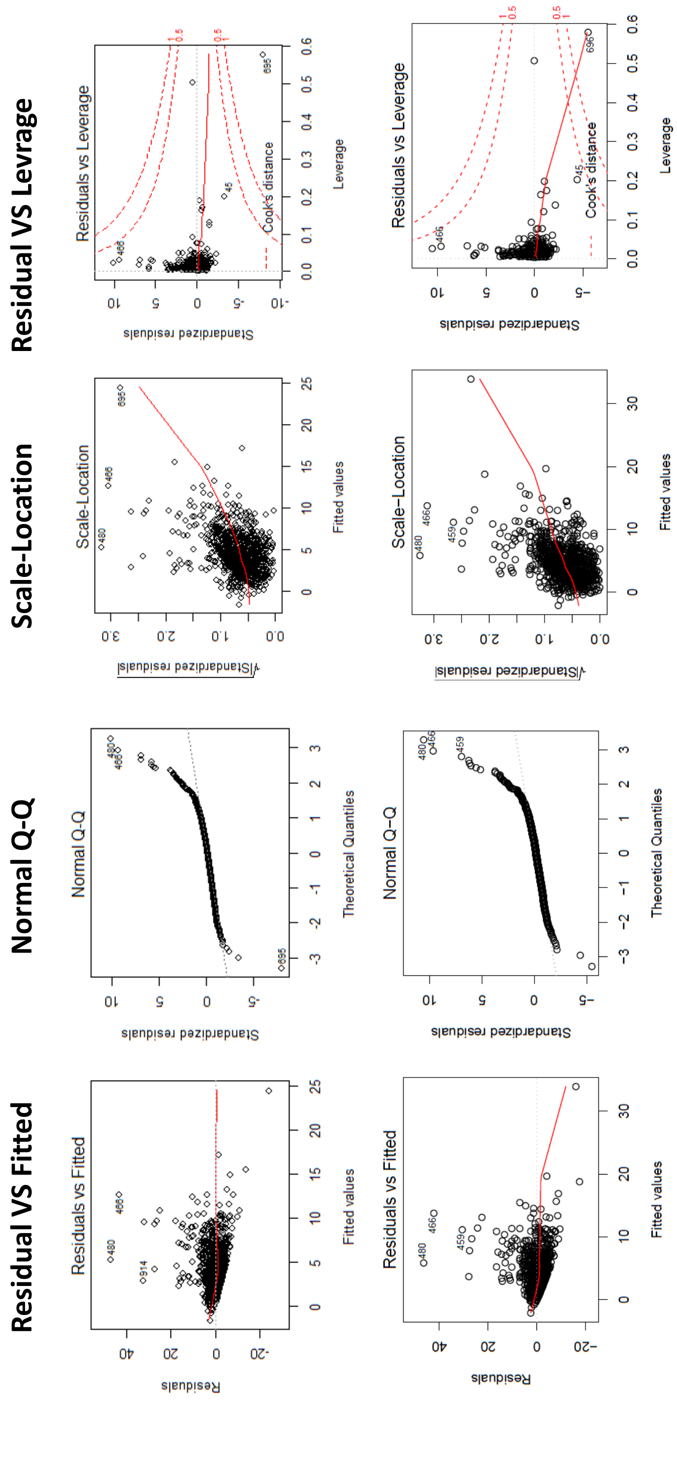
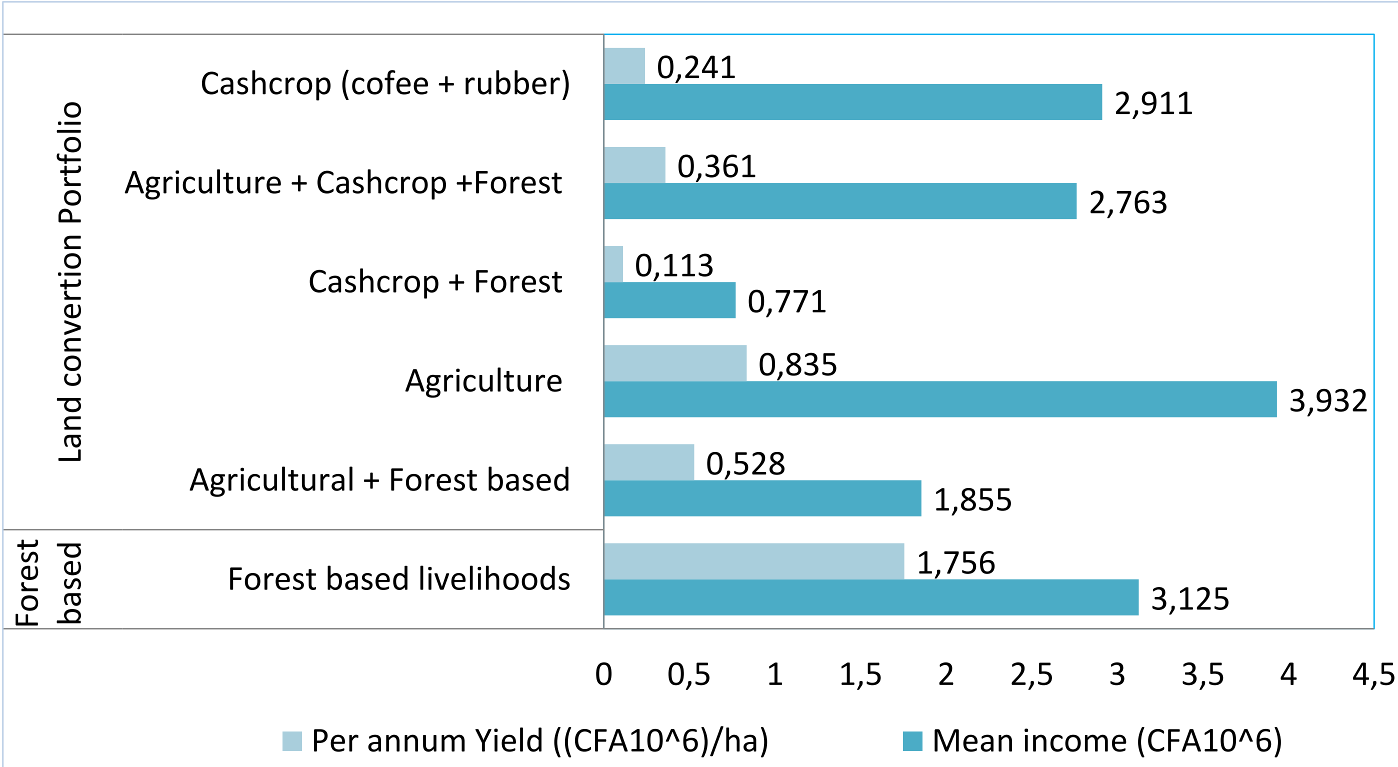
AppendixA. Figures

AppendixA.1. Diagnostic Plots for Regression Analysis



AppendixA.2. Livelohoods Strategies and Per Annum Yiels/ha



AppendixB. Tables

AppendixB.1. Full Spatial Autoregressive Model

	SPATIAL AUTOREGRESSIVE FULL MODEL				
	Coef.	SD	z value	Pr(>|z|)	
(Intercept)	-4,1857	2,2804	-1,8355	0,0664	*
AGENT'S DECISION PARAMETERS					
Income of households adopting diversification livelihoods' strategies (FCFA10^3)					
FamilyIncome_ACF_$households$	0,0101	0,0013	7,905	0	***
FamilyIncome_AF_$households$	0,0024	0,0012	2,0399	0,0414	**
FamilyIncome_CF_$CashcropForest$	0,0109	0,0021	5,326	0	***
Income of households adopting specialisation livelihoods' strategies (FCFA10^3)					
FamilyIncome_F_$Forestbased$	-0,0002	0,0004	-0,4287	0,6682	
FamilyIncome_A_$Agriculture$	0,0026	0,0012	2,2638	0,0236	**
FamilyIncome_C_$Cashcrop$	0,0178	0,0021	8,3798	0	***
Other decision variables					
Autocons_Share (% of total value)	-2,2003	0,7772	-2,8308	0,0046	***
Capital & factor constraints					
Finance_asset (FCFA10^3)	0,0089	0,0043	2,0988	0,0358	**
Landconflict Dummy (1=yes)	0,33	0,3763	0,8771	0,3804	
Human_Wildlife (FCFA10^3)	-0,2033	0,0978	-2,0785	0,0377	**
HOUSEHOLDS CHARACTERISTICS					
Gender (1=Male)	0,6824	0,3508	1,9451	0,0518	*
Age (continuous. in years)	0,0208	0,0121	1,7115	0,087	*
Ages_thr	-0,0014	0,0006	-2,2333	0,0255	**
Marit_single (1=Maried)	0,42	0,3485	1,2051	0,2282	
Hsize (continuous)	0,1582	0,0376	4,2037	0	***
Schoolcycl_2 (1=secondary school)	-0,1703	0,314	-0,5423	0,5876	
Autochbaka (1=Pygmy. 0=Bantou)	-0,5574	0,6761	-0,8244	0,4097	
Seniority (continuous. in years)	0,0391	0,008	4,859	0	***
CommunityGroup Dummy (1=yes)	0,524	0,3235	1,62	0,1052	
Pygmy_employement (coutinuous)	0,1518	0,0504	3,0118	0,0026	***
Labourduration	-0,0483	0,0319	-1,5107	0,1309	
CONTEXTUAL VARIABLES					
Country (1=Cameroun. 0=Gabon)	0,8112	0,4593	1,7661	0,0774	*
Distmarket Km	-0,0037	0,0029	-1,2952	0,1952	
Distance to P. Area (Km)	0,0006	0,0066	0,0903	0,928	
Biophysical factor					
Rainfall	0,0014	0,0014	0,9974	0,3186	
Rho (ρ)	0.1947	**			
Log Likelihood	-2849				
ML residual σ	4.350				
AIC Criterion	5754				
Wald Statistic	4.8115	**			
Observations	986				
residual autocorrelation	0.0728				

*, ** and *** = significance level at 1% 5% 10% respectively