Electrification and Deforestation in Côte d'Ivoire: a spatial econometric analysis

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The objective of this paper is to analyze the link between electrification and deforestation in Côte d'Ivoire. We first checked the compatibility of night lights intensity data with official electricity coverage statistics in Côte d'Ivoire available at the regional level. Then, using night lights intensity panel data, we study the links between electrification and deforestation, at a fine resolution (departments level), taking into account both spatial autocorrelation and individual heterogeneity. Our results show that electrification and deforestation rates are positively linked. Indeed, deforestation continues to gain ground in the country alongside the vast national electrification access programs ongoing since 2011.

JEL: C21, C23, O13, Q51
Keywords: Spatial Models, panel Models, Electrification, Deforestation

I. Introduction

Deforestation rates in Côte d'Ivoire are among the highest in the world. From over 16 million hectares of forest in the 1960s, the country now has only about 2.5 million hectares.[1] In this context, in 2011 the Ivorian government launched a vast rural electrification program as part of its Social Program, which aims to strengthen electricity coverage in the country in order to fight this deforestation phenomenon, but also to accelerate structural transformation and create new employment opportunities in the country. This vast program has three (3) components. The main component remains the National Rural Electrification Program (PRONER) which aims to electrify all localities with more than 500 inhabitants by the end of 2020 and all localities in the country by 2025 (total investment cost estimated at more than 10 billion euros according to the Ivorian authorities). The second is the Electricity for All Program (PEPT), which aims to subsidize the cost of connecting low-income households to the electricity network by up to 150,000 CFA francs (EUR 229). The third component is the introduction of a 20% reduction in the social tariff for low-income households.

Installed capacity increased from 1,391 MW in 2011 to 2,215 MW at the end of 2018 (Ps-Gouv). This substantial increase in power generation, combined with efforts to improve transmission and sector management, have improved access to electricity in the country. Thus, between 2011 and 2018, the program made it possible to electrify 2,122 localities, bringing the coverage rate to 58%, compared to 33% at the end of 2010. On average, more than 265 localities were electrified each year during this period. However, the rate of deforestation in Côte d'Ivoire remains quite high, being of the order of 150,000 ha to 200,000 ha per year (Eaux et forêts N^{o}7, December 2021). Indeed, according to recent analyses by the Côte d'Ivoire Ministry of Water and Forests, changes in forest cover, measured by satellite imagery, reflect a clear trend towards deforestation. The Ivorian forest fell from 7.8 million hectares in 1990 to only 3.4 million hectares in 2015. To understand the fact that deforestation is generally continuing to increase in Côte d'Ivoire despite the country's rapid increase in electrification, it is necessary to recall certain characteristics of the Ivorian environment. In fact, Côte d'Ivoire has based its development on agricultural expansion, which is the main cause of the loss of its forests (Climate chance). A survey conducted by the BNETD, ETC TERRA and RONGEAD teams in the country's Agro-Ecological Zones (AEZs) confirmed the very significant contribution of

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[1] Source: Africa Green Side.

agricultural expansion - with cocoa farming at the top of the list - to the deforestation process over the past 25 years (62%). Given that cocoa is a cash crop (as opposed to a subsistence crop), any improvement in productivity (particularly thanks to irrigation techniques made possible by access to electricity) will not necessarily slow down the detrimental effect of farming on the forests (Ly, Chakir and Cretì, 2021). The main indirect factors cited in this survey were the economic attractiveness of activities leading to deforestation (25%), population growth, including migration (12.5%) and war/political crises (12%). The idea is that electrified localities will tend to attract more economic migrants than similar localities without access to electricity, which is likely to increase the pressure on the forests of these electrified localities, leading to deforestation.

The objective of this paper is to answer the question of whether electrification is really a mean to fight deforestation in Côte d'Ivoire as claimed by most studies in other parts of the world, and even in some African countries. Indeed, for most studies, electrification reduces the need both to expand arable farms (through improved agricultural productivity) and to collect firewood, and is therefore an effective way to mitigate deforestation (An et al., 2002; Dube, Musara and Chitamba, 2014; Mensah and Adu, 2015; Tanner and Johnston, 2017; Ly, Chakir and Cretì, 2021; Bakehe and Hassan, 2022). Nevertheless, some authors recognize that the extension of the electricity network or the improvement in agricultural profitability generated by electrification for example could be a source of deforestation (Geist and Lambin, 2002; Villoria, Byerlee and Stevenson, 2014). Let us also recall that the great majority of the authors reporting that electrification reduces deforestation have not in fact measured the global or overall effect of electrification on deforestation.[2] This is the case, for example, for Mensah and Adu (2015) who focus on the decrease in the use of wood for cooking due to electrification in Ghana and Ly, Chakir and Cretì (2021) who focus on both the decrease in the share of households collecting firewood and in the average size of agricultural parcels resulting from electrification within cohorts of households in Côte d'Ivoire. The only authors, to our knowledge, who have attempted a more global analysis are Tanner and Johnston (2017). Using data on a panel of 158 countries for the years 1990, 2000 and 2010, they show that access to electricity in rural areas (measured by the percentage of the rural population with access to electricity) reduces deforestation rates. However, Tanner and Johnston (2017) believe that a caveat is necessary for any study of this nature. They believe that using entire countries as the unit of analysis is not ideal. In fact, intra-country heterogeneity is the rule in the real world, not the exception, a problem that affects country-level indicators of any kind. They point out that future work using disaggregated data (at the level of provinces, districts, regions, etc.) would help to clarify the relevant dynamics within the areas of interest. This is why we have conducted this analysis at the regional and departmental level and show the impact of spatial resolution on the results.

Indeed, in the economic literature, the role of spatial interactions in explaining deforestation is highly important. For Baggio and de Barros (2021), spatial interactions are to be considered when analysing forest conversion and land use change. This is why it is imperative to always control for spatial interactions in these types of analysis, as this could have an effect on the different relationships and improve the predictive power of the model (Maddison, 2006; Chakir and Lungarska, 2017; Choumert, Motel and Dakpo, 2013). In the same vein, Robalino and Pfaff, 2012 consider that spatial interactions are relevant to understand the phenomenon of deforestation. Finally, Robalino and Pfaff (2012) show that in Costa Rica, deforestation in neighbouring localities (regardless of political boundaries) significantly increases the probability of deforestation in a given locality. However, the interaction between localities is not necessarily dependent on geographical proximity. In fact, even if a locality is far away from the major agglomerations, if it is well integrated into the transport network, it is obvious that the demand for forest goods (such as wood and firewood) and agricultural goods (pressure on land) is quite high for this locality compared

[2] This overall effect includes how electrification operates through the key players involved in deforestation, which include companies (logging, mining, oil, etc.), the state (extension of road infrastructure, construction of hydroelectric dams, urbanization policy, etc.) and households (agriculture, firewood collection, livestock rearing, gold panning, etc.).

to similar localities that would not be as well served by road and rail transport infrastructures. This results in accelerated deforestation (Asher, Garg and Novosad, 2020). Some authors, such as Ferreira and Coelho (2015), even think that the deforestation process begins with the opening of roads that encourage the collection of wood and the clearing of the forest for agriculture or pasture. Empirical analyses by authors such as Newman, McLaren and Wilson (2014) or Kleinschroth et al. (2019) confirm that the phenomenon of deforestation is more important on the shelf of roads. Moreover, according to Alves (2002), the deforestation of the 1990s in Brazil occurred within a radius of 100 km of the main roads and highways in the Amazon and Barber et al. (2014) showed that 95% of the forest loss was located within a radius of 5.5 km on roads and 1 km on rivers. It should also be noted that deforestation is also affected by geographical and climatic conditions, particularly through its impact on the costs of building and maintaining transport infrastructure. For example, high levels of precipitation can make runoff difficult and reduce the potential for agricultural production, reducing the profitability margin, and acting as a barrier to deforestation (Hargrave and Kis-Katos, 2013). Baggio and de Barros (2021) also considered some geographical variables are for control purposes. For them, this aims to improve the specification of the model and avoid the problem of omitted variables. Finally, to illustrate the application of spatial analysis in the literature, we can cite for example Amin et al. (2019) who use a dynamic spatial model that takes into account both location bias and spatial interaction effects between municipalities and allows the impact of different types of protected areas (integral protected areas, sustainable protected areas and indigenous lands) on deforestation to be assessed. For them, the effectiveness of protected areas on deforestation is open to debate because they are not randomly distributed. Neglecting for instance this location bias could lead to an overestimation of the impact of protected areas on deforestation.

Our contribution to the existing literature is fourfold. First, we check the concordance of the night lights intensity data (satellite data) with the official data on progress with electrification in Côte d'Ivoire (data available only at the regional level). Indeed, satellite data, due to their availability at different spatial scales, are frequently used to approximate economic activity (GDP), population density, or electrification to compensate for the frequent absence of official data on these variables at the sub-national scale in developing countries (Dai, Hu and Zhao, 2017; Kumar et al., 2019; Sutton et al., 2001 Sutton et al., 2007; Beyer, Franco-Bedoya and Galdo, 2021). We show that the use of the electricity coverage rate data provided by the Ivorian authorities and the night lights intensity data provide the same results (no effect) at the regional scale. This means that there is a concordance of the official data and the night lights intensity data at regional scale. Second, we test the hypothesis according to which the existence of spatial interaction also depends on the chosen aggregation level. Indeed, we show that aggregated data at the regional level (N=33) show no spatial autocorrelation. However, at the department level (N=108), the spatial lag model is the best model according to statistical tests. Third, we investigate whether conducting the analysis at a lower level of aggregation (108 departments) while taking into account both spatial effects and unobservable individual and temporal specific effects could help to improve the specification of the model. Finally, we analyse the global effect of electrification on deforestation at the country's regional and departmental levels in order to be able to draw parallels with the results obtained by Tanner and Johnston (2017) using a panel of developing countries. Contrary to Tanner and Johnston (2017), our empirical results suggest that electrification increases deforestation in line with the situation on the ground in Côte d'Ivoire.

The rest of the paper is as follow: data and variables are presented in the section II, the section III presents the choice for the best spatial specification, section IV presents our estimations and results, and the section V concludes.

II. Data and variables

This section includes respectively the variables description and summary statistics, the concordance between night lights data and official electrification coverage rate data, and our exploratory spatial data analysis.

A. Variables description and summary statistics

Table 1 summarises our main data sources with the different descriptions. These are mainly satellite data such as forest cover data, night lights intensity data, weather data, conflict data, economic activity data and demographic data.

We will mainly exploit data on forest cover in 2000 (>20% trees) and deforestation 2001-2018 provided by Hansen et al. (2013). In order to estimate the electrification rate by region and department, we will exploit high resolution satellite data on night lights intensity provided by the Earth Observation Group, NOAA National Centers for Environmental Information (NCEI).

We also retain the control variables that are commonly used in studies undertaken on the evolution of the deforestation rate. To measure the effect of economic factors, we use GDP (by region, by department). As a reminder, in the economic literature, the debate on the relationship between deforestation and economic growth is summarised by the existence of an inverted U-shaped relationship called the "environmental Kuznets curve".[3]

Also, several authors have identified large and/or growing populations as a causal factor of deforestation (Celentano et al., 2012; Tacconi, 2011). This is why demography also requires special attention in this analysis, since population is considered to be one of the main causes of environmental degradation, and therefore of deforestation. In developing countries with forest resources, the population migrates when access to land is improved and converts forests into arable land (Bakehe and Hassan, 2022). Since the pioneering work of Cropper and Griffiths (1994), several econometric analyses have shown that population density increases deforestation in developing countries. In this study, the potential role of demographic factors on deforestation is taken into account through the population density per locality (region or department). Demographic data on population density by locality are available from NASA's Socioeconomic Data and Applications Center (SEDAC).[4]

Our control variables also include weather (temperature and precipitation), forest cover, conflict and market access (distance to a major city). The weather and market access variables are mainly used to control agricultural activity. The forest cover variable is used to capture the role of forest abundance. Finally, the conflict variable also remains very important because in case of conflict in a locality, two effects may emerge: a decrease in deforestation due to emigration or an increase in deforestation due to the violation of certain protected areas (parks, reserves, etc.).

In Table 2, on average and at the regional scale, the AGR analysis suggests that deforestation as well as electrification have steadily increased over the period 2011-2018 (19% forest loss on average and 36% increase in lights intensity which is a proxy for electrification).[5] Similarly, we have an increase in average temperature over the same period, while rainfall has continued to decline. The forest cover is about 34% on average per region. However, when we observe the minimum and maximum values for all of these quantities, there is strong heterogeneity between the regions, as Tanner and Johnston (2017) pointed out in the context of the limit of an analysis by country that would ignore this phenomenon of intra-country heterogeneity. Also, we can see that electrification continues to grow by looking at either the official data (row 3) or the lights intensity data (row 2). However, the difference in the magnitude of AGR is due to changes in the measurement of night lights intensity data over the period, which makes the rate larger for this data source.

The trend in Table 3 (departmental scale) is almost the same as described in Table 2 (regional scale). The fundamental difference is that we do not have official data on forest cover at the departmental level and that we have more heterogeneity at this departmental level as shown by the St. Dev. values and the differences between the minimum and maximum values. Keeping only the regional level of disaggregation therefore runs the risk of ignoring these huge intra-regional heterogeneities. Therefore it is important for us to check more or less the concordance between the official data and the regional night lights intensity data in order to be able to use the departmental night lights intensity data as a proxy for electrification in Côte d'Ivoire.

[3]Here we will not test for the existence of an environmental Kuznets curve.

[4]NOAA (National Oceanic and Atmospheric Administration)

[5]AGR = (Annual) Average Growth Rate

TABLE 1—MAIN DATA DESCRIPTION

Data	Description	Source/Authors
VIIRS Nighttime Lights (Radiance)	Yearly VIIRS day night band nighttime lights data (without stray light correction).	Christopher, Chi et al. (2017)
DMSP-OLS Nighttime Lights (digital number 0-63)	The lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded.	NOAA National Geophysical Data Center
Evolution of the coverage rate 2011 - 2018	Evolution of the number of electrified localities and the coverage rate by region from 2011 to 2018.	Ministry of Petroleum, Energy and Renewable Energies (MPEER)
Precipitation (Yearly Average)	Average monthly precipitation per year in millimeters. Created using UDel Precipitation dataset (v5.01)	University of Delaware
Air Temperature (Yearly Average)	Average monthly air temperature per year in degrees Celsius. Created using UDel Air Temperature dataset (v5.01)	University of Delaware
Tree canopy cover for year 2000 (percent forest cover)	Tree cover in the year 2000, defined as canopy closure for all vegetation taller than 5m in height. In the range 0-100.	Hansen et al. (2013)
Year of gross forest cover loss event (pixels of forest loss)	Forest loss during the period 2000-2018, defined as a stand-replacement disturbance, or a change from a forest to non-forest state.	Hansen et al. (2013)
Population Density (persons per square kilometer)	Population density (UN Adjusted values) from Gridded Population of the World v4. GPWv4 depicts the density of human population across the globe.	Warszawski et al. (2017)
Gross Domestic Product (millions of dollars)	Map of total economic activity, including both formal and informal economic activity for 2006; created from nighttime lights and LandScan population grid.	Ghosh et al. (2010)
ACLED Conflict Events (Africa)	Number of conflict event counts per 0.1 decimal degree grid cell using ACLED (Armed Conflict Location & Event Data Project) v3.	Raleigh et al. (2010)
Travel time to major cities (time in minutes)	Estimated travel time (in minutes) to the nearest city of 50,000 or more people in year 2000.	Nelson (2008)

TABLE 2—DESCRIPTIVE STATISTICS (33 REGIONS)

Statistics	N	Mean	St. Dev.	Min	Max
Forest loss AGR 2011-2018	33	18.817	12.148	−3.199	41.209
Night lights AGR 2011-2018	33	35.568	29.398	0.693	131.205
Elec. coverage AGR 2011-2018	33	9.880	9.682	0.148	36.138
Average temperature AGR 2011-2017	33	0.212	0.304	0	1
Average precipitation AGR 2011-2017	33	−1.329	2.000	−7.597	3.521
Population density AGR 2010-2020	33	2.768	0.864	1.372	4.741
Percent forest cover	33	33.848	12.947	13	60
Gross Domestic Product	33	1,196	1,637	44	9,329
ACLED Conflict Events	33	82.788	38.654	18	186
Travel time to major cities	33	260.364	126.197	93	637

TABLE 3—DESCRIPTIVE STATISTICS (108 DEPARTMENTS)

Statistics	N	Mean	St. Dev.	Min	Max
Forest loss AGR 2011-2018	108	22.367	19.045	−12.446	104.179
Night lights AGR 2011-2018	108	46.138	49.453	−5.579	262.188
Average temperature AGR 2011-2017	108	0.254	0.308	0	1
Average precipitation AGR 2011-2017	108	−1.401	2.180	−9.059	3.789
Population density AGR 2010-2020	108	2.803	1.817	0.000	11.514
Percent forest cover	108	34.546	13.777	8	67
Gross Domestic Product	108	365.750	945.970	10	9,330
ACLED Conflict Events	108	26.111	18.043	4	123
Travel time to major cities	108	258.648	131.132	85	858

TABLE 4—DESCRIPTIVE STATISTICS (PANEL OF 108 DEPARTMENTS OVER 2001-2017)

Statistics	N × T	Mean	St. Dev.	Min	Max
Forest loss	1,836	23,496	31,444	0	307,665
Night lights	1,836	3,237	5,957	0	81,497
Average temperature	1,836	26.687	0.786	24	28
Average precipitation	1,836	111.377	24.952	56	210
Population density	1,836	80.366	219.565	7	2,312
Percent forest cover	1,836	34.546	13.717	8	67
Gross Domestic Product	1,836	365.750	941.837	10	9,330
ACLED Conflict Events	1,836	26.111	17.964	4	123
Travel time to major cities	1,836	258.648	130.559	85	858

Table 4 summarises our variables for the panel analysis at department level over the period 2001-2017. The Forest loss variable is in pixels, while the Night lights variable is in radiance, thus not relevant to interpret in an economic point of view. The average temperature per department over this period is 27 degrees Celsius on average with a minimum temperature of 24 degrees Celsius and a maximum temperature of 28 degrees Celsius. The average rainfall is 111 millimetres per year. The average density is 80 people per km^2. The departments have an average GDP of 366 million USD and there is an average of 26 conflicts per department, this characterises the fact that the period has been particularly turbulent in the country (post-election crisis, conflicts between rebel forces from the north and pro-governmental forces, etc.).

B. *Concordance between night lights data and official coverage rate data*

The first map in Figure 1 indicates that there is a strong spatial concentration between night lights intensity data and electricity coverage (official data).[6] The regions that have experienced rapid increases in coverage are those that predominantly have above-average increases in lights intensity (solid triangles). This proves, in somewhat, the concordance between these two data sources. With the exception of some northern regions on the border with Mali and Burkina Faso (area under threat from extremist groups, thus decreasing population due to emigration and thus less pressure on forests) and some central regions where a kind of negative spatial correlation can be noticed, the second map in Figure 1 also seems to show a trend of positive spatial correlation between electrification and the highest deforestation rates.

Moreover, the table A1 (Appendix A) presents the results of the a-spatial model by comparing the coefficients (sign and significance) of the night lights intensity data and the official coverage rate data. As already shown in Table 2, at the regional scale, the average annual growth rates are increasing for both variables over the period 2011 to 2018. The two rates do not evolve with the same magnitude because there has been a change in the scale of measurement over the period for the night lights intensity variable. This is also reflected in the difference in magnitudes of the two coefficients expressed in this table. However, both coefficients remain insignificant in this model and keep the same positive sign.

Finally, the Figure 2 represents the administrative division of the national territory into 33 regions. This figure also represents the average annual growth rates (2011-2018) of our main variables at the regional level. By analysing the last two maps, we can see that the variables night lights intensity and coverage rate reflect the same phenomenon of spatial polarisation (or spatial heterogeneity) in favour of localities in the north of the country. Indeed, these localities have long remained on the sidelines of the country's development process, but as soon as the current president (originating from the north of the country) took the country's presidency, massive investments were undertaken in these localities. This once again demonstrates the reliability of the night lights intensity data. The first map shows a strong concentration of high deforestation rates in the east and west of the country (spatial autocorrelation).

Even if the reliability of night lights intensity data is sometimes questioned, at least in the case of Côte d'Ivoire, our results show that it seem to be suitable as a proxy of electrification in the country at the regional level. Given the unavailability of official data on the evolution of electrification at disaggregated levels (notably at the departmental level) in developing countries, and more particularly in Côte d'Ivoire, we will use these data as a proxy for electrification at a lower aggregation level (departmental level) in the rest of this analysis.

C. *Exploratory spatial data analysis*

Let us now define the spatial interaction matrix. It is obvious that in order to implement a spatial econometric model, the construction of a weight matrix W that best describes the spatial interactions between observations (localities, regions and departments in our case) is essential. A neighbourhood matrix W must indeed respect several technical constraints to ensure in particular the invertible character of the matrix, and the identification of the models (Lee, 2004; Elhorst, 2010). According to Insee (2018), the usual con-

[6]Our Local Indicators of Spatial Association (LISA) clustering maps also highlight the similar trends (see Figure A1 in Appendix A)

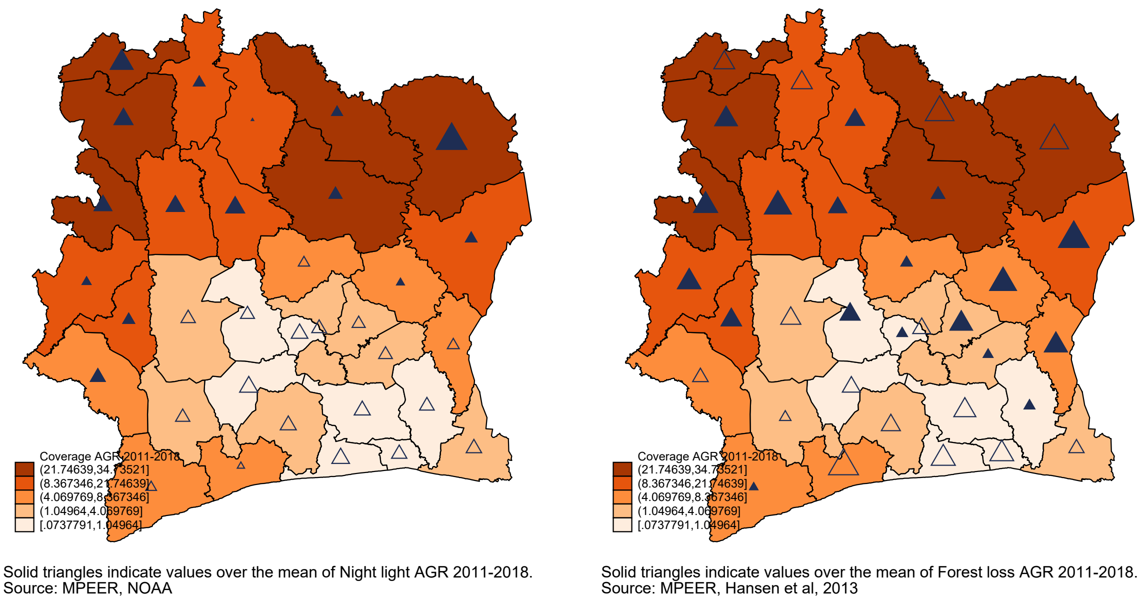

FIGURE 1. *Spatial concentration of high and low values*

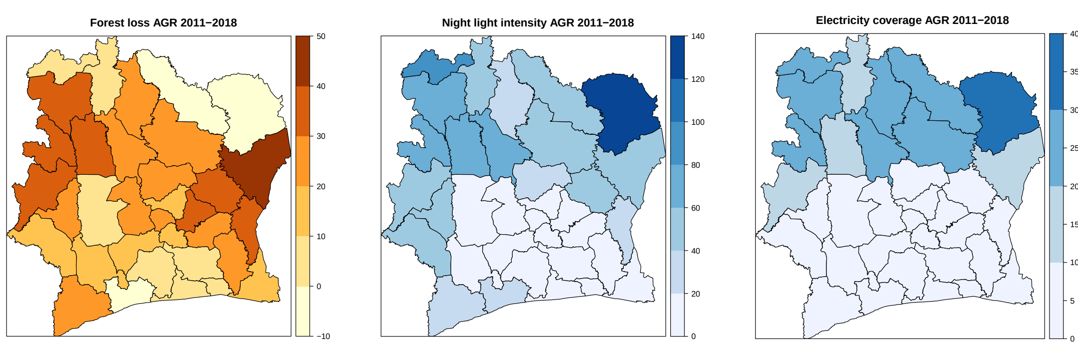

FIGURE 2. *Average growth rates (AGR) for the main variables at the regional and departmental scale*

tiguity matrix respects these two different constraints. Only one shared border point fulfils the condition of contiguity (queen=TRUE). Otherwise, more than one shared point would be required or simply a shared boundary line. Figure 3 summarises the neighbourhood networks of the country's regions and departments.

Then, before opting for a potential spatial model, it is essential to ensure the existence of spatial interaction between the observations, in particular by means of graphic maps and statistical tests (the main one being Moran's I). For the quantitative variables, Moran's index (I_W) is often preferred to Geary's because of its greater general stability (Upton and Fingleton, 1985):

$$I_W = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(Y_i-\bar{Y})\,(Y_j-\bar{Y})}{\sum_{i=1}^{n}(Y_i-\bar{Y})^2} \tag{1}$$

$H_0 : I_W = 0 \rightarrow$ No spatial autocorrelation.
$H_1 : I_W \neq 0 \rightarrow$ Spatial autocorrelation (positive or negative depending on the sign of I_W).

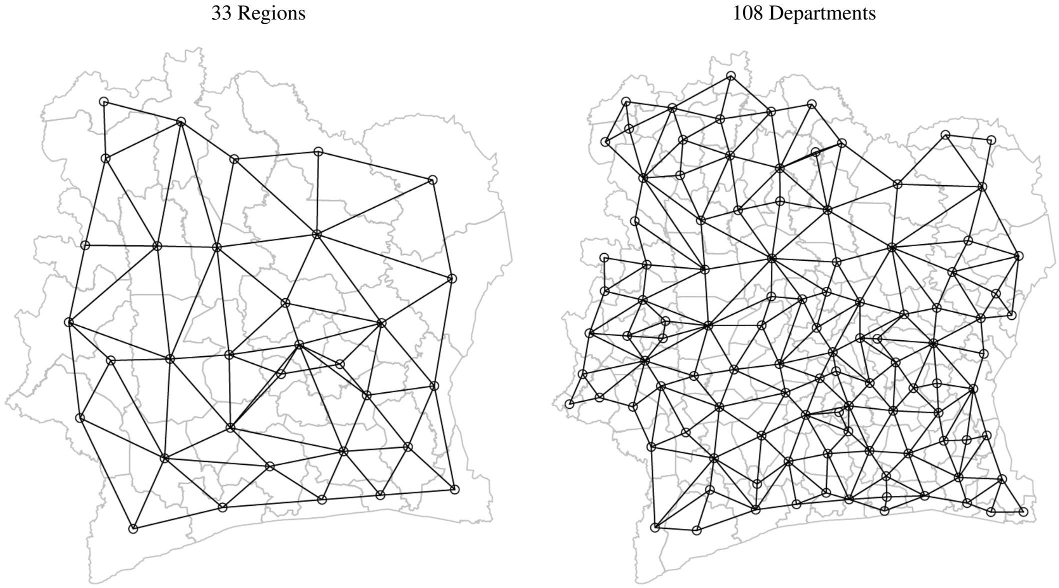

FIGURE 3. *Neighbourhood network using Contiguity (queen) matrix*

In order to carry out the Moran test, it is necessary to specify the distribution for each of our main variables in the absence of spatial autocorrelation (Insee, 2018). In this context, statistical inference is generally carried out by considering either the Normality Hypothesis (each of the values of the variable is the result of an independent draw from the normal distribution specific to each geographical area on which this variable is measured), or the Randomisation Hypothesis (the estimate of the statistic obtained from the data is compared with the distribution of that obtained by randomly reordering the data).

The Moran diagrams (Figure 4) allow a quick reading of the spatial interaction at both the regional and departmental levels for each of our main variables.

Through tables 5 and 6 (but also the tables in appendix B), we show that whatever the definition of the neighbourhood or the scale of aggregation chosen, the spatial autocorrelation of electrification and deforestation is positive and significant. The strength of the spatial autocorrelation does not change enough following the type of neighbourhood chosen, but varies drastically for the Forest loss variable following the aggregation level. Indeed, the significance of the test remains weak at the level of the 33 regions for this variable. Nevertheless, it does not present any ambiguity when a lower level of aggregation is adopted (108 departments).

III. Choice of the best spatial specification

From a statistical point of view, many analyses (linear regressions in particular) are based on the hypothesis of independence of the observations of a variable. When a variable is spatially autocorrelated, the independence assumption is no longer respected, thus calling into question the validity of the assumptions on which these analyses are based. Thus, as highlighted in the introduction section, the analysis of the deforestation phenomenon requires the consideration of spatial interactions between different localities (regions and departments in Côte d'Ivoire in our case). In order to take into account the relative location and interactions of localities in Côte d'Ivoire, we will opt for spatial econometric models. Spatial econometrics is certainly a recent discipline, but it is already the subject of interesting applications, particularly in the field of environmental economics. To illustrate this, we can, for example, recall its application in land use models by Chakir and Lungarska (2017). Indeed, in their comparison of different econometric models of land use, the two authors manage to show that taking into account spatial effects significantly improves the quality of the predictions of the different models studied.

Spatial econometric models extend linear re-

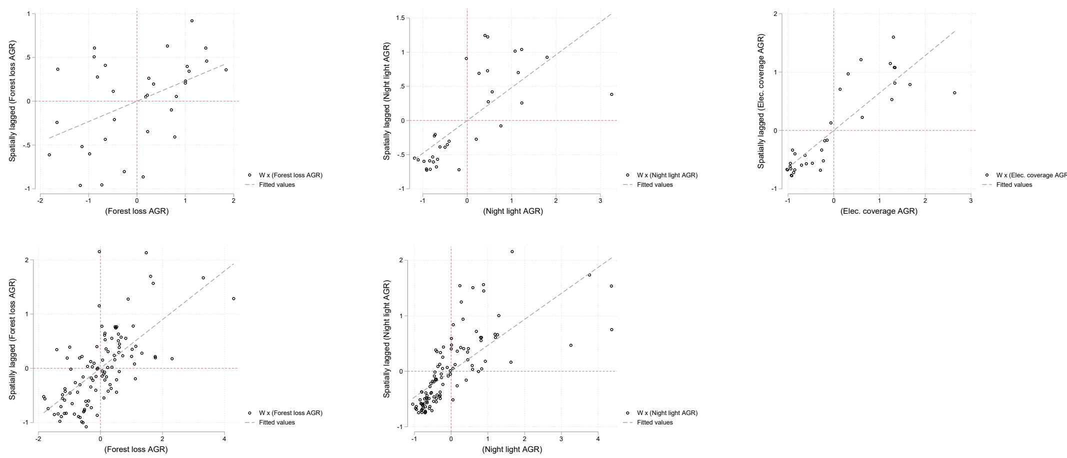

FIGURE 4. *Moran plot using Contiguity (queen) matrix at the regional and departmental scale*

TABLE 5—MORAN TEST FOR OUR MAIN VARIABLES USING CONTIGUITY (QUEEN) WEIGHT MATRIX - REGIONS

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.243	-0.031	0.011	2.59	0.0048
Forest loss (randomisation)	0.243	-0.031	0.012	2.55	0.0054
Night lights (normality)	0.498	-0.031	0.011	5	2.9e-07
Night lights (randomisation)	0.498	-0.031	0.011	5.15	1.3e-07
Elec. coverage (normality)	0.680	-0.031	0.011	6.72	$<$1e-08
Elec. coverage (randomisation)	0.680	-0.031	0.011	6.72	$<$1e-08

TABLE 6—MORAN TEST FOR OUR MAIN VARIABLES USING CONTIGUITY (QUEEN) WEIGHT MATRIX - DEPARTMENTS

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4583	-0.0093	0.0036	7.78	$<$1e-08
Forest loss (randomisation)	0.4583	-0.0093	0.0035	7.89	$<$1e-08
Night lights (normality)	0.5654	-0.0093	0.0036	9.56	$<$1e-08
Night lights (randomisation)	0.5654	-0.0093	0.0034	9.91	$<$1e-08

gressions by taking into account the non independence of observations across space.[7] In other words, these models may contain spatial lags of the outcome variable and/or spatial lags of the covariates, and/or spatial lags of error terms. Formally, the model which groups together all these interactions is the model of Manski (1993) or GNS:

$$D = \rho W D + X\beta + W X\theta + u$$
$$u = \lambda W u + \varepsilon \tag{2}$$

where, D represents deforestation (or forest loss), X represents a set of explanatory variables (electrification, population density, precipitation, temperature, forest cover, gross domestic product, conflicts, travel time to major cities or access to markets). The model of Manski (1993) is not identifiable (Insee, 2018). To make

[7]Spatial Autoregressive Models Reference Manual (Stata, Release 17)

the model identifiable, the literature proposes to impose restrictions on the different parameters of the model such as:

$\theta = 0$, $\lambda = 0$, $\rho \neq 0 \rightarrow$ SAR
$\theta = 0$, $\lambda \neq 0$, $\rho = 0 \rightarrow$ SEM
$\theta \neq 0$, $\lambda = 0$, $\rho = 0 \rightarrow$ SLX
$\theta \neq 0$, $\lambda = 0$, $\rho \neq 0 \rightarrow$ SDM (SAR+SLX)
$\theta \neq 0$, $\lambda \neq 0$, $\rho = 0 \rightarrow$ SDEM (SLX+SEM)
$\theta = 0$, $\lambda \neq 0$, $\rho \neq 0 \rightarrow$ SAC (SAR+SEM)

After having established the existence of spatial interactions between our localities in the subsection II.C, we proceed now to the choice of the best spatial specification. To do this, first, we will opt for the bottom-up approach proposed by Florax, Folmer and Rey (2003) which consists in starting with the a-spatial model using the Lagrange multiplier (LM) tests proposed by Anselin et al. (1996) to decide between the different spatial specifications and the a-spatial model. These tests are also robust to the presence of other types of spatial interactions (beyond the specifications of the SAR or SEM models). This approach is based on the residuals of the a-spatial model and has the advantage of being computationally inexpensive. Florax, Folmer and Rey (2003) have also shown, using simulations, that this procedure is the most efficient in the case the true model is a SAR or a SEM.

From the constrained or a-spatial model (OLS in our case), we use the statistics of the LM test to guide the selection of the correct specification. According to Anselin (2013), if neither of the two tests (LMerr and LMlag) is significant, then the model to adopt is the a-spatial model (OLS). On the other hand, if LMerr is the only one of the two tests to be significant, then we opt for a SEM. Otherwise, if LMlag is the only one of the two tests to be significant, then the SAR is chosen. However, if both are significant, the robust versions (RLMerr and RLMlag) are used to discriminate between them.

Through Table C1 (Appendix C), we conclude that the best spatial specification remains the a-spatial model (OLS) when considering the administrative division of the 33 regions. This is the case regardless of whether the night lights intensity data or the official electricity coverage data provided by the country's authorities are used as the variable of interest. However, when considering the administrative division of the 108 departments, it appears that the best spatial specification to use is the SAR or Spatial Lag Model (SLM) specification. [8]

Indeed, the administrative division of a territory as vast as Côte d'Ivoire (with its 322,462 km^2) into only 33 regions did not allow the identification of spatial interaction phenomena. On the other hand, when we move to a much lower level of aggregation (108 departments), we realise the need to opt for a spatial model that takes into account the strong heterogeneity between the different entities. Spatial division therefore has an influence on the results of statistical processing or modelling, as emphasised by Openshaw (1984) through the concept of MAUP (Modifiable Areal Unit Problem). More precisely, the irregular shapes and limits of administrative grids which do not necessarily reflect the reality of the spatial distributions studied are an obstacle to the comparability of unequally subdivided spatial units. According to Openshaw (1984), the MAUP is a combination of two distinct but related problems. The first is the problem of scale, which is related to a variation in information generated when a set of spatial features is aggregated to form fewer and larger units for the purposes of analysis or for data availability issues. The second is the problem of aggregation (or zoning), which is related to a change in the diversity of information generated by different possible aggregation schemes at the same scale. This effect is characteristic of administrative (particularly electoral) boundaries and is in addition to the scale effect.

The fact that we have the SAR model as our best spatial model means that deforestation in a given locality is determined jointly with that of neighbouring localities.

This implies that: (i) the global spillover effects: on average, the value of deforestation for

[8]The Top-down approach (starting with the Spatial Durbin Model or SDM) due to LeSage and Pace (2009) also gives the SAR as the best spatial specification in this application (see Appendix D). Elhorst (2010)'s "mixed" approach, which is a combination of the top-down and bottom-up approaches, is usually conducted in case of different results. In our case, the result is the same. Thus, this approach also would lead us to a SAR specification. Finally, we also used the two-way comparison approach (see Appendix E). In this last approach, we could see that SAC prevails over GNS. Then, SDM and SDEM also outperform GNS, and SLX. OLS also prevails over SLX. However, SEM is preferred to SDM, SDEM and OLS. However, SAC prevails over SEM. Finally, SAR prevails over SAC, SDM and OLS. We conclude for all these approaches that the SAR is the best model adapted to our data.

a locality is not only explained by the values of the explanatory variables for that locality, but also by those associated with all localities (spatial multiplier effect); and (ii) a global spatial diffusion effect: a random shock in a locality affects the value of deforestation of this locality as well as those of other localities. In our case this means that deforestation in a particular locality depends on the electrification rate of other localities. The interaction effects among the error terms do not require a theoretical model but instead, are consistent with a situation where determinants of deforestation omitted from the model are spatially autocorrelated, or with a situation where unobserved shocks follow a spatial pattern.

IV. Estimation and results interpretation

In this section, we analyse the overall effect of electrification on deforestation at the departmental level taking into account only spatial specificities, and then consider spatial effects and unobservable individual and temporal specific effects in order to correctly identify the overall effect of electrification on deforestation

A. Spatial analysis at departmental level

Table 7 presents the results of the a-spatial model (OLS) and all the possible spatial specifications (SEM, SAR, SDM, SAC, SLX, SDEM and GNS) at the scale of the country's departments. The analysis of the AIC confirms our choice of the SAR model (AIC=899.681 being the lowest). However, the AIC of the SAR model is very close to that of the SAC model (AIC=901.679). Moreover, when we focus on the coefficients for these two models, we notice that they are almost identical. Also, these two coefficients have the highest electrification effects on deforestation (0.036) except for the linear model (which has to be compared to the marginal effects that we will calculate later). On closer inspection, we notice that $\hat{\lambda} = 0$ for the SAC model, which simply reduces it to the SAR model. Finally, we also notice that LM test for residual autocorrelation is not significant for the SAR model. Thus, the possible risk of an omitted relevant variable is eliminated. As we defined also the SAR as the composition of SEM and SLX, this absence of spatial interaction effects in error terms lead to the fact that our SAR model implies finally that: (i) deforestation in a given locality depends on the electrification rate of other localities; (ii) there are the global spillover effects (on average, the value of the deforestation for a locality is not only explained by the level of the electrification for that locality, but also by those associated with all localities, spatial multiplier effect); and (iii) there is a global spatial diffusion effect (a random shock in a locality affects not only the value of the deforestation of this locality but also has an effect on the values of the deforestation of other localities).

Following LeSage and Pace (2009), the effect of the explanatory variables on the dependent variable is decomposed into direct and indirect effects. The direct effect of electrification on deforestation measures the effect of a change in the rate of electrification (improvement of electrification for example) of a given department on deforestation in this same department. The indirect effect measures the effect of a change in electrification in one department on deforestation in all other departments. In other words, indirect effects are global spillovers because they occur in all departments and are not necessarily limited to neighbourhood departments. However, these indirect effects relate more to the neighbourhood of a given department because they decrease with distance.

Table 8 presents the direct and indirect effects of electrification on deforestation from the SAR specification at departmental level in Côte d'Ivoire. The empirical confidence intervals are obtained using 200 simulations from the empirical distribution (Table 7, column 4). Only the direct effects of conflict and rainfall are significant and negative. Indeed, areas that experienced conflict, notably during the post-election crisis or during armed attacks in the north of the country (border with Burkina Faso and Mali) experienced population displacement to other areas. This would have reduced the demographic pressure on the forests in these areas. With regard to rainfall, Hargrave and Kis-Katos (2013) recall that a high level of rainfall can make runoff difficult and reduce the potential for agricultural production, thus reducing the profitability margin, and acting as a barrier to deforestation. Thus, only the precipitation variable would have a significant indirect effect. We get the same sign with the direct effect of this variable because

TABLE 7—REGRESSION RESULTS

	OLS	SEM	SAR	SDM	SAC	SLX	SDEM	GNS
Night lights intensity AGR 2011-2018	0.059	0.025	0.036	−0.010	0.036	−0.011	0.004	−0.000
	(0.045)	(0.045)	(0.036)	(0.050)	(0.037)	(0.062)	(0.048)	(0.049)
Average temperature AGR 2011-2017	2.261	2.491	2.167	1.750	2.172	1.475	0.210	0.962
	(5.643)	(4.719)	(4.535)	(4.635)	(4.544)	(5.819)	(4.989)	(4.943)
Average precipitation AGR 2011-2017	−4.050***	−3.136***	−2.032***	1.176	−2.036**	0.341	1.459	1.429
	(0.813)	(1.163)	(0.720)	(2.089)	(1.000)	(2.622)	(2.051)	(2.095)
Percent forest cover in 2000	0.360**	0.270	0.187	0.123	0.178	0.256	0.093	0.085
	(0.147)	(0.189)	(0.121)	(0.274)	(0.134)	(0.344)	(0.254)	(0.261)
Population density AGR 2010-2020	0.306	0.718	0.694	0.589	0.694	0.190	0.558	0.592
	(1.025)	(0.808)	(0.824)	(0.867)	(0.825)	(1.088)	(0.960)	(0.964)
Gross Domestic Product	−0.002	−0.001	−0.001	−0.001	−0.001	−0.002	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ACLED Conflict Events	−0.166	−0.167**	−0.153*	−0.139	−0.153*	−0.159	−0.132	−0.133
	(0.102)	(0.085)	(0.082)	(0.087)	(0.083)	(0.109)	(0.095)	(0.093)
Travel time to major cities	−0.017	−0.012	−0.010	−0.008	−0.010	−0.017	−0.003	−0.003
	(0.017)	(0.018)	(0.014)	(0.020)	(0.014)	(0.024)	(0.019)	(0.019)
$\hat{\rho}$			0.613***	0.577***	0.612***			0.134
			(0.089)	(0.097)	(0.223)			(0.569)
$\hat{\lambda}$		0.608***			0.003		0.626***	0.530
		(0.094)			(0.374)		(0.091)	(0.421)
lag.Night lights intensity AGR 2011-2018				0.050		0.096	0.115	0.102
				(0.074)		(0.093)	(0.093)	(0.100)
lag.Average temperature AGR 2011-2017				−3.254		−1.629	−9.027	−7.316
				(9.268)		(11.636)	(12.158)	(11.590)
lag.Average precipitation AGR 2011-2017				−3.959		−4.950	−7.598***	−6.749*
				(2.661)		(3.283)	(2.921)	(3.775)
lag.Percent forest cover in 2000				0.102		0.145	0.536	0.440
				(0.351)		(0.436)	(0.394)	(0.454)
lag.Population density AGR 2010-2020				−2.289		−2.531	−2.309	−2.237
				(2.004)		(2.516)	(2.385)	(2.330)
lag.Gross Domestic Product				−0.003		−0.007*	−0.001	−0.001
				(0.003)		(0.004)	(0.004)	(0.004)
lag.ACLED Conflict Events				−0.041		−0.146	−0.128	−0.103
				(0.164)		(0.204)	(0.228)	(0.239)
lag.Travel time to major cities				0.011		0.011	−0.020	−0.014
				(0.031)		(0.038)	(0.038)	(0.039)
Constant	9.548	12.474	2.596	7.060	2.613	18.413	7.510	7.321
	(7.116)	(8.222)	(5.809)	(12.057)	(6.273)	(15.093)	(18.614)	(17.993)
Observations	108	108	108	108	108	108	108	108
Adjusted R^2	0.229					0.239		
Akaike Inf. Crit.		903.858	899.681	910.975	901.679		910.67	912.618
Moran's Test	0.000					0.000		
LM-Error Test	0.000					0.000		
LM-Lag Test	0.000					0.000		
Robust LM-Error Test	0.509					0.019		
Robust LM-Lag Test	0.021					0.002		
Common Factor Test				0.352				
LM test for residual auto.			0.991	0.627				

*p<0.1; **p<0.05; ***p<0.01

TABLE 8—EFFECT MEASURES, SPATIAL AUTOREGRESSIVE MODEL

	Direct	Indirect	Total
Night lights intensity AGR 2011-2018	0.0396	0.053	0.092
Average temperature AGR 2011-2017	2.409	3.198	5.607
Average precipitation AGR 2011-2017	-2.259***	-2.998**	-5.258***
Percent forest cover in 2000	0.208	0.276	0.483
Population density AGR 2010-2020	0.771	1.023	1.795
Gross Domestic Product	-0.001	-0.002	-0.003
ACLED Conflict Events	-0.171*	-0.226	-0.397
Travel time to major cities	-0.011	-0.015	-0.026

*p<0.1; **p<0.05; ***p<0.01

neighbouring departments would certainly have similar levels of precipitation.

In spite of taking into account spatial effects through the SAR model, we notice that the overall effect of electrification on deforestation at the department level remains positive but not significant, contrary to what we had expected through the statistical analysis of the data. This leads us to include specific unobservable effects (individual and temporal) using the panel dimension.

B. *Inclusion of unobservable individual and time specific effects*

For Amin et al. (2019), taking into account individual and temporal dimensions allows a considerable gain of information linked to the exploitation of the double dimension of the data (control of the presence of unobservable heterogeneity), gives rise to a size of the samples generally higher (improvement of the precision of the estimates) and allows the modelling of dynamic relations. Indeed, even if spatial cross-sectional models allow spatial dependence effects to be captured, panel data also allow some form of unobservable heterogeneity to be controlled for (individual and time specific effects).

As in the case of cross-sectional data, taking into account spatial effects in panel data also requires specification tests. The first specification test is the Hausman test for spatial models. This test makes it possible to arbitrate between a fixed effects (FE) model and a random effects (RE) model. If the null hypothesis of this test is not rejected, the two estimators GLS (random effects model) and Within (fixed effects model) will converge, but only the GLS will be consistent.[9] Otherwise, the GLS estimator will not be convergent, while the Within estimator will remain convergent. The result of the Hausman test for spatial models (Appendix F) leads to the non-rejection of the null hypothesis of the absence of correlation between the individual effects and the explanatory variables. We therefore opt for a random effects model in the rest of this empirical analysis.

The specification tests for the spatial effects are then carried out in order to select the most appropriate specification for taking account of spatial dependence. The most commonly used spatial autocorrelation specification tests for panel data are based on the Lagrange multiplier test. They make it possible to test for the absence of each of the spatial terms without having to estimate the unconstrained model (Insee, 2018). These two tests are very often completed by their robust version to the alternative form of taking into account the spatial autocorrelation (RLMlag or RLMlag). The results of all the tests (Appendix F) guide us to estimate a random effects model with a SAR process.

Table 9 summarises the results of the model estimation with spatial autocorrelation taken into account using a SAR model (Baltagi error term specification). The calculation of direct, indirect and total effects followed the approach of Piras (2014). Electrification (night lights intensity), percentage of forest cover and conflicts appear to have significant effects on deforestation. Contrary to the results of Tanner and Johnston (2017) which showed, using data from 158 countries, that improving access to electricity in rural areas reduces the rate of deforestation, our main results suggest that electrification broadly increases deforestation. In other words, the improvement of the electrification rate reduces the forest cover at the scale of the departments of Côte d'Ivoire. This result appears after successively taking into account spatial effects and specific individual and temporal unobservable effects.

The direct positive effect of electrification on deforestation could be explained by several mechanisms. First, when a locality is connected to the national electricity grid, this creates new employment opportunities and could contribute to the well-being of that locality. This will therefore lead to an inflow of migrants to that locality and the installation of new industrial actors for example (thus more pressure on the forests in terms of habitats, firewood collection, timber exploitation or mining, etc.). Furthermore, as mentioned in the introduction, there is the case of the very important weight of cash crops (notably cocoa and rubber) in Côte d'Ivoire. Therefore, any improvement in the productivity of these cash crops (notably via irrigation techniques made possible by access to electricity) will not necessarily have an effect on the slowing down of farming to the detriment of forests, and could even increase the expansion of agricultural land to the detriment of forests (Ly, Chakir and Cretì,

[9] GLS = Generalized Least Squares

TABLE 9—EFFECT MEASURES, ML PANEL WITH SPATIAL LAG, RANDOM EFFECTS, BALTAGI SPATIAL ERROR CORRELATION

	Direct	Indirect	Total
Night lights intensity	0.425***	-0.095**	0.331***
Average temperature	372.124	-82.794	289.330
Average precipitation	93.766	-20.862	72.904
Percent forest cover	769.228***	-171.146***	598.082***
Population density	-27.525	6.124	-21.401
Gross Domestic Product	5.452	-1.213	4.239
ACLED Conflict Events	605.629***	-134.747***	470.882***
Travel time to major cities	-7.398	1.646	-5.752

*p<0.1; **p<0.05; ***p<0.01

2021). This is known as Jevons' paradox.[10]

The indirect effect of electrification on deforestation is rather negative and strongly significant even if its magnitude is much smaller than that found with the direct effect. This could be explained by the fact that an increase in deforestation resulting from electrification that is significant enough in the surrounding localities could reduce the internal pressure on the forests (less migrants and more immigrants). Moreover, deforestation increases with the abundance of the forest resource. Also, the fact of surrounding oneself with territories rich in forest resources relatively reduces the pressure on the forest of a given locality. Finally, conflicts increase deforestation because during conflicts even protected areas are affected. For example, in their analysis of the dynamics of the designated forest of Haut-Sassandra (Côte d'Ivoire) in a post-armed conflict situation, Sangne et al. (2015) found that the area, once considered one of the country's best protected designated forests, was experiencing several intrusions into its historical boundaries as a result of the country's military-political crisis that lasted from 2002 to 2011. Numerous pioneering fronts were opened, leading to the clearance of several thousand hectares of natural forest (formerly controlled by rebel armed groups from the north) followed by the plantation of cash crops (mainly cocoa).

[10]The Jevons paradox implies that since technical progress improves the efficiency of the use of a resource, the total consumption of that resource may increase rather than decrease.

V. Conclusion

The objective of our study was mainly to highlight the importance of spatial resolution and spatial interaction in studying the links between electrification and deforestation in Cote d'Ivoire. First, we tested the reliability of the night lights intensity data and showed that its is comparable at the regional level to the official data on electricity coverage provided by the Ivorian authorities. Second, we tested for the existence of spatial autocorrelation in deforestation both at the regional and departmental level. Results show that aggregating the data at regional level hides the spatial autocorrelation observed at the departmental level. Third, we run spatial statistical tests and show that SAR model is the best specification both in cross-sectional and panel data model. Finally, we showed that taking into account both spatial auto-correlation and individual heterogeneity in the spatial panel framework allows to show that electrification have an overall positive impact on deforestation with a positive direct impact and negative indirect impact of neighboring areas.

Our results suggest that electrification increases overall deforestation in Côte d'Ivoire. Nevertheless, as highlighted in many analyses, electrification could have partially favorable effects on some deforestation factors (e.g. reduced wood collection, reduced need to expand arable farms for subsistence crops etc.). In addition, electrification is a powerful tool for reducing poverty. Electrification also accelerates structural transformation and is a source of job creation in most developing countries. While increasing access to electricity, Ivorian authorities should ensure that forest protection brigades are put in place, not only to enforce protected area designations, but also to create a barrier against pressure on forests all over the country.

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Appendix A: Concordance between night lights data and official data

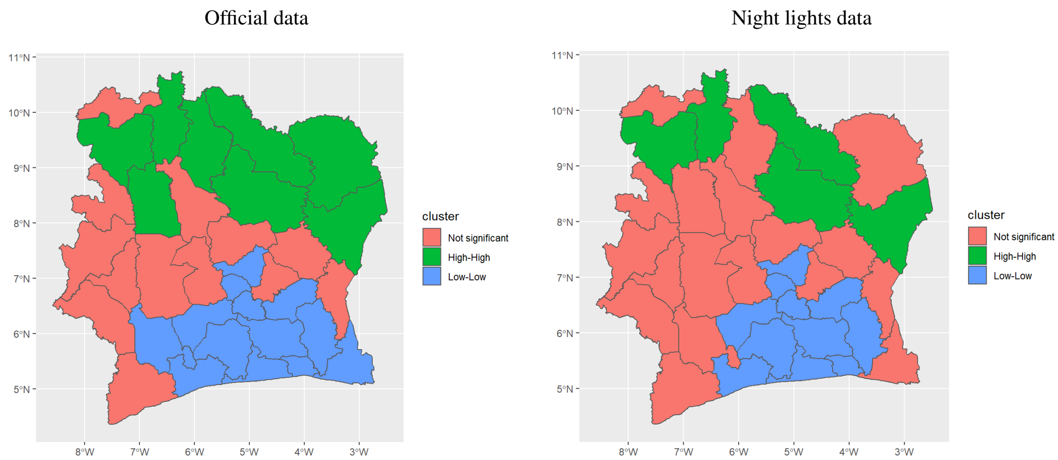

FIGURE A1. *Local Indicators of Spatial Association (LISA)*

TABLE A1—FOREST LOSS AGR 2011-2018 AS DEPENDENT VARIABLE, OLS REGRESSION RESULTS

	(1)	(2)
Night lights intensity AGR 2011-2018	0.088	
	(0.148)	
Electricity coverage AGR 2011-2018		0.332
		(0.419)
Average temperature AGR 2011-2017	−4.962	−5.120
	(7.255)	(7.190)
Average precipitation AGR 2011-2017	−3.080*	−3.416**
	(1.506)	(1.330)
Percent forest cover in 2000	0.338	0.392
	(0.222)	(0.244)
Population density AGR 2010-2020	1.463	1.569
	(3.139)	(3.017)
Gross Domestic Product	−0.002	−0.002
	(0.001)	(0.001)
ACLED Conflict Events	−0.045	−0.068
	(0.074)	(0.079)
Travel time to major cities	−0.039	−0.035
	(0.030)	(0.023)
Constant	14.033	11.906
	(14.558)	(14.581)
Observations	33	33
R^2	0.356	0.363
Adjusted R^2	0.141	0.150
Residual Std. Error (df = 24)	11.259	11.198
F Statistic (df = 8; 24)	1.657	1.708

*p<0.1; **p<0.05; ***p<0.01

Appendix B: Moran's I tests using alternatives neighbourhood matrix

B1. Moran I for Regions

TABLE B1—MORAN TEST FOR OUR MAIN VARIABLES USING CONTIGUITY (GABRIEL) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.289	-0.031	0.014	2.68	0.0036
Forest loss (randomisation)	0.289	-0.031	0.015	2.64	0.0041
Night lights (normality)	0.513	-0.031	0.014	4.57	2.5e-06
Night lights (randomisation)	0.513	-0.031	0.013	4.71	1.2e-06
Elec. coverage (normality)	0.698	-0.031	0.014	6.12	<1e-08
Elec. coverage (randomisation)	0.698	-0.031	0.014	6.12	<1e-08

TABLE B2—MORAN TEST FOR OUR MAIN VARIABLES USING DISTANCE (WITH K=1) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.093	-0.031	0.016	0.977	0.16
Forest loss (randomisation)	0.093	-0.031	0.017	0.962	0.17
Night lights (normality)	0.550	-0.031	0.016	4.56	2.5e-06
Night lights (randomisation)	0.550	-0.031	0.015	4.7	1.3e-06
Elec. coverage (normality)	0.631	-0.031	0.016	5.19	1e-07
Elec. coverage (randomisation)	0.631	-0.031	0.016	5.19	1e-07

TABLE B3—MORAN TEST FOR OUR MAIN VARIABLES USING DISTANCE (WITH K=5) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.0048	-0.0312	0.0028	0.676	0.25
Forest loss (randomisation)	0.0048	-0.0312	0.0029	0.666	0.25
Night lights (normality)	0.3659	-0.0312	0.0028	7.45	<1e-08
Night lights (randomisation)	0.3659	-0.0312	0.0027	7.67	<1e-08
Elec. coverage (normality)	0.4901	-0.0312	0.0028	9.78	<1e-08
Elec. coverage (randomisation)	0.4901	-0.0312	0.0028	9.78	<1e-08

TABLE B4—MORAN TEST FOR OUR MAIN VARIABLES USING TRIANGULATION WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.2180	-0.0312	0.0096	2.54	0.0055
Forest loss (randomisation)	0.2180	-0.0312	0.0099	2.5	0.0062
Night lights (normality)	0.4761	-0.0312	0.0096	5.17	1.2e-07
Night lights (randomisation)	0.4761	-0.0312	0.0091	5.33	4.9e-08
Elec. coverage (normality)	0.6622	-0.0312	0.0096	7.07	<1e-08
Elec. coverage (randomisation)	0.6622	-0.0312	0.0096	7.07	<1e-08

TABLE B5—MORAN TEST FOR OUR MAIN VARIABLES USING 2-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.166	-0.031	0.023	1.3	0.097
Forest loss (randomisation)	0.166	-0.031	0.024	1.28	0.1
Night lights (normality)	0.573	-0.031	0.023	3.97	3.6e-05
Night lights (randomisation)	0.573	-0.031	0.022	4.09	2.1e-05
Elec. coverage (normality)	0.685	-0.031	0.023	4.71	1.3e-06
Elec. coverage (randomisation)	0.685	-0.031	0.023	4.71	1.3e-06

TABLE B6—MORAN TEST FOR OUR MAIN VARIABLES USING 4-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.227	-0.031	0.011	2.41	0.008
Forest loss (randomisation)	0.227	-0.031	0.012	2.37	0.0089
Night lights (normality)	0.514	-0.031	0.011	5.1	1.7e-07
Night lights (randomisation)	0.514	-0.031	0.011	5.25	7.5e-08
Elec. coverage (normality)	0.679	-0.031	0.011	6.63	$<$1e-08
Elec. coverage (randomisation)	0.679	-0.031	0.011	6.63	$<$1e-08

TABLE B7—MORAN TEST FOR OUR MAIN VARIABLES USING 6-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.2308	-0.0312	0.0071	3.12	0.00091
Forest loss (randomisation)	0.2308	-0.0312	0.0073	3.07	0.0011
Night lights (normality)	0.4250	-0.0312	0.0071	5.43	2.9e-08
Night lights (randomisation)	0.4250	-0.0312	0.0067	5.59	1.1e-08
Elec. coverage (normality)	0.5899	-0.0312	0.0071	7.39	$<$1e-08
Elec. coverage (randomisation)	0.5899	-0.0312	0.0071	7.39	$<$1e-08

B2. Moran I for departments

TABLE B8—MORAN TEST FOR OUR MAIN VARIABLES USING CONTIGUITY (GABRIEL) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.5054	-0.0093	0.0043	7.84	$<$1e-08
Forest loss (randomisation)	0.5054	-0.0093	0.0042	7.95	$<$1e-08
Night lights (normality)	0.5411	-0.0093	0.0043	8.38	$<$1e-08
Night lights (randomisation)	0.5411	-0.0093	0.0040	8.69	$<$1e-08

TABLE B9—MORAN TEST FOR OUR MAIN VARIABLES USING DISTANCE (WITH K=1) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4313	-0.0093	0.0036	7.36	$<$1e-08
Forest loss (randomisation)	0.4313	-0.0093	0.0035	7.47	$<$1e-08
Night lights (normality)	0.6239	-0.0093	0.0036	10.6	$<$1e-08
Night lights (randomisation)	0.6239	-0.0093	0.0033	11	$<$1e-08

TABLE B10—MORAN TEST FOR OUR MAIN VARIABLES USING DISTANCE (WITH K=5) WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.25706	-0.00935	0.00087	9.04	$<$1e-08
Forest loss (randomisation)	0.25706	-0.00935	0.00084	9.17	$<$1e-08
Night lights (normality)	0.41993	-0.00935	0.00087	14.6	$<$1e-08
Night lights (randomisation)	0.41993	-0.00935	0.00081	15.1	$<$1e-08

TABLE B11—MORAN TEST FOR OUR MAIN VARIABLES USING TRIANGULATION WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4215	-0.0093	0.0031	7.78	$<$1e-08
Forest loss (randomisation)	0.4215	-0.0093	0.0030	7.89	$<$1e-08
Night lights (normality)	0.4448	-0.0093	0.0031	8.2	$<$1e-08
Night lights (randomisation)	0.4448	-0.0093	0.0028	8.51	$<$1e-08

TABLE B12—MORAN TEST FOR OUR MAIN VARIABLES USING 2-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.6252	-0.0093	0.0078	7.2	$<$1e-08
Forest loss (randomisation)	0.6252	-0.0093	0.0076	7.3	$<$1e-08
Night lights (normality)	0.6418	-0.0093	0.0078	7.38	$<$1e-08
Night lights (randomisation)	0.6418	-0.0093	0.0072	7.66	$<$1e-08

TABLE B13—MORAN TEST FOR OUR MAIN VARIABLES USING 4-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4931	-0.0093	0.0040	7.9	$<$1e-08
Forest loss (randomisation)	0.4931	-0.0093	0.0039	8.02	$<$1e-08
Night lights (normality)	0.5111	-0.0093	0.0040	8.19	$<$1e-08
Night lights (randomisation)	0.5111	-0.0093	0.0038	8.49	$<$1e-08

TABLE B14—MORAN TEST FOR OUR MAIN VARIABLES USING 6-NEAREST NEIGHBOURS WEIGHT MATRIX

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4211	-0.0093	0.0026	8.39	$<$1e-08
Forest loss (randomisation)	0.4211	-0.0093	0.0026	8.51	$<$1e-08
Night lights (normality)	0.4457	-0.0093	0.0026	8.87	$<$1e-08
Night lights (randomisation)	0.4457	-0.0093	0.0024	9.2	$<$1e-08

Appendix C: Bottom-up approach (Florax, Folmer and Rey, 2003)

Table C1—Lagrange multiplier diagnostics for spatial dependence

	Obs: 33 / X = Night light			Obs: 33 / X = Elec. Coverage			Obs: 108 / X = Night light		
Tests	statistic	df	p.value	statistic	df	p.value	statistic	df	p.value
LMerr	2.040606	1	0.1531	2.39356	1	0.1218	24.95165	1	5.879e-07
LMlag	1.578866	1	0.2089	1.57515	1	0.2095	29.80226	1	4.784e-08
RLMerr	0.542341	1	0.4615	1.15133	1	0.2833	0.43516	1	0.5095
RLMlag	0.080601	1	0.7765	0.33292	1	0.5639	5.28577	1	0.0215

Appendix D: Top-down approach (LeSage and Pace, 2009)

Table D1—Likelihood ratio tests

	First stage			Second stage		
Tests	Statistics	df	p-value	Statistics	df	p-value
LR_θ	4.7053	8	0.7886			
LR_ρ	22.013	1	2.709e-06	27.833	1	1.323e-07
LR_λ	8.8829	8	0.3523			

Appendix E: Two-way comparison approach

Table E1—Results of Likelihood ratio tests for spatial models

	statistic	df	p-value
OLS versus SEM ($H_0 : \lambda = 0$)	24	1	1.2e-06
OLS versus SAR ($H_0 : \rho = 0$)	28	1	1.3e-07
OLS versus SLX ($H_0 : \theta = 0$)	11	8	0.23
SAR versus SAC ($H_0 : \lambda = 0$)	8e-05	1	0.99
SAR versus SDM ($H_0 : \theta = 0$)	4.7	8	0.79
SEM versus SAC ($H_0 : \rho = 0$)	4.2	1	0.041
SEM versus SDM ($H_0 : \theta = -\rho\beta$)	8.9	8	0.35
SEM versus SDEM ($H_0 : \theta = 0$)	9.2	8	0.33
SLX versus SDM ($H_0 : \rho = 0$)	22	1	2.7e-06
SLX versus SDEM ($H_0 : \lambda = 0$)	22	1	2.3e-06
SDM versus GNS ($H_0 : \lambda = 0$)	0.35	1	0.55
SDEM versus GNS ($H_0 : \rho = 0$)	0.048	1	0.83
SAC versus GNS ($H_0 : \theta = 0$)	5.1	8	0.75

APPENDIX F: PANEL SPECIFICATION TESTS

TABLE F1—SPECIFICATION TESTS UNDER PANEL MODELS

Tests name	Statistics	Alternative hypothesis
Hausman test for spatial models	chisq = 23.715, df = 8, p-value = 0.9829	one model is inconsistent
LM test for spatial lag dependence	LM = 912.28, df = 1, p-value $<$ 2.2e-16	spatial lag dependence
LM test for spatial error dependence	LM = 889.81, df = 1, p-value $<$ 2.2e-16	spatial error dependence
Robust LM test for spatial lag dependence	LM = 33.226, df = 1, p-value = 8.203e-09	spatial lag dependence
Robust LM test for spatial error dependence	LM = 10.754, df = 1, p-value = 0.001041	spatial error dependence