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

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Abstract

This study analyses the links between electrification and deforestation in Côte d'Ivoire. First, we assess the alignment of night lights intensity data with the official electricity coverage statistics, which are available only at the regional level. Then, using panel data on night lights intensity, we investigate the relationship between electrification and deforestation in greater detail, focusing on a fine resolution at departmental level. In this analysis, we take into account both spatial autocorrelation and individual heterogeneity. Our findings reveal that electrification has an overall positive impact on deforestation with a direct positive impact in electrified localities and a negative indirect impact on neighboring ones. This empirical evidence, contrasting with prior findings on developing countries, carries significant implications for environmental policy and sustainable development efforts.

JEL Classification: C21, C23, O13, Q51

Keywords: Spatial Models, panel Models, Electrification, Deforestation

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1 Introduction

In 2011, Côte d'Ivoire experienced a post-electoral crisis, and in its aftermath, the government launched a comprehensive rural electrification program as part of its Social Program (PsGouv). The primary objective of this program was to enhance electricity coverage in the country, combat rapid deforestation, expedite structural transformation, and create new employment opportunities. The total installed capacity in the country significantly increased from 1,391 MW in 2011 to 2,215 MW by the end of 2018, which, when combined with improved electricity transmission and sector management, resulted in improved access to electricity. As a result, between 2011 and 2018, the program successfully electrified 2,122 localities, raising the coverage rate from 33% to 58%.However, despite these efforts, Côte d'Ivoire continues to face alarming deforestation rates, with the country losing a substantial portion of its forest cover over the years. In the 1960s, the country possessed over 16 million hectares of forest, but this area has shrunk to merely about 2.5 million hectares, reflecting an annual deforestation rate of approximately 150,000 to 200,000 hectares. Satellite imagery-based assessments by the Côte d'Ivoire Ministry of Water and Forests have clearly illustrated the persistent trend of forest loss, with the Ivorian forest shrinking from 7.8 million hectares in 1990 to only 3.4 million hectares in 2015. Meanwhile, little evidence is available to date on the potential impacts of electrification on deforestation or forest loss. Indeed, some studies in the existing literature suggest that electrification might reduce the demand for expanding arable farms due to improved agricultural productivity and also decrease the reliance on firewood, thereby potentially serving as an effective measure to mitigate deforestation (An et al., 2002; Dube et al., 2014; Mensah and Adu, 2015; Tanner and Johnston, 2017; Bakehe and Hassan, 2022). On the other hand, other authors acknowledge that the expansion of the electricity network or enhanced agricultural profitability resulting from electrification could potentially contribute to deforestation (Geist and Lambin, 2002; Villoria et al., 2014).

The present study aims to shed light on the potential effects of electrification on deforestation in Côte d'Ivoire. Its primary objective is to empirically assess the impact of increased access to electricity on overall deforestation rates in the country. The central research question is: To what extent does improved electricity access influence overall deforestation in Côte d'Ivoire? By addressing this crucial research question, the paper intends to offer valuable insights for policymakers and stakeholders. These insights can help in the design and implementation of effective strategies that strike a balance between the important goals of expanding electricity access and fighting deforestation in Côte d'Ivoire.

Our research provides insights that address various gaps in the existing literature regarding the relationship between electrification and deforestation. First, many previous studies have not conducted an overall impact analysis of electrification on deforestation, focusing instead on specific aspects (e.g Mensah and Adu, 2015 focused only on the decrease in the use of firewood for cooking due to electrification in Ghana). This research seeks to fill this gap by providing a comprehensive assessment of the global effect of electrification, considering the involvement of various key players in deforestation, including companies, the state, and households. Second, there is an ongoing debate about the appropriate level of aggregation for such studies. While some studies have used country-level data (see Tanner and Johnston, 2017 for instance), this research recognizes the importance of intra-country heterogeneity and conducts its analysis at the regional and departmental level. By using disaggregated data, the study aims to shed light on relevant dynamics within specific areas of interest. Third, this study contributes to the growing body of literature that considers the spatial dimension when analyzing deforestation (see Baggio and de Barros, 2021 for an illustration). It emphasizes the significance of accounting for spatial interactions in understanding forest conversion and land use change. By controlling for spatial interactions, we aim to improve the predictive power of our model (as suggested by Maddison, 2006; Robalino and Pfaff, 2012; Choumert et al., 2013; Chakir and Lungarska, 2017) and gain insights into the effects of neighboring localities on deforestation. Finally, our research takes into account geographical and climatic conditions (as in Alves, 2002; Hargrave and Kis-Katos, 2013; Barber et al., 2014; Newman et al., 2014; Ferreira and Coelho, 2015; Kleinschroth et al., 2019; Asher et al., 2020; Baggio and de Barros, 2021), as they influence the costs of building and maintaining transport infrastructure, which, in turn, affects deforestation. By considering these factors, the study aims to enhance our model's accuracy and avoid the problem of omitted variables. Overall, this research seeks to provide a comprehensive and spatially aware analysis of the impact of electrification on deforestation, taking into account various key factors and shedding light on the dynamics at different levels of aggregation.

This paper makes contributions in four key areas. First, it examines the concordance between night lights intensity data (derived from satellite data) and official data on electrification progress in Côte d'Ivoire at the regional level. This is crucial as satellite data is commonly used to estimate economic activity, population density, and electrification in developing countries due to the lack of official data at sub-national scales (e.g. Sutton et al., 2001; Sutton et al., 2007; Dai et al., 2017; Kumar et al., 2019; Beyer et al., 2021). The study reveals that the electricity coverage rate data provided by Ivorian authorities and night lights intensity data yield consistent results at the regional level. Second, the article delves into how the extent of spatial interaction is influenced by the selected level of aggregation. Through rigorous statistical tests, it demonstrates that aggregated data at the regional level (N=33) show no spatial autocorrelation, while at the departmental level (N=108), a spatial lag model is found to be the most suitable. This sheds light on the importance of considering different levels of aggregation when analyzing deforestation phenomenon. Third, the article investigates whether conducting the analysis at a finer level of aggregation (108 departments) while accounting for both spatial effects and unobservable individual and temporal specific effects can lead to improved model specification. This approach provides valuable insights into enhancing the accuracy and robustness of the model. Finally, we contribute to the understanding of the global impact of electrification on deforestation, both at the regional and departmental levels in Côte d'Ivoire. By drawing parallels with a previous study on a panel of developing countries (see Tanner and Johnston, 2017), the research uncovers a noteworthy finding: contrary to previous results, electrification appears to increase deforestation in Côte d'Ivoire. This empirical evidence aligns with the situation on the ground in the country and provides important implications for environmental policy and sustainable development efforts.

The rest of the paper is as follow: an overview of the literature on the drivers of deforestation and related spatial issues is presented in section 2, data and variables are presented in section 3, section 4 presents the choice for the best spatial specification or econometric models, section 5 presents our estimation results, section 6 engages further discussions, and section 7 concludes.

2 Drivers and spatial issues in deforestation analysis: overview of the literature

In this section, we begin by providing a concise overview of the existing literature regarding the drivers of deforestation, with a particular emphasis on studies that have examined the impact of electrification. Subsequently, we delve into the importance of considering spatial interactions when seeking to understand the drivers of deforestation.

2.1 Deforestation traditional drivers and the potential role of electrification

Investigating the underlying factors driving deforestation represents a long-standing research inquiry (Angelsen and Kaimowitz, 1999a). However, despite extensive research, a consensus has yet to emerge, and recent studies continue to introduce new perspectives and insights into this complex issue Pendrill et al. (2022). For example, Geist and Lambin (2002) document the direct and indirect causes of deforestation. For these two authors, factors such as the extension of infrastructure, the expansion of agriculture, wood extraction directly impact forest cover. They also point out that demographic (density, migration and population distribution), economic (market size, urbanization, etc.), technological (changes in agricultural techniques), and cultural factors can indirectly affect deforestation. Several other studies particularly single out infrastructure expansion. Based on a land use model, Chomitz and Gray (1999) document that infrastructure (e.g. roads) increases agricultural expansion because it facilitates access to markets. Therefore, while such infrastructure can reduce poverty, it also increases deforestation and induces environmental degradation. Similarly, in a meta-analysis of the causes of tropical deforestation, Angelsen and Kaimowitz (1999b) document that a fairly large transport network –and therefore higher prices for agricultural products– generally leads to more deforestation. The other major source of deforestation is lack of opportunity in the non-agricultural sector, which keeps much of the labor force in plantations. Indeed, Angelsen (2010) argues, on the basis of a meta-analysis of 140 economic models of deforestation, that lack of non-agricultural employment is one of the main causes of deforestation. Angelsen and Kaimowitz (1999b) document from a meta-analysis of the causes of tropical deforestation that low wages and a shortage of non-agricultural employment generally lead to more deforestation. The creation of employment opportunities in non-agricultural sectors would therefore help to safeguard much of the forest. Armed conflicts are also detrimental to the preservation of forests. 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.

Although relatively few previous studies have provided evidence on the impact of electrification on deforestation, one of the most influential is that by Tanner and Johnston (2017). Using a panel of 158 countries for the years 1990, 2000 and 2010, the authors find that rural electrification reduces deforestation and better explains this phenomenon compared to factors such as population growth or development. Moreover, electrification often acts indirectly on deforestation, notably through the adoption of new techniques requiring electricity. This is illustrated by Shively and Pagiola (2004) who find that improvement of irrigation systems in the Philippines would have made it possible to reduce deforestation by half. They explain this by the fact that extensive farmers, who are not very competitive with the intensive farmers who have benefited from this improvement, are being squeezed out of the market. Also, Angelsen et al. (2001) argue that the adoption of new technologies could reduce the need to expand farms. On the other hand, Villoria et al. (2014) suggest that the promotion of agricultural innovation could improve agricultural profitability and thus encourage deforestation through the expansion of agricultural land.

2.2 The importance of spatial interactions in understanding deforestation

Spatial interactions are a common effect when considering land use changes in general and deforestation in particular. Indeed, spatial spillovers are relevant to understand deforestation, with a strong spatial interactions which could negatively impact the environment (Baggio and de Barros, 2021; Chakir and Le Gallo, 2021). For instance, if one locality experiences increased deforestation due to certain activities like agricultural expansion or logging, it can potentially create pressures for neighboring areas to follow a similar pattern. This could happen due to changes in migration patterns, land use dynamics, or resource demands. Spatial econometrics techniques help us explicitly model and account for these spatial interactions. By using such methods, we can identify the drivers of deforestation and gain insights into the spatial dynamics of deforestation processes (Maddison, 2006; Choumert et al., 2013). This understanding is crucial for policymakers as it allows them to devise targeted strategies to address deforestation in specific localities while considering potential spillover effects on neighboring areas. Additionally, spatial factors such as infrastructure development (e.g., roads or railways) can be related to the observed electrification and deforestation patterns (Hargrave and Kis-Katos, 2013; Barber et al., 2014; Ferreira and Coelho, 2015; Asher et al., 2020). Infrastructure development can lead to easier access to remote areas, increasing their susceptibility to deforestation as economic activities expand. The integration of spatial factors in the analysis can help in understanding how electrification initiatives may influence deforestation patterns across various localities. For instance, areas with better infrastructure and electricity access might experience increased economic activities, potentially leading to both positive and negative impacts on deforestation rates. To sum up, by incorporating spatial econometrics and considering spatial factors in deforestation analysis, policymakers can make informed decisions to strike a balance between promoting electricity access and combating deforestation. They can identify areas where electrification may lead to increased deforestation and implement appropriate measures to mitigate the negative impacts. Simultaneously, they can also support sustainable practices in areas where electrification might create opportunities for economic growth without significant forest loss. The use of spatial econometrics and the consideration of spatial factors in deforestation analysis provide valuable insights for policymakers to design effective strategies that harmonize the goals of expanding electricity access and conserving forests in Côte d'Ivoire. It highlights the importance of understanding the complex spatial relationships between electrification, deforestation, and other related factors to achieve sustainable development outcomes.

3 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.

3.1 Variables description and summary statistics

In Table 1, we provide a description of the data sources and variables utilized in our analysis to assess the impact of electrification on deforestation. Specifically, we focus on two key variables: forest loss and night lights. These variables are crucial in understanding the relationship between electrification and its effect on deforestation.

We mainly exploit data on forest cover in 2000 (>20% trees) and deforestation or forest loss over 2001-2018 provided by Hansen et al. (2013). The forest loss variable is derived from pixel-level data and offers detailed information about changes in forest cover over time. Each pixel in the dataset represents a specific geographic area, and the forest loss variable quantifies the extent of deforestation that has occurred in these individual pixels. These pixel-level values provide a comprehensive view of the spatial distribution and magnitude of forest loss, allowing us to analyze the impact of electrification on deforestation at regional and departmental levels in Cote d'Ivoire.

In order to estimate the electrification rate by region and department, we exploit high resolution satellite data on night lights intensity provided by the Earth Observation Group, NOAA National Centers for Environmental Information (NCEI). The night lights variable is based on radiance data sourced and captures the amount of light emitted from various sources during nighttime. This variable provides insight into the level of electrification in different areas in Cote d'Ivoire. By examining changes in radiance before and after electrification, we can gauge shifts in nighttime activity patterns, potentially indicating changes in electricity access that could influence deforestation rates.

In our analysis, we leverage these two distinct variables —forest loss and night lights-– to investigate the complex interplay between electrification efforts and deforestation trends in Cote d'Ivoire. While the forest loss variable allows us to directly quantify changes in forest cover, the night lights variable offers a measure of electrification evolution in the country.

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".[1]

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 documented 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

[1] Here we do not test for the existence of an environmental Kuznets curve.

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 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)

Applications Center (SEDAC).[2]

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).[3] 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.

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

[2] NOAA (National Oceanic and Atmospheric Administration)

[3] AGR = (Annual) Average Growth Rate. Our choice for an AGR over the 2011-2018 period is conditioned by the availability of the official electrification data in Côte d'Ivoire.

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

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 documented 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.

Table 4 summarises our variables for the panel analysis at department level over the period 2001-2017. The Forest loss variable is in pixels and the Night lights variable is in radiance as described in details earlier. 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.).

3.2 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).[4] 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 document a trend of positive spatial correlation between electrification and the highest deforestation rates.

Finally, 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 observing the last two maps, we can see that the variables night lights intensity and coverage

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

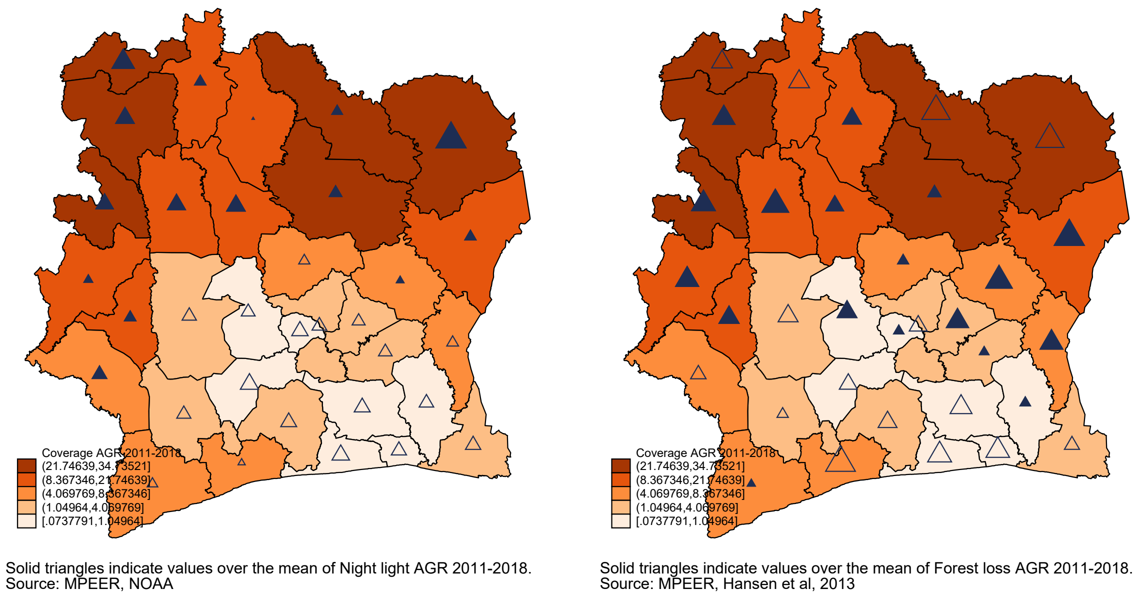

Figure 1: Spatial concentration of high and low values

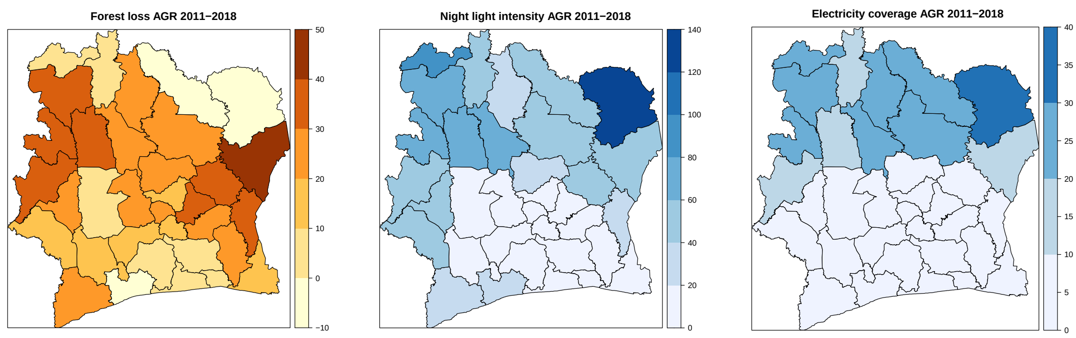

Figure 2: Average growth rates (AGR) for the main variables at the regional scale

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 documents 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 document that it seems 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 use these data as a proxy for electrification at a lower aggregation level (departmental level) in the rest of this analysis.

3.3 Exploratory spatial data analysis

Let us now define the spatial interaction matrix. 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 contiguity 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.

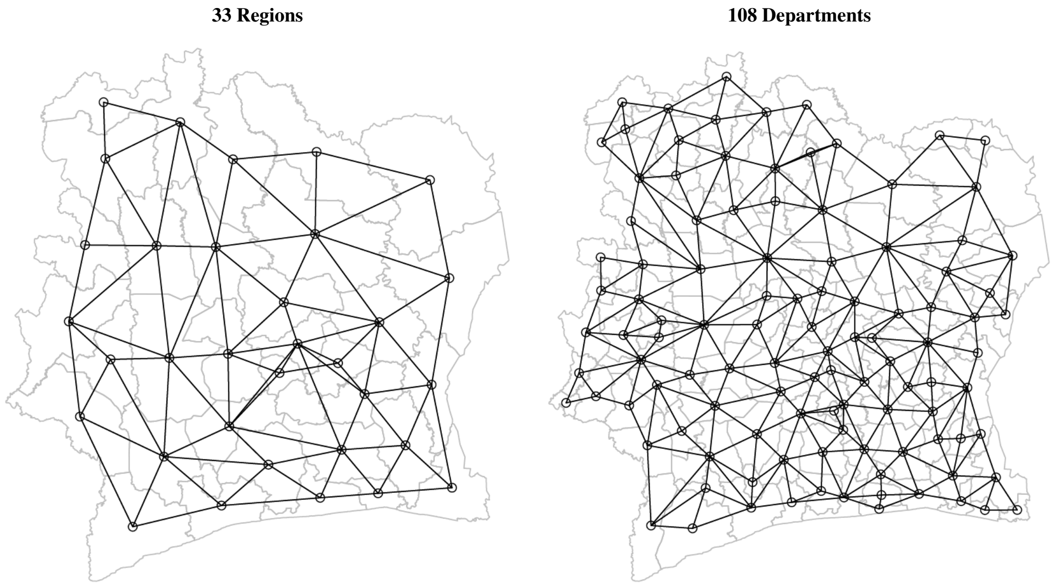

Figure 3: Neighbourhood network using Contiguity (queen) matrix

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).

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.

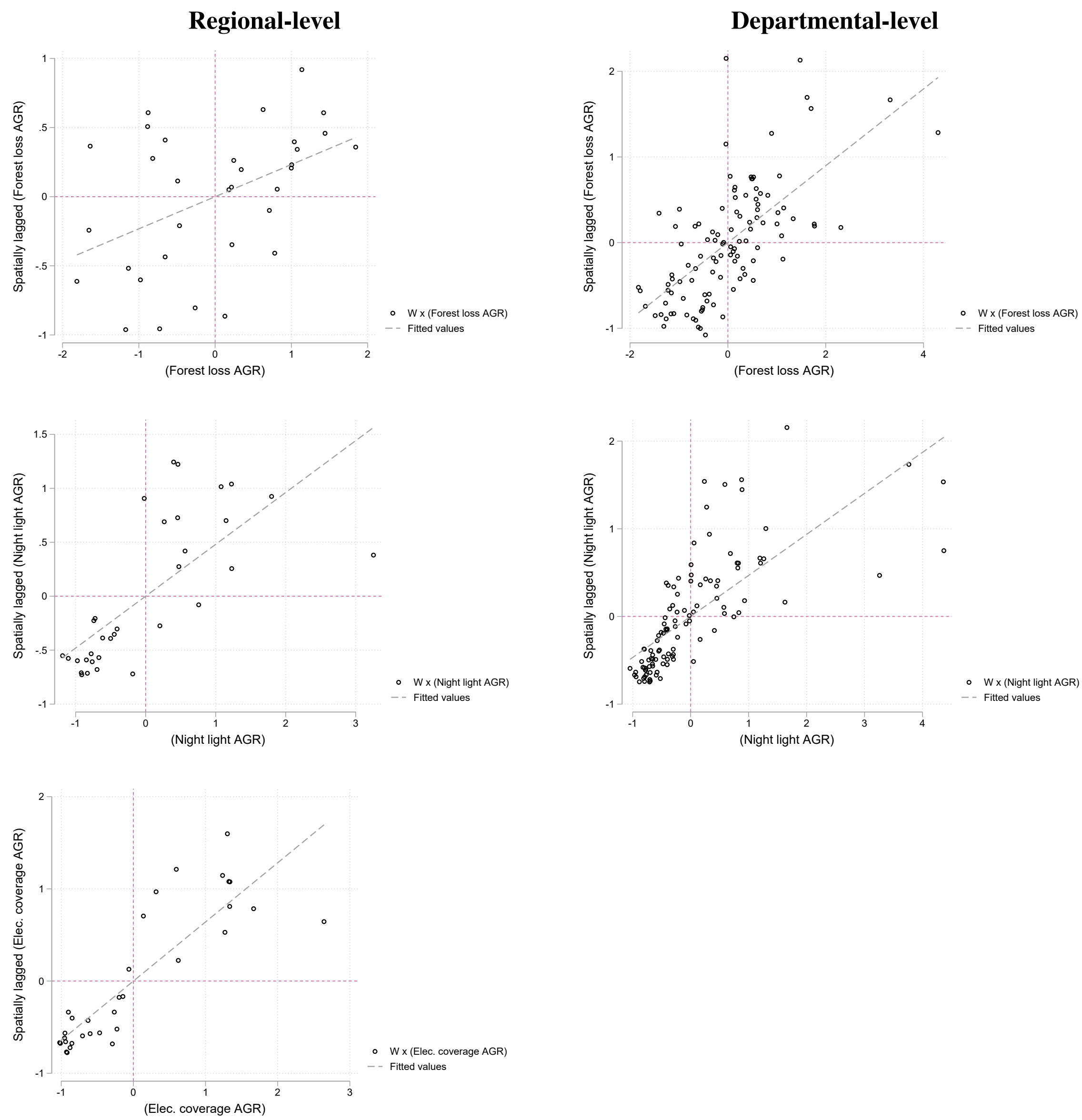

Figure 4: Moran plot using Contiguity (queen) matrix at the regional and departmental scale

Through Table 5 (but also the tables in appendix B), we document that whatever the definition of the neighbourhood or the scale of aggregation chosen (and the hypothesis put forward, normality or randomisation), the spatial autocorrelation of both electrification and deforestation are positive and significant.[5] 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).

4 Econometric models

The aim of this paper is to test the links between electrification and deforestation in Cote d'Ivoire. To achieve this goal we estimate and compare several econometric specifications: (i) cross-sectional model at

[5]See appendix B for the results under the Randomisation Hypothesis as well.

Table 5: Moran tests for our main variables using Contiguity (queen) weight matrix, Normality Hypothesis

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Panel A: regional-level (N=33)					
Forest loss	0.243	-0.031	0.011	2.59	0.0048
Night lights	0.498	-0.031	0.011	5	2.9e-07
Elec. coverage	0.680	-0.031	0.011	6.72	<1e-08
Panel B: departmental-level (N=108)					
Forest loss	0.4583	-0.0093	0.0036	7.78	<1e-08
Night lights	0.5654	-0.0093	0.0036	9.56	<1e-08

regional level (N=33), (ii) cross-sectional model at departmental level (N=108), and (iii) panel model at departmental level (N$\times$T=108$\times$17=1836). For all these models we tested the existence of spatial autocorrelation and we run specification tests to choose the best specification.

After having established the existence of spatial autocorrelation between our localities in subsection 3.3, we proceed now to the choice of the best spatial specification. To do this, first, we opt for the bottom-up approach proposed by Florax et al. (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 et al. (2003) have also documented, 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.

4.1 Aggregated a-spatial regional model: comparing night lights intensity with official electrification coverage data as explanatory variable

Through the results from the previously described specification tests (see Table C1 in appendix C), we conclude that the best spatial specification remains the a-spatial model (OLS) when considering the administrative division of the 33 regions:

$$\mathrm{DEF} = \alpha + \mathrm{ELEC}\beta + \mathbf{X}\gamma + \varepsilon \tag{2}$$

where, DEF represents deforestation (annual) average growth rate (AGR) at regional-level, ELEC represents electrification (annual) average growth rate (AGR) at regional-level, $\mathbf{X}$ represents a set of explanatory variables (population density, precipitation, temperature, forest cover, gross domestic product, conflicts, travel time to major cities or access to markets). 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.

4.2 Fine scale spatial departmental model

Meanwhile, 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:[6]

$$\text{DEF} = \delta W \text{DEF} + \text{ELEC}\lambda + \mathbf{X}\omega + \theta \tag{3}$$

where, DEF represents deforestation (annual) average growth rate (AGR) at departmental-level, ELEC represents electrifiction (annual) average growth rate (AGR) at departmental-level, $\mathbf{X}$ represents a set of explanatory variables (population density, precipitation, temperature, forest cover, gross domestic product, conflicts, travel time to major cities or access to markets), W represents the spatial matrix. 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 (as some deforestation mechanisms are more local so less strong across the 33 regions). 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 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 also 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

[6]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.

shocks follow a spatial pattern.

4.3 Spatial panel model at departmental scale

The previous models rely on cross-sectional estimation and generally fail to account for potential unobservable omitted variables. This limitation has led some recent studies to exploit the panel dimension (Amin et al., 2019). This allow to take into account individual and temporal dimensions and provides 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) would converge, but only the GLS would be consistent.[7] Otherwise, the GLS estimator would not be convergent, while the Within estimator would 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). In addition, Pesaran (2004)'s CD test for cross-sectional dependence in panels and CD test for local cross-sectional dependence in panels, plus Millo (2017)'s Randomized W test for spatial correlation of order 1 support the cross-sectional dependence in our data. Finally, Baltagi et al. (2003)'s LM*- mu conditional LM test confirms the existence of the Random regional effects, and Baltagi et al. (2003)'s LM*-lambda conditional LM test confirms the existence of Spatial autocorrelation. The results of all the tests (appendix F) guide us to estimate a Random Effects model with a SAR process:

$$\mathrm{DEF}_{dt} = \rho W \mathrm{DEF}_{dt} + \mathrm{ELEC}_{dt}\phi + \mathbf{X_{dt}}\gamma + \psi_{dt} \text{ with } \psi_{dt} \overset{i.i.d.}{\sim} N\left(0, \sigma^2\right) \tag{4}$$

where, DEF_{dt} represents deforestation (or forest loss) at departmental-level d in year t, ELEC_{dt} represents electrifiction at departmental-level d in year t, $\mathbf{X}_{dt}$ represents a set of explanatory variables (population density, precipitation, temperature, forest cover, gross domestic product, conflicts, travel time to major cities or access to markets) at departmental-level d in year t, W represents the spatial matrix. Finally, d indexes departments and t indexes years.

[7] GLS = Generalized Least Squares

5 Estimation results

In this section, we document the overall effect of electrification on deforestation at the regional level using the a-spatial model, 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 at the departmental level in the country.

5.1 Aggregated a-spatial regional model: comparing night lights intensity with official electrification coverage data as explanatory variable

In Table 6, we consider the level of aggregation by region (33 regions), we have no spatial model. Furthermore, the results show that there is no statistically significant link between deforestation and electrification, both as measured by night light (column 1) and official statistics (column 2). However, both coefficients remain insignificant in this model and keep the same positive sign. Finally, both models give almost the same results for the other control variables in the model. This result is further proof that nights light intensity data are good proxies for electrification in Côte d'Ivoire.

Table 6: 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

5.2 Spatial analysis at departmental level

Table G1 (see Appendix G) 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 calculate). 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 low at this lower level of aggregation. 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 7: 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

Table 7 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 (see Table G1 in Appendix G, 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 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 in the following sub-section.

5.3 Spatial panel model

Table 8 below 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 documented, 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 Côte d'Ivoire. 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.

Table 8: 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

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 would 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) would 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. This is known as Jevons' paradox.[8]

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

[8] 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.

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).

Finally, we summarize how our study captures the causal effects of electrification on deforestation by controlling for for spatial dependencies, conducting the analysis at a finer departmental level, and by considering extensive control variables to minimize biases. In other words, we have designed our study to leverage the exogenous variation introduced by the ongoing rural electrification program while accounting for potential endogeneity. First, we have collected a comprehensive dataset that includes spatial and temporal information on both electrification and deforestation across various localities (regions and departments) of Cote d'Ivoire. By utilizing a spatial panel data framework, we controlled for spatial dependencies and heterogeneity across regions while capturing the dynamic interactions between electrification and deforestation over time. Second, to account for spatial autocorrelation and potential spillover effects, we employ a random effects model with a spatial lag process. This model allowed us to examine how electrification in one department may impact deforestation in neighboring departments, thus capturing indirect causal effects that might arise due to geographical proximity. By adopting a spatial panel data methodology, we controlled for unobserved heterogeneity, time-varying confounders, and spatial dependencies, thereby providing a more rigorous assessment of the direct causal impacts of electrification on deforestation. Our study acknowledges and embraces the exogenous variation introduced by the rural electrification program and leverages it within a comprehensive analytical framework. Third, our analysis was conducted at a finer level of aggregation, specifically at the departmental level, which allowed us to capture localized variations in electrification and deforestation patterns. This granularity enabled us to identify nuanced relationships and account for potential confounding factors that may have been overlooked in previous studies that used larger geographical units. Finally, we included an extensive set of control variables that encompassed various aspects, such as climate, economy, geography, demography, and infrastructure. The inclusion of these covariates allowed us to minimize the risk of spurious correlations and carefully controlled for omitted variable biases. By doing so, we mitigated potential endogeneity concerns and ensured that the observed effects were attributable to electrification. To sum up, our study contributes to the understanding of the impact of electrification on deforestation in Cote d'Ivoire by conducting an analysis at a finer level of aggregation while controlling for various confounding factors. We believe that our findings support a positive causal effect of electrification on deforestation rates, but we also acknowledge that causality cannot be definitively ascertained based solely on observational data. Thus, we encourage further research through experimental approaches to supplement our findings and advance the understanding of this critical issue.

6 Discussion

In this discussion section, we first explore the potential impact of targeted electrification policies on deforestation patterns. Then in the second part, we suggest that understanding specific administrative rules governing electrification decisions could yield insights into mechanisms driving deforestation, inform policymakers, and address potential unintended consequences.

First, considering administrative decisions in electricity provision, especially those targeting lower-income areas, might be a crucial aspect to explore in this kind of analysis. This led us here to provide a short discussion on how targeted electrification policies might have influenced deforestation patterns differently across various areas in the country. First, targeted electrification policies aimed at providing electricity to lower-income areas could lead to increased access to modern energy sources for communities that were previously underserved. Improved access to electricity in these areas can have positive socio-economic impacts, such as increased productivity, better living conditions, and enhanced economic opportunities. As a result, communities with improved access to electricity may engage in alternative income-generating activities, reducing their dependence on deforestation for livelihoods. Second, with targeted electrification, lower-income areas may witness shifts in land use patterns for instance. As access to electricity fosters economic diversification, communities may transition away from traditional agricultural practices that necessitate deforestation. Instead, they might embrace new income-generating activities that are less harmful to forests, such as small-scale industries, services, or value-added agricultural ventures. Third, targeted electrification initiatives often involve community engagement and awareness campaigns. As electricity becomes available in previously marginalized areas, there may be greater emphasis on forest conservation and sustainable resource management. Increased awareness of the environmental consequences of deforestation could lead to more responsible practices and a reduction in illegal logging and forest degradation. In the same vein, to facilitate targeted electrification, there might be concurrent investments in infrastructure development, such as roads and transportation networks. While this could potentially increase accessibility to forest areas, it can also enable better monitoring and law enforcement to prevent illegal deforestation activities. This discussion on how targeted electrification policies might have impacted deforestation patterns differently in various areas in Cote d'Ivoire enhances the policy relevance and practical implications of our study. By investigating these nuanced aspects, we aim to provide a comprehensive understanding of the potential environmental and socio-economic impacts of electrification initiatives in the country, which could inform future policy decisions and contribute to sustainable development goals.

In addition, the discussion of the potential effects of the specific administrative rules that influenced electricity provision decisions for similar areas in Cote d'Ivoire could yield valuable insights into the mechanisms driving deforestation in electrified areas, thereby enhancing the robustness and policy relevance of our study. First, administrative rules and policies play a crucial role in shaping electrification strategies in any country. Cote d'Ivoire is likely no exception, and understanding the specific rules governing electricity provision is essential to contextualize our findings accurately. By identifying the rules that influenced electrification decisions, we can assess their potential impact on deforestation patterns more precisely. Second, investigating administrative rules can reveal the causal mechanisms underlying the relationship between electrification and deforestation. For example, certain rules may prioritize electrification in areas with high agricultural potential, leading to changes in land use and potential deforestation. By examining such mechanisms, we can provide a more nuanced understanding of the interactions between electrification policies and environmental outcomes. Third, knowledge of administrative rules can inform policymakers about the potential unintended consequences of electrification initiatives. If specific rules are found to have contributed to deforestation, policymakers can design targeted interventions to mitigate negative impacts while still promoting access to electricity. This could involve integrating sustainable land-use planning or conservation measures into electrification policies. Finally, the identification of administrative rules can also shed light on equity considerations in electricity provision. If specific rules result in uneven access to electricity among different socio-economic groups or geographic areas, understanding these disparities is essential for ensuring equitable and sustainable development. Overall, discussing an investigation of specific administrative rules governing electricity provision decisions in Cote d'Ivoire would help to provide policymakers with more nuanced and context-specific recommendations for sustainable development across the country.

7 Conclusion

This study conducts a comprehensive analysis of electrification's impact on deforestation, bringing new insights to prior research in several ways. Firstly, it takes a global perspective, considering various stakeholders in deforestation rather than focusing on specific aspects. Secondly, it acknowledges intra-country heterogeneity by analyzing regional and departmental levels, offering a more nuanced understanding of deforestation dynamics within specific areas. The study underscores the importance of spatial interactions in comprehending forest conversion and land use change. By accounting for these interactions, it enhances the model's accuracy, revealing the influence of neighboring areas on deforestation. Furthermore, the research explores finer model specifications, considering spatial effects and unobservable factors, enhancing model accuracy and robustness.

Our results allow us to validate satellite-derived night lights intensity data against official electrification data in Côte d'Ivoire at regional level, strengthening data reliability in estimating electrification in developing countries. Through rigorous statistical tests, the study emphasizes the significance of aggregation levels in deforestation analysis. Regional data show no spatial autocorrelation, while departmental data benefit from a spatial lag model. Notably, the study reveals that electrification in Côte d'Ivoire appears to increase deforestation, contrasting with prior research on developing countries. This empirical evidence carries important implications for environmental policy and sustainable development efforts.

Our results suggest that electrification increases overall deforestation in Côte d'Ivoire. Nevertheless, as highlighted in some previous analyses, electrification could have partially favorable effects on specific deforestation factors (e.g. reduced wood collection, reduced need to expand arable farms for subsistence crops, etc.). In addition, electrification would be a powerful tool for reducing poverty. Electrification also might accelerate structural transformation and would be a source of job creation in most developing countries. While increasing access to electricity, Ivorian authorities should ensure that forest protection agents are 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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A Concordance between night lights data and official data

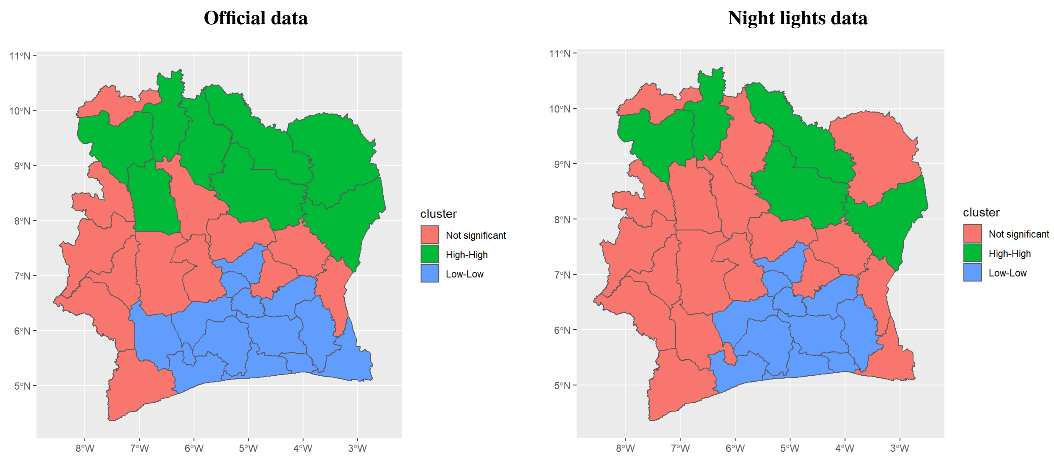

Figure A1: Local Indicators of Spatial Association (LISA)

B Moran's I tests using alternatives neighbourhood matrix

B.1 Moran I for Regions

Table B1: Moran test for our main variables using Contiguity (queen) weight matrix

	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 B2: 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 B3: 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 B4: 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 B5: 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 B6: 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 B7: 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 B8: 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

B.2 Moran I for departments

Table B9: Moran test for our main variables using Contiguity (queen) weight matrix

	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

Table B10: 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 B11: 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 B12: 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 B13: 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 B14: 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 B15: 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 B16: 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

C Bottom-up approach (Florax et al., 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

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			

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

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
Pesaran CD test for cross-sectional dependence in panels	z = 67.209, p-value < 2.2e-16	cross-sectional dependence
Pesaran CD test for local cross-sectional dependence in panels	z = 39.267, p-value < 2.2e-16	cross-sectional dependence
Randomized W test for spatial correlation of order 1	p-value = 0.02	twosided
Baltagi, Song and Koh LM*- mu conditional LM test (assuming lambda may or may not be = 0)	LM*-mu = 52.588, p-value < 2.2e-16	Random regional effects
Baltagi, Song and Koh LM*-lambda conditional LM test (assuming sigma^2_mu >= 0)	LM*-lambda = 32.25, p-value < 2.2e-16	Spatial autocorrelation

G Regression results at departmental scale

Table G1: 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