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Abstract

African countries are natural resource-rich. The continent has natural forests, homes of endemic biodiversity and various ores. This richness brings hope for sustainable and inclusive development in a continent whose population is rapidly growing. It also raises fears of environmental degradation. This article studies mining-driven deforestation using unique fine-scale data from 2001 to 2019. The dataset covering all Sub-Saharan African countries entails 2,207 polygons with an average size of about 12,000 square kilometres. 926 polygons were forested in 2001, of which 198 hosted industrial mines. A spatial autoregressive model allows taking dependence between deforestation decisions at the polygon level. The econometric results show that an additional mine increases deforestation by about 155 square kilometres. Protected areas mitigate deforestation poorly. One hundred square kilometres under protected areas enable only a 9.7 square kilometres reduction in forest loss. More than doubling protected areas would be necessary to offset mining-driven forest loss. Protected areas cannot alone mitigate the adverse effects of mining on forest loss and other environmental consequences. Moreover, the effectiveness of protected areas is not uniform across space: it vanishes in highly conflicted regions.

Keywords

Deforestation, Mining, Protected areas, Panel data, Spatial econometrics, Sub-Saharan Africa.

JEL codes

C23, L70, O13, N57, Q23, Q32

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1 Introduction

Many African countries are rich in natural resources and aspire to better livelihoods. With a steadily growing population expected to be just under four billion by the end of the 21st century, [1] African countries face a challenge: achieving inclusive and sustainable development. Tapping natural resources, particularly ores, can generate significant income and reduce poverty. Today, according to the World Development Indicators, mineral and forest rents are above the world averages as a percentage of GDP. Still, natural resource extraction can also irreversibly damage essential natural assets for sustainable development, especially the forest.

21.7% of tropical African forests have been deforested since 1900 (Aleman, Jarzyna and Staver, 2018). West and East African forests have practically vanished. In recent years, while deforestation has slowed down worldwide, it seems to have accelerated in Africa, with a net forest loss of 3.94 million ha per year from 2010 to 2020 against 3.4 million ha per year in the previous decade (Mansourian and Berrahmouni, 2021). The deforestation and forest degradation drivers are multiple. The literature (Geist and Lambin, 2002) distinguishes between the proximate causes of deforestation (agriculture and pastoral expansion, wood extraction, infrastructure extension, mining activities) and underlying causes (macroeconomic variables, societal factors). On a global scale, agriculture is the main proximate driver of deforestation. A meta-analysis concludes that deforestation is more likely when the economic returns of agriculture are higher (Busch and Ferretti-Gallon, 2017).

Africa is on the verge of a mining boom (Edwards *et al.*, 2014). With its promise of high incomes, the mining sector is expected to grow in Africa. The 5th edition of the mining contribution index of the International Council on Mining and Metals (ICMM) evidences that five African countries, including the Democratic Republic of Congo and Madagascar, rank high in the list of mining-dependent countries. This dependency will likely endure as 30% of the world's total mineral reserves is in Africa (Adu and Dramani, 2018). The existing literature evidence several effects of mining development in Sub-Saharan African (SSA) countries. For instance, mining positively impacted African agricultural sectors though the authors also

[1] United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022, Online Edition.

evidenced transient and gender-specific employment effects (Kotsadam and Tolonen, 2016). Several authors attracted attention to the fact that SSA countries could undertake a mineral-fuelled forest transition (Rudel, 2013). There is also evidence that mining fosters conflicts (Berman *et al.*, 2017) and deleteriously impacts local governance (Knutsen *et al.*, 2017).

This paper focuses on mining-driven deforestation in SSA countries. To the best of our knowledge, the link between deforestation and mining activities is still little studied (Maddox *et al.*, 2019, p. xii), especially in Africa. Sub-Saharan countries' mineral resource occurrences are often located near or in forested areas harbouring outstanding endemic biodiversity. Mining is deemed to have a massive influence on the natural environment in Africa and especially on the forests (Edwards *et al.*, 2014). Mining damages the environment through the prospection, extraction, transport of inputs and outputs, or use of environmentally harmful inputs. Arsenic, cyanide, and mercury generate a persistent detrimental effect on the forest. Also, these chemical compounds could impact surrounding areas through waterways, sediments, or the atmosphere (Eisler, 2004; Eisler and Wiemeyer, 2004). Hence, the process of reforestation after mining activities is long-lasting. However, perspectives from local communities provide a balanced view with positive impacts of providing improved water sources, healthcare facilities, roads and schools (Leuenberger *et al.*, 2021).

Mining activities trigger direct and indirect effects on deforestation. On the one side, mining activities directly fuel forest clearances. They generate population shifts: local people may be forced to leave and relocate, while new employment opportunities attract others. These new populations may increase the demand for fuelwood and agricultural land. Overall, these movements can contribute to the deforestation pressure. Indirect channels pertain to providing communication infrastructures and buildings needed to develop mining facilities.

The literature on protected areas as an instrument for reducing deforestation in SSA usually concludes that they are effective (Bowker *et al.*, 2017). Nevertheless, few studies assess the impact of protected areas in the context of deforestation accelerated by mining activities. However, the legal protection afforded by protected areas may differ depending on the nature of the economic activity that infringes on the forest. In the case of legal mining, mining companies may escape environmental regulations in the context of corruption. Artisanal-scale mining activities are often illegal and, therefore, not sensitive to environmental regulations.

This article studies the link between mining activities and deforestation and questions the effectiveness of protected areas in response to mining-induced deforestation. More precisely, we aim to answer the two following questions. How do mining activities contribute to deforestation? How do conservation instruments such as protected areas dampen mining-driven deforestation?

We estimate a deforestation spatial econometric model that allows us to consider interactions between neighbouring spatial units. Each spatial unit covers 12,070 square kilometres on average. Overall, we have 2,207 spatial units, namely polygons, from 2001 to 2019, of which 926 are forested at the beginning of the study period. The dataset gathers information on deforestation, mining activities, protected areas and other relevant socio-economic variables affecting deforestation. To our knowledge, our study is the first to address mining-driven deforestation using sub-national data. This level of analysis is the most relevant because clearing and land use conversion both take place at a fine spatial scale. Existing studies are conducted at the national level (Azomahou and Ouédraogo, 2021). We contribute to the literature on the effectiveness of protected areas in curbing deforestation since we examine the role of protected areas as a lever for mitigating deforestation induced by mining activity, which has never been investigated in SSA. The estimation results show that mining activities increase deforestation while protected areas reduce deforestation. Moreover, it does not appear that the presence of protected areas dampens the impact of mining on deforestation. We highlight a spatial heterogeneity: the negative t impact of mines on forests and the poor effect of protected areas occur when the local institutional quality is poor.

The remainder of the article is as follows. Section 2 reviews the existing literature. We present the econometric framework in Section 3. We detail the elaboration of the fine-scale data set from which we extract descriptive statistics in section 4. Section 5 successfully gives the main results and estimates how much mining drives forest losses in Sub-Saharan Africa. We provide concluding remarks in section 6.

2 Literature review

We will first present the studies devoted to the impact of mining activities on deforestation. We will then review the main findings of studies dealing with the relationship between protected areas (and forest management) and deforestation. Finally, we will describe the few studies focusing on the role of protected areas as a tool for mitigating the effects of mining on forest cover and present our hypotheses.

2.1 Mining activity and deforestation

Several studies have studied the link between mining activities and deforestation. Most of them focus on the Amazonian forest and use high-resolution geospatial data. For instance, mining significantly increased deforestation in the Brazilian Amazon (Sonter *et al.*, 2017). Moreover, forest losses extend well beyond the mining lease boundaries and account for 9% of deforestation between 2005-2015. In Colombia, the contribution of legal mining activities inside concessions to deforestation grew during the 2010s and reached a 5.6% peak in 2017. The two minerals mainly causing deforestation are gold and coal (González-González, Clerici and Quesada, 2021).

Some artisanal-scale gold mining activities would be particularly detrimental to forest conservation. Indeed, these activities are often illegal and therefore do not comply with environmental regulations. This phenomenon is reported in several Latin American countries, for instance: Suriname (Peterson and Heemskerk, 2001) or Peru (Caballero Espejo *et al.*, 2018). In the case of the Brazilian Amazon, deforestation of illegal gold mining increased by more than 90% from 2017 to 2020 (Siqueira-Gay and Sánchez, 2021). Furthermore, once abandoned, the mining area is not correctly restored, and therefore the regeneration of the primary forest is hampered. Periods of rising gold prices are particularly detrimental to forest conservation in the Peruvian Amazon (Swenson *et al.*, 2011). In Latin America, the increase in the demand for gold after the international financial crisis fueled deforestation from 2007 to 2013 (Alvarez-Berríos and Aide, 2015).

Only a few studies have examined the impact of mining activities on deforestation in Asia. For instance, there is evidence of adverse effects of mining activities on forest cover at the district level in India (Ranjan, 2019). The effect is heterogeneous and depends on the mineral involved. In Indonesia, mining activities are increasingly responsible for the loss of forest cover from 2001 to 2016 (Austin *et al.*, 2019). However, palm oil plantations encroachments outweigh mining activities since the former represents 23% of deforestation compared to 2%.

Africa has experienced lower deforestation rates than South America and South and South East Asia for several decades. For instance, oil and gas receipts substantially reduced deforestation from 2000 to 2005 (Rudel, 2013). The extractive sector's contribution to urbanisation may have hampered deforestation's proximate drivers. However, a recent study relying on panel data from 2001 to 2017 found a positive effect: a one-point percentage of GDP increase in mineral rents generated about 50 square kilometres of forest loss (Azomahou and Ouédraogo, 2021). An oil and mineral-fueled forest transition may have started in Africa, especially in the Congo Basin humid forest. Indirect effects of deforestation in the surroundings of mining areas are likely at work. Direct deforestation within the mining areas concerns few countries, while indirect deforestation is a problem for two-thirds of tropical countries. The indirect deforestation impact is remarkably high in some African countries, such as Gabon and Zambia (Giljum *et al.*, 2022).

2.2 Protected areas and deforestation

"A protected area is a clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values." (IUCN Definition 2008).[2] 14.6% of the land area was designated as protected, and 16% of the forest fell within a legally established protected area in 2015. In Africa (Democratic Republic of Congo), the proportion of forest areas with legally protected areas was 23.37% (12.38%) in 2000 and 25.73% (18.45%) in 2020 (Ritchie, Spooner and Roser, 2022).

A bulk of econometric studies study the effectiveness of protected areas. Early studies date back to the early 2000s (Joppa and Pfaff, 2010; Nelson and Chomitz, 2011). The main challenge is the location bias of protected areas (Cropper, Puri and Griffiths, 2001; Joppa and Pfaff,

[2] Protected areas can also be managed locally, nationally, or internationally. Moreover, the degree of legal protection provided by the protected area depends on their category. The different categories are the following: strict nature reserve (Ia); wilderness area (Ib); national park (II); natural monument of feature (III); habitat/species management area (IV); protected landscape/seascape (V); protected areas with sustainable use of natural resources (VI). The most restrictive categories are I, II and III. Categories IV, V and VI allow a sustainable use of resources. Source: IUCN available at https://www.iucn.org/theme/protected-areas/about.

2009). Authors usually address this issue by implementing matching methods with control groups. Once the location bias is controlled for, the authors found that protected areas reduce deforestation. Most existing results pertain to Latin America: Costa Rica (Andam *et al.*, 2008; Pfaff *et al.*, 2009; Robalino *et al.*, 2015; Robalino, Pfaff and Villalobos, 2017), Guatemala and Mexico (Bray *et al.*, 2008), the Brazilian state of Acre (Pfaff *et al.*, 2014) or Sumatra in South East Asia (Gaveau *et al.*, 2009).

Heterogeneity effects in the impact of protected areas on deforestation may occur. For example, in the case of the legal Amazon, the protected areas with the highest impact are those located near cities and roads (Pfaff *et al.*, 2015). Strictly protected areas are more effective. Existing studies on Brazil support that claim once accounting for location bias (Nolte *et al.*, 2013; Kéré *et al.*, 2017). The results hold with considering contextual bias and spatial dependence (Kéré *et al.*, 2017).

Spatial interactions are another critical issue. Deforestation in one location could impact deforestation in neighbouring areas, for instance, through transportation infrastructure development (Angelsen, 2001; Schwartz *et al.*, 2022). These spatial interactions are likely at work in the "arc of deforestation" in Brazil. In addition, protected areas can foster deforestation leakages. Deforestation leakage occurred into forests from concession areas in the Peruvian Amazon (Oliveira *et al.*, 2007). Parks facing tremendous deforestation pressure show more significant leakage in Costa Rica (Robalino, Pfaff and Villalobos, 2017). However, the proximity to a protected area can also contribute to reducing forestry activity, for example, by creating more difficulties in accessing the forest resource. Indigenous lands raise deforestation nearby, contrary to federal-protected areas in the Brazilian Pará State (Herrera, Pfaff and Robalino, 2019). Strictly protected areas and indigenous lands allow reducing deforestation, unlike sustainable protected areas in the Brazilian Legal Amazonia (Amin *et al.*, 2019). Moreover, these two types of protected areas generate a positive spillover effect: they reduce deforestation in their vicinity.

There are similar questions about the effectiveness of forest management plans which are considered a step towards sustainable forest management, particularly in the Congo Basin (Democratic Republic of Congo), which represents the second largest primary forest in the world (Karsenty *et al.*, 2008). These plans entail selective logging to ensure maximum harvest rates while at the same time preserving the resource. Protected areas surrounded by logging concessions operated with a forest management plan ("unified conservation landscape") could be considered as means to both achieve economic development and biodiversity conservation (Brandt, Nolte and Agrawal, 2016). Deforestation and timber production are higher in concessions with registered forest management (Brandt, Nolte and Agrawal, 2016, 2018) though the results are questioned (Karsenty *et al.*, 2017). Between 2000 and 2010, deforestation was also found to be significantly lower in concessions operating under a forest management plan (Tritsch *et al.*, 2020).

2.3 Mining, protected areas and deforestation

A very understudied issue is the effectiveness of protected areas in the face of mining-induced deforestation. (Weisse and Naughton-Treves, 2016) studied the effect of protected area buffer zones on formal and informal mining extent in the Peruvian Amazon. These buffer zones have been poorly studied because of the ambiguity of their management rules and their sometimes-informal status. Nevertheless, these buffer zones cover more than 10% of the country and positively impact forest cover by limiting the extent of mining concessions. However, they could be more efficient in mitigating the development of illegal mining activities.

Expanding mining concessions increased the forest cover loss from 1990 to 2010 in the Democratic Republic of Congo (DRC) (Butsic *et al.*, 2015). One of the particularities of the Congo Basin is the prevalence of conflicts. It appears that they fuel deforestation, but in times of conflict, the impact of mining concession on deforestation was mitigated. Moreover, protected areas reduced deforestation, even in times of conflict.

In this article, we seek to answer two questions. Is mining a driver of deforestation in Sub-Saharan Africa? Are protected areas an effective tool for mitigating the effects of mining on deforestation? These questions are relevant in the SSA context, where low institutional quality prevails and where mining companies can use corruption to circumvent environmental regulation.

3 Methodology

We present first the econometric framework. It takes advantage of fine-scale data, allowing the investigation of spatial dependence in activities potentially contributing to deforestation. Then we discuss the identification of neighbours and how we intend to interpret the results.

3.1 Econometric framework

The spatial lag model is theoretically appropriate for investigating spatial dependence (e.g. (Ndiaye, 2018).[3] In this paper, we claim that deforestation in one area interacts with neighbours' deforestation. Following the literature, the spatial dependence of deforestation between polygons is theoretically interpreted as evidence that the decisions conducing to deforestation are strategic complements (Brueckner, 2003; Schwartz *et al.*, 2022). [4] Deforestation in one area favours deforestation in its vicinity by facilitating access to the forest and thus reducing the costs of deforestation.

Building on this theoretical intuition, we estimate a spatial panel data model in which the level of deforestation in a spatial unit (see the definition of spatial units, namely polygons in section 4.1) depends on the level of deforestation in neighbouring units and on a set of observed local characteristics. Formally, let the index $i = 1, \dots, N$ denotes a spatial unit and $t = 1, \dots, T$ denotes a time period. $t = 2005$ for the 2001-2005 period, $t = 2010$ for the 2006-2010 period, $t = 2015$ for the 2011-2015 period and $t = 2019$ for the 2016-2019 period. Using average years rather than yearly data allows us to grasp the medium-term effects of mining activities and protected areas on deforestation.[5] Our identification strategy is based on a panel spatial autoregressive model (SAR) with spatial units and period-fixed effects. This model writes as follows:

[3] Early examples of the spatial econometric models date back to the 2000s (Brueckner and Saavedra, 2001; Solé Ollé, 2003).

[4] Providing theoretical foundations for spatial interactions allows addressing the criticisms of the last 10 years concerning these models (McMillen, 2010; Corrado and Fingleton, 2012; Gibbons and Overman, 2012).

[5] Moreover, five-year panel data are justified for other reasons: i) Some observations are not available every year. ii) This strategy allows to smooth out yearly variations in deforestation data that may be driven by measurement issues; iii) The inter-annual variability of some variables is low; iv) Not using annual data allows to neutralize the problems specific to time series: presence of a cointegration relationship or unit roots.

$$Forest\_loss_{it} = \rho \sum_{j=1,j\neq i}^{N} w_{ij}Forest\_loss_{jt} + \beta_1 Mine_{it} + \beta_2 LagPA_{it} + \beta_3 LagPA_{it} \times Mine_{it} + \gamma_k x_{it}^k + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

Where $Forest\_loss_{it}$ refers to the level of forest loss observed for the spatial unit i at period t. w_{ij} corresponds to the spatial weight's matrix that is an $N \times N$ pre-specified row-normalised weights matrix with zeros on the diagonal. $\sum_{j=1,j\neq i}^{N} w_{ij}Forest\_loss_{jt}$ thus refers to the spatially lagged deforestation variable and represents the average deforestation of neighbouring spatial units. The spatial scalar parameter ρ reflects the endogenous spatial interaction between a spatial unit and its neighbours. $\rho = 0$ means no spatial interaction. If ρ is positive, the level of deforestation in a spatial unit tends to mimic the neighbours', suggesting a complementarity effect. On the other hand, a negative ρ means a substitution in deforestation levels that may result from deforestation leakage.

$LagPA_{it}$ and $Mine_{it}$ are respectively the one-year-lagged value of protected areas and the number of mines for unit i at period t. The interactive variable $LagPA_{it} \times Mine_{it}$ assesses the specific influence of protected areas on mining-driven forest loss. x_{it}^k is the k-th control variable for unit i at period t. We add spatial unit-fixed effects μ_i to capture time-invariant spatial unit-specific attributes such as natural endowments or distance to markets, and period-fixed effects η_t to capture common trends in deforestation or the influence of other variables, such as international commodity prices. The omission of these characteristics might bias the estimates in a panel data analysis (Elhorst, 2010; Baltagi, 2021).

Besides the simultaneity bias generated by the spatial lag of the dependent variable, namely the lagged forest loss, another issue comes from potential additional endogenous variables. In particular, we use the one-year-lagged value of the protected areas variable to avoid simultaneity bias between protected areas and forest loss.[6] ε_{it} is the spatially correlated error term such as $\varepsilon_{it} = \lambda \sum_{j=1,j\neq i}^{N} w_{ij}\varepsilon_{jt} + u_{it}$ where u_{it} represents idiosyncratic shocks uncorrelated across spatial units and over time.

[6] In the robustness check, we consider a spatial lag for each explanatory variable to reduce the finite-sample bias of endogeneity implied by measurement error and simultaneity (Fingleton and Le Gallo, 2010).

According to our hypotheses, one should observe the following:

$\beta_1 > 0$ namely mining activities favour deforestation; $\beta_2 < 0$, namely protected areas dampen deforestation. Moreover, if protected areas mitigate mining-induced deforestation, then we have $\beta_3 < 0$, which means that the impact of mining on deforestation should be lower in the larger protected areas.

The previous specification is the benchmark model to uncover spatial interactions in the deforestation process. We add another specification to check the validity of the results by allowing for strong cross-sectional dependence under the form of common factors (Pesaran, 2006; Chudik, Pesaran and Tosetti, 2011).[7] As a robustness check, we, therefore, have the following equation:

$$\begin{aligned} Forest\_loss = & \\ \rho \sum_{j=1, j\neq i}^{N} & w_{ij} Forest\_loss_{jt} + \beta_1 Mine_{it} + \beta_2 LagPA_{it} + \beta_3 LagPA_{it}\, Mine_{it} + \gamma_k x_{it}^k \\ & + \Gamma_1 \overline{Forest\_loss}_t + \Gamma_2 \overline{Mine}_t + \Gamma_3 \overline{LagPA}_t + \Gamma_4 \overline{LagPA \times Mine}_t + \Gamma_5 \bar{x}_t^k + \mu_i + \eta_t \\ & + \varepsilon_{it} \end{aligned} \qquad (2)$$

where $\overline{Forest\_loss}_t = 1/N \sum_{i=1}^{N} Forest\_loss_{it}$ is the cross-sectional average of the deforestation variable. $\overline{Mine}_t$, $\overline{LagPA}_t$, $\overline{LagPA \times Mine}_t$ and $\bar{x}_t^k$ are the cross-sectional averages of the independent variables at time t. These common factors are parameters to be estimated (Shi and Lee, 2018).

3.2 Identification of neighbours and interpretation of the results

Building the spatial weight matrix is crucial in identifying spatial neighbours. We rely on the k-nearest matrix with $k = 5$. Hence, w_{ij} is equal to 1 if j is one of i's five nearest neighbours

[7] Initially, in panel data, a common strategy to deal with unobservable heterogeneity set about (i) using a transformation of variables (fixed effects model) or (ii) by setting out assumptions about the structure of the error term (random effects model). However, in these both cases, a restriction is made on the form of heterogeneity for each individual that is constant in the temporal dimension. By definition, common factors and spatial panels make it possible to capture interactions between individuals (Bouayad Agha, Le Gallo and Védrine, 2018). In addition, the presence of common factor allows to considering residual unobserved effects. In spatial econometrics, (Shi and Lee, 2018) proposed a decomposition of the error term in SAR panel into a common factor component (strong spatial dependence) and an idiosyncratic component (weak spatial dependence). In our study, as additive individual and time effects can potentially not be explained entirely the heterogeneity effects, we also add common factor component in order to verify the robustness of our results in presence of weak and strong cross-section dependence (Chudik, Pesaran and Tosetti, 2011).

and 0 otherwise. We also consider two alternative weight matrices: Gabriel neighbours and the inverse distance.[8]

The spatial lag variable does not allow directly interpreting the coefficients from equations (1) and (2). We, therefore, compute partial derivatives, i.e. marginal effects (LeSage and Pace, 2009). The matrix of partial derivatives of $Forest\_loss_{it}$ with respect to an explanatory variable z_{it} is:

$$\frac{\partial Forest\_loss_{it}}{\partial z_{it}} = \left((I - \rho \sum_{j=1, j \neq i}^{N} w_{ij})^{-1} \right) \delta \qquad (3)$$

Where δ is the coefficient of the explanatory variable z_{it}.

A change in an explanatory variable in a spatial unit directly affects that spatial unit and indirectly affects the neighbouring ones. The total effect of the variable on deforestation is the sum of the direct and indirect effects.[9]

[8] Gabriel neighbours are defined by a Gabriel graph (Gabriel and Sokal, 1969). Inverse distance weight matrix is a geographical definition of neighbourhood based on the inverse geographical distance between spatial units.

[9] From a technical point of view, the direct effects are measured by the average of the diagonal entries of the spatial weight matrix whereas the average of non-diagonal elements measures the indirect effects.

4 Data

We build an original panel dataset. The following subsections describe the observation units, namely the spatial units that are polygons. We then present the variables and give descriptive statistics.

4.1 Polygons in Africa

We relied on geolocalised data from (Hansen *et al.*, 2013) to build the most comprehensive dataset from 2000 to 2019. These data define the spatial units of study that are square polygons covering all SSA countries.[10] Each polygon has an area of approximately 12,070 square kilometres. It is the finest possible subdivision which allows obtaining units with available observations. Overall we have 2,207 polygons in SSA, 926 of which were forested in 2001. Forested polygons in 2001 had at least 10% of their area covered by the forest (Figure A.1 in Appendix). We take advantage of the time dimension to define four five-year periods. We eventually have $926 \times 4 = 3{,}704$ observations.

We use raster files containing the necessary information for each variable to extract the geolocated data belonging to each polygon. These high-definition image files containing geolocated information for each variable came from various sources. Table A- 1 in Appendix overviews our variables and their sources.

4.2 Study variables

We present below the dependent variable, our interest variables and other controls.

4.2.1 Dependent and interest variables

$Forest\_loss$ is our measure of deforestation that we borrow from the Hansen et al. database (Hansen *et al.*, 2013).[11] The variable covers the 2000 to 2019 period. Measures are

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[10] Gridded data is quite widespread in econometrics when faced with a lack of data at the micro level. For example, (Buys *et al.*, 2009), studying the determinants of digital division in SSA countries, used 993,401 square polygons. Interplay between pastoralism, climate change and conflict in Africa is another example (McGuirk and Nunn, 2020).

[11] https://glad.earthengine.app/view/global-forest-change#dl=1;old=off;bl=off;lon=20;lat=10;zoom=3. The data set comes from a collaboration between the GLAD (Global Land Analysis Discovery) lab, USGS, Google, and NASA. The global database consists of files with a spatial resolution of one arc-second per pixel, corresponding to approximately 30 meters per pixel at the equator. The data was generated using multispectral satellite imagery from Landsat 5, Landsat 7, and Landsat 8 satellites.

at an approximately 30×30-meter resolution. In this database, tree cover is any vegetation taller than 5 metres. Thus, the tree cover could represent natural forests or plantations. The loss of vegetation cover can refer to deforestation due to human activities or natural causes such as extreme weather events or forest fires. The deforestation variable is the cumulated tree cover loss over each period in the polygon.

The World Database on Protected Areas (WDPA) gives the surface of protected areas.[12] It allows identifying other effective area-based conservation measures (OECM). [13] These databases are products of the UN Environment Program and IUCN (International Union for Conservation of Nature).

The Minex Consulting[14] database delivers information about the geolocalisation of each industrial mining operation, its state of operation, and its year of opening or discovery. Thus, for each unit, we have the number of industrial mines present for each period, irrespective of their status.[15]

4.2.2 Control variables

We control for other drivers of deforestation, such as climate conditions ($Temp$ and $Rain$), night-time luminosity ($Activity$) population density (Pop) and violence ($Fatalities$). Climatic conditions influence the profitability of agricultural activity and, thus, land use (Nelson and Chomitz, 2011). It is also possible that temperatures and rainfall affect the occurrence and intensity of forest fires. Economic activity and population density are underlying drivers of deforestation. Night-time luminosity is a proxy of economic activity at the subnational level (Chen and Nordhaus, 2011). The effect of the population could be ambiguous: on the one side, population density fuels the demand for cultivated land, but on the other side, it could favour the demand for forest products (Amin et al., 2019). The impact of violence and conflicts on deforestation is also ambiguous. On the one hand, insecurity could lead to more deforestation: the poor institutional quality that translates into violent events fosters

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[12] https://www.iucn.org/theme/protected-areas/our-work/world-database-protected-areas

[13] https://www.iucn.org/commissions/world-commission-protected-areas/our-work/oecms

[14] https://minexconsulting.com/useful-links/

[15] The number of artisanal mines is unknown.

deforestation while downgrading environmental protection. Furthermore, deforestation provides a source of funding for armed insurrection. On the other hand, insecurity penalises economic activity, which can slow down deforestation (Prem, Saavedra and Vargas, 2020).

$Temp$ is the absolute value of the temperature deviation from the period average. It comes from the GISS Surface Temperature Analysis (GISTEMPv4) database. We extract $Rain$ from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database. $Activity$ comes from the Defense Meteorological Program -Operational Line-Scan System (DMSP-OLS) dataset. Pop is the population density from the Gridded Population of the World, Version 4 (GPWv4) database. We consider the death toll related to conflicts from the ACLED database to build $Fatalities$.

4.3 Descriptive statistics

Figure 1 provides the location of forested polygons, protected areas and mining activities. We report descriptive statistics in Table 1 and Table 2.

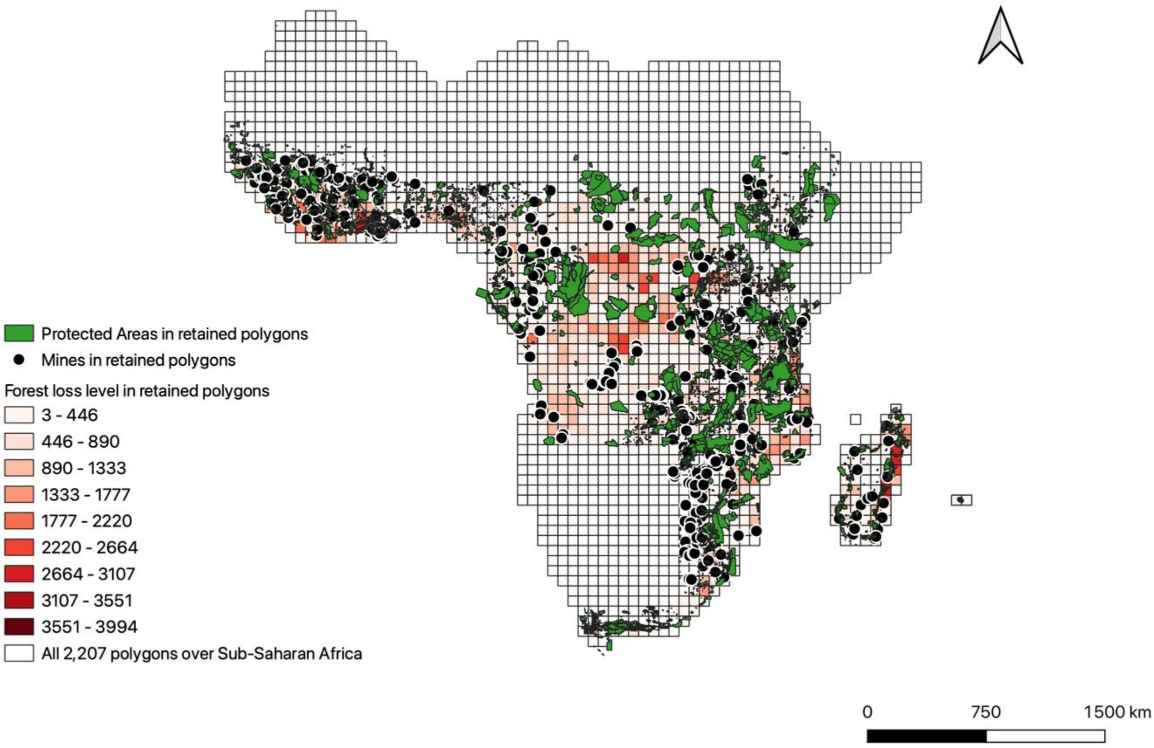
Table 1 gives the essential characteristics of our dataset. The statistics pertain to the 3,704 polygons. Namely, they cover all polygons over the four-year periods. Considering that a polygon's average area is 12,070 square kilometres, the forest loss amounts to 1.1% of the polygon's surface, while the figure for protected areas is 11.4%. It aligns with the percentages of protected areas released in the literature (Chape *et al.*, 2005).

In Table 2, we report the total number of observations, the number of polygons on which these variables are observed, the probability of observing a non-zero value of the variable, the totalled and disaggregated values over the four periods, the mean of the variable per polygon.

The probability of forest loss close to one tells us that forest loss concerns almost all polygons over the period. When we break down by sub-period, we also see an increase in forest loss. One-fifth of the polygons contain mines. Protected areas are present in three-quarters of the observed units. In the last six rows, we see the level of deforestation in the spatial units below and above the protected areas (mines) median. We observe that the polygons with an area of protected areas above the median experience less deforestation on average. Deforestation is higher in polygons with mining activities on average. This observation concerning the deforestation impact of mining activities is still valid even in polygons where protected areas are above the median.

Considering the pairwise correlations (Table A- 2 in Appendix), we observe a significant and positive correlation between the number of mines and the extent of deforestation. Moreover, the surface of protected areas correlates negatively with mining activities and deforestation.

Figure 1. Forest losses, Protected areas and Mines 2000 2019



Source: authors calculation; Hansen et al. 2013 database, Minex Consulting Datasets and World Database on Protected Areas.

Table 1. Descriptive Statistics - Overview

Variables	**Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Measurement unit**
$Forest\_loss$	3,704	139.640	184.698	0	1,927	Square kilometres
PA	3,704	1,371.197	2,276.034	0	11,793	Square kilometres
$Mine$	3,704	0.423	1.160	0	12	Integer
$Temp$	3,704	297.211	2.586	286	303	Kelvin degrees
$Rain$	3,704	1,202.968	559.936	0	3,321	Millimetres
$Activity$	3,704	0.313	1.285	0	15	Pixel (luminosity)
$Fatalities$	3,704	22.584	210.191	0	7,630	Units, number of deaths
Pop	3,704	57.063	113.776	0	1,562	Inhabitants per square kilometer

Table 2. Descriptive Statistics – Mines and Protected Areas in the Forest

				Whole period	**Sub-periods**				
Variable	**Obs.**	**Nb of polygons**	**Prob.**	**2001 2019**	**2001-2005**	**2006-2010**	**2011-2015**	**2016-2019**	**Polygon mean**
$Forest\_loss$	3,704	926	0.999	517,227	67,930	98,142	156,120	195,034	140
$Mine$	3,704	926	0.197	1,566	303	383	435	445	0.4
PA	3,704	926	0.759	5,078,915	1,246,554	1,270,489	1,279,934	1,281,938	1,371
$Forest\_loss$ If $PA > Median$	1,850	468	0.999	218,503	29,962	43,991	65,663	78,887	118
$Forest\_loss$ If $PA < Median$	1,854	477	0.999	298,722	37,968	54,151	90,457	116,147	157
$Forest\_loss$ if $Mine > 0$	728	198	1	141,347	13,913	22,355	45,538	59,540	194
$Forest\_loss$ if $Mine = 0$	2976	772	0.999	375,879	54,017	75,787	110,582	135,494	126
$Forest\_loss$ if $PA > Median$ and $Mine > 0$	341	94	1	55,198	6,871	10,143	17,352	20,832	162
$Forest\_loss$ if $PA < Median$ and $Mine = 0$	1,467	394	0.999	212,575	30,926	41,939	62,271	77,439	145

5 Results

We first evidence the relevance of the spatial econometric model. Then, we assess the marginal impact of mines and protected areas on forest loss. Finally, we implement a robustness check and consider different heterogeneities.

5.1 The relevance of the spatial econometric model

Table 3 displays the evolution of the standardised value of Moran's I statistic over the period for each spatial weight matrix. These results suggest that immediate proximity matters more for deforestation interactions. In particular, the Moran's I statistic is increasing over time, thus suggesting that the levels of deforestation are positively and significantly clustered in SSA areas. The computed statistics are consistent with the hypothesis of a positive spatial clustering of deforestation among nearby SSA polygons.

Table 3. Standardised Moran's I statistics

Year	std_nn5	std_dinverse	std_gabriel
2005	1,233.179***	1,327.680***	1,438.183***
2010	1,081.750***	1,187.847***	1,261.682***
2015	1,345.908***	1,431.672***	1,544.010***
2019	1,438.017***	1,534.271***	1,663.758***

*** p<0.001, ** p<0.01, * p<0.05

We estimate equations (1) and (2). We gradually introduce explanatory variables in the model to control for multicollinearity bias (Models 1 to 8). Table 4 reports the estimated spatial parameters ρ and λ for the standard spatial autoregressive model (Eq. 1).

Table 4. Estimation results for the benchmark spatial autoregressive model.

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
ρ	0.798***	0.791***	0.790***	0.790***	0.789***	0.789***	0.789***	0.789***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
λ	-0.228***	-0.228***	-0.230***	-0.230***	-0.228***	-0.228***	-0.226***	-0.228***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)

Dependent variable: $Forest\_loss$; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; Standard errors in parentheses; the list of variables in the different specifications are given in Table 6

Table 5 reports estimated ρ and λ for the spatial autoregressive model with common factors (Eq. 2). The estimated values of ρ and λ are consistent, whatever the specifications (Table 4 and Table 5). [16]

Table 5. Estimation results for the spatial autoregressive model with common factors
Dependent variable: Deforestation

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**
ρ	0.798***	0.791***	0.790***	0.790***	0.789***	0.789***	0.789***	0.789***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
λ	-0.229***	-0.229***	-0.230***	-0.230***	-0.229***	-0.228***	-0.226***	-0.228***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)

Dependent variable: $Forest\_loss$; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; Standard errors in parentheses; the list of variables in the different specifications are given in Table 7

The spatial autocorrelation is positive and statistically significant, corroborating that deforestation decisions are complements. The coefficients range from 78.9% to 79.1%. The smallness of the finest spatial units, namely the polygon, could explain this high level of interaction. When including strong cross-sectional dependence with common factors (Table 5), the autoregressive coefficients are unchanged results. Overall, our spatial interaction results align with previous studies on deforestation determinants outside Sub-Saharan African countries (Amin *et al.*, 2019). The evidence in Africa is scanter. Interestingly, (Heß, Jaimovich and Schündeln, 2021) found that Community-Driven Development (CDD) programs generated positive spillover effects of deforestation in West African drylands.

5.2 Impact measures

We find that all explanatory variables' estimated direct, indirect and total effects are very similar without (Table 6) or with common factors (Table 7). We only interpret the total effects. As expected, $Activity$ has a positive and significant impact on deforestation (Models 4 to 8 in

[16] Following (Pesaran, 2015), we find evidence for strong spatial dependence while computing the correlation coefficients between the observations of each pair of spatial polygons in SSA. Pesaran's null hypothesis of cross-sectional dependence is that the values are only weakly cross-sectionally dependent. The test yields a statistic value of 442.28, which is strongly significant. We conclude that the spatial estimator should include both weak and strong spatial dependence. Although the coefficients vary slightly, the results are robust when common factors are included. In particular, significance and the sign of both the spatial parameters and the marginal effects of the different specifications remain broadly the same.

Table 6 and Table 7). $Temp$, $Rain$, $Fatalities$ and Pop remain statistically insignificant (Models 5 to 8 in Table 6 and Table 7).[17], [18]

Protected areas ($LagPA$) have a significant negative effect at the 5% or 1% level, depending on the specification) on forest loss: models 4 to 8 in Table 6 and Table 7. Second, regarding mining activity, estimation results show a positive and significant (at the 0.1% level) effect of $Mine$ on deforestation, regardless of the specification. This result is consistent with previous findings in DRC (Butsic *et al.*, 2015). This result also suggests that mines impact deforestation in their location polygons and neighbouring polygons. An additional mine leads to a forest loss of 39.8 km2 directly and 115.5 km2 indirectly (Table 6, model 4). The total effect is, therefore, impressive since an additional mine leads to a 155.4 km2 increase in forest loss. It is interesting to compare this result with that obtained for protected areas. An additional mine results in 155.4 km2 of forest loss in a polygon, whereas 1 km2 of an additional protected area only prevents 0.097 km2 of forest cover loss. Put differently, an additional 1598 km2 in a protected area would be required to offset the effect of an additional mine. Avoiding mining-driven forest loss, therefore, would at least necessitate a twice-fold increase in the average protected area if we assume that each extra square kilometre of protected area delivers the same reduction in forest loss.

We can assess whether protected areas dampen the harmful role of mining activities by considering the interactive variable: $Lag\ PA \times Mine$. The sign of the interactive variable is

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[17] We regress the error terms of our benchmark model (Eq. 1) on the set of explanatory variables. Results validate the hypothesis of no correlation between the error term and explanatory variables suggesting the effectiveness of our procedure in controlling for endogeneity. These results are presented in Table A- 5 in Appendix.

[18] In addition, to (i) Moran test for spatial autocorrelation and (ii) Pesaran test for cross-section dependence, we also perform additional tests in order to validate our empirical specification (Table A- 6 in Appendix for the full model including spatially lagged independent variables). First, using the robust version of the Hausman test to spatial autocorrelation of errors, the result leads to rejection of the null hypothesis of absence of correlation between individual effects and explanatory variables. Hence this test confirms that fixed effect models are statistically required. Second, we also test for spatial autocorrelation into account by SAR (LM_lag) or SEM (LM_error), the results confirm the rejection of the null hypothesis (taken independently) suggesting the inclusion of spatial parameter in lag form of the dependent variable (forest loss level) or via a spatial error component. In a more credible way, we also add robust versions of LM_lag, LM_error to test for the absence of a spatial autoregressive term when the model already contains a spatial autoregressive term in the error (Robust LM_lag), or vice versa (Robust LM_error). These robust versions are highly significant suggesting the choice of a fixed-effect model with both an autoregressive spatial process in the dependent variable and in the errors (SARAR). However, it should be noted that the test statistic for a Robust LM_lag version is higher than that for a Robust LM_error version.

negative but not significant, regardless of the specification used. In other words, the impact of mining on the forest does not decrease with protected areas. However, interpreting the coefficients on the mines and protected variables as the average effect of these variables on deforestation can be questioned (Brambor, Clark and Golder, 2006). We decided to study the evolution of the impact of mines on deforestation according to the distribution of protected areas. We consider here the model including all explanatory variables (model 8 in Table 6). Figure 2(A) shows that the impact of mining on deforestation does not change significantly with the size of protected areas whose distribution is given in Figure 2(B). The impact of mining on forest loss is only slightly decreasing according to the distribution of protected areas, with values ranging between 155 to 150 km². Mining activities do not condition the dampening effect of protected areas on deforestation.

Table 6. Marginal effects of covariates on deforestation; Spatial autoregressive model without common factors

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**
	Direct							
Lag_PA	-0.014 (0.012)	-0.019 (0.012)	-0.017 (0.013)	-0.025** (0.013)	-0.025* (0.014)	-0.026** (0.012)	-0.026* (0.012)	-0.026* (0.012)
$Mine$		39.052*** (5.788)	40.670*** (6.335)	39.834*** (6.721)	39.843*** (6.068)	39.771*** (6.690)	39.550*** (6.709)	39.488*** (5.970)
$Lag\_PA \times Mine$			-0.002 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
$Activity$				16.328*** (4.577)	16.148*** (4.825)	16.362*** (4.495)	16.274*** (4.233)	15.343*** (5.008)
$Temp$					2.297 (5.829)	2.420 (5.844)	2.374 (5.963)	2.522 (5.498)
$Rain$						-0.011 (0.010)	-0.011 (0.010)	-0.012 (0.010)
$Fatalities$							-0.008 (0.008)	-0.007 (0.007)
Pop								0.041 (0.082)
	Indirect							
Lag_PA	-0.042 (0.036)	-0.055 (0.035)	-0.048 (0.038)	-0.072** (0.037)	-0.074* (0.041)	-0.076* (0.037)	-0.075* (0.037)	-0.074* (0.039)
$Mine$		112.167*** (21.455)	117.210*** (23.046)	115.540*** (25.093)	115.508*** (22.638)	114.494*** (24.060)	113.648*** (23.373)	113.450*** (21.875)
$Lag\_PA \times Mine$			-0.004 (0.009)	-0.004 (0.010)	-0.004 (0.010)	-0.004 (0.009)	-0.003 (0.009)	-0.003 (0.009)
$Activity$				47.359*** (14.089)	46.813*** (15.118)	47.104*** (3.916)	46.763*** (12.550)	44.080*** (16.078)
$Temp$					6.658 (17.517)	6.966 (16.951)	6.821 (16.963)	7.246 (15.985)
$Rain$						-0.031 (0.029)	-0.032 (0.028)	-0.033 (0.029)
$Fatalities$							-0.023 (0.022)	-0.021 (0.021)
Pop								0.120 (0.248)
	Total							
Lag_PA	-0.056 (0.042)	-0.074 (0.047)	-0.065 (0.052)	-0.097** (0.050)	-0.0990* (0.054)	-0.102* (0.049)	-0.101* (0.049)	-0.100* (0.051)
$Mine$		151.219*** (26.528)	157.880*** (28.7748)	155.374*** (31.181)	155.351*** (27.993)	154.265*** (30.126)	153.198*** (29.455)	152.937*** (27.018)
$Lag\_PA \times Mine$			-0.006 (0.012)	-0.005 (0.013)	-0.005 (0.013)	-0.005 (0.012)	-0.004 (0.012)	-0.005 (0.012)
$Activity$				63.687*** (18.415)	62.961*** (19.742)	63.466*** (18.202)	63.037*** (16.596)	59.423*** (20.888)
$Temp$					8.955 (23.319)	9.386 (22.772)	9.195 (22.900)	9.767 (21.454)
$Rain$						-0.041 (0.040)	-0.043 (0.038)	-0.045 (0.039)
$Fatalities$							-0.031 (0.029)	-0.029 (0.029)
Pop								0.160 (0.329)

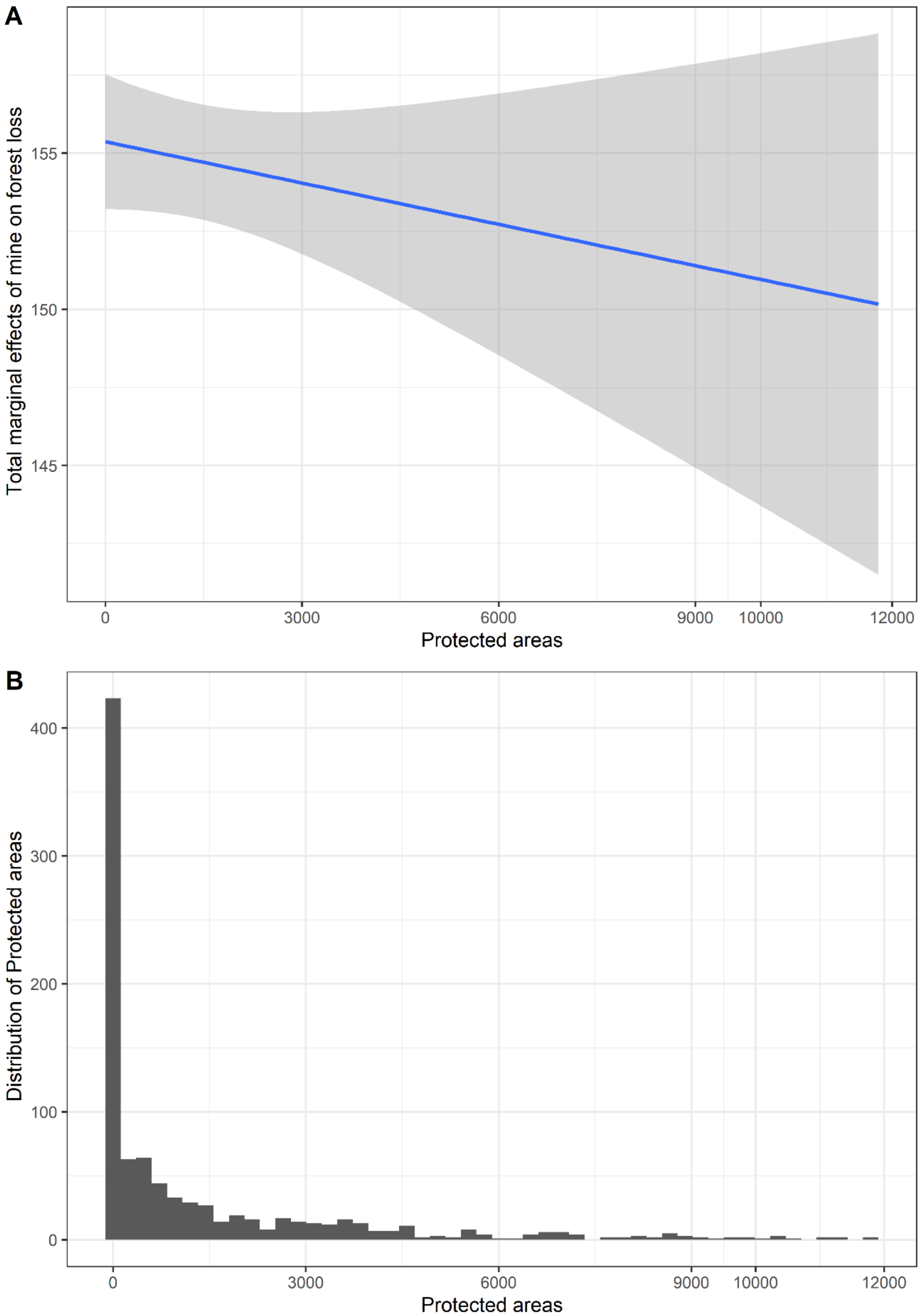
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses.

Table 7. Marginal effects of covariates on deforestation; spatial autoregressive model with common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
	Direct							
Lag_PA	-0.0140 (0.011)	-0.019* (0.011)	-0.017 (0.013)	-0.025* (0.013)	-0.025** (0.012)	-0.026** (0.014)	-0.026** (0.012)	-0.026** (0.013)
$Mine$		39.057*** (5.202)	40.707*** (6.333)	39.874*** (6.100)	39.883*** (6.720)	39.812*** (6.321)	39.590*** (5.819)	39.526*** (6.339)
$Lag\_PA \times Mine$			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
$Activity$				16.351*** (4.715)	16.171*** (4.442)	16.383*** (4.520)	16.295*** (4.659)	15.369*** (5.386)
$Temp$					2.290 (6.169)	2.411 (6.112)	2.365 (6.265)	2.513 (5.405)
$Rain$						-0.011 (0.009)	-0.011 (0.009)	-0.011 (0.010)
$Fatalities$							-0.008 (0.007)	-0.007 (0.008)
Pop								0.041 (0.081)
	Indirect							
Lag_PA	-0.042 (0.034)	-0.056* (0.033)	-0.048 (0.039)	-0.073* (0.038)	-0.074** (0.036)	-0.077* (0.043)	-0.076* (0.038)	-0.075** (0.041)
$Mine$		113.523*** (19.420)	118.723*** (23.819)	117.066*** (22.638)	117.033*** (22.667)	116.004*** (23.000)	115.155*** (21.479)	114.945*** (24.452)
$Lag\_PA \times Mine$			-0.004 (0.009)	-0.004 (0.010)	-0.004 (0.009)	-0.004 (0.010)	-0.003 (0.009)	-0.004 (0.009)
$Activity$				48.005*** (14.742)	47.451*** (13.594)	47.738*** (14.941)	47.400*** (14.251)	44.693*** (16.552)
$Temp$					6.720 (17.943)	7.026 (18.158)	6.880 (18.717)	7.307 (16.223)
$Rain$						-0.031 (0.027)	-0.031 (0.026)	-0.033 (0.030)
$Fatalities$							-0.023 (0.022)	-0.022 (0.022)
Pop								0.112 (0.241)
	Total							
Lag_PA	-0.056 (0.045)	-0.075* (0.043)	-0.065 (0.042)	-0.097* (0.050)	-0.099** (0.048)	-0.103* (0.056)	-0.102** (0.051)	-0.101** (0.054)
$Mine$		152.580*** (23.984)	159.430*** (23.436)	156.939*** (28.076)	156.916*** (28.715)	155.815*** (28.469)	154.745*** (26.548)	154.471*** (30.159)
$Lag\_PA \times Mine$			-0.006 (0.012)	-0.006 (0.013)	-0.005 (0.012)	-0.005 (0.013)	-0.005 (0.012)	-0.005 (0.013)
$Activity$				64.356*** (19.242)	63.622*** (17.865)	64.121*** (19.234)	63.692*** (18.681)	60.062*** (21.750)
$Temp$					9.009 (24.089)	9.437 (24.844)	9.245 (24.955)	9.820 (21.599)
$Rain$						-0.041 (0.036)	-0.042 (0.035)	-0.045 (0.040)
$Fatalities$							-0.031 (0.029)	-0.0291 (0.030)
Pop								0.160 (0.032)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses.

Figure 2. Marginal effect of mine on forest loss according to the distribution of protected areas



Note: The grey area represents the confidence interval at the 5% level.

5.3 Robustness check

To handle omitted variables in the spatial context, we also perform the spatial Durbin model (SDM) (Table A- 7 and Table A- 8 in Appendix). The main outcomes remain stable across specifications. The coefficients of the variables of interest retain the same sign, and most spatially lagged exogenous variables are insignificant. In addition, comparing the Akaike information criterion (AIC) and Bayes' information criterion (BIC), results show that models without including spatially lagged independent variables are better than those with the spatially lagged exogenous explanatory variables (Table A- 9 in Appendix).

5.4 Testing Heterogeneities

Because of its importance, we estimate a SARAR model with spatial units and time-fixed effects only on the Congo Basin.[19] Table A- 10 in Appendix reports the marginal effects. A noticeable result is the lack of significance of the protected area variable. Therefore, the unstable institutional context of the region likely makes this environmental protection instrument ineffective. This result is also in line with (Brandt, Nolte and Agrawal, 2016, 2018) though it was challenged by (Karsenty *et al.*, 2017).

We continue to explore the heterogeneity driven by local institutional variability. Poor institutional quality leads to many conflicts and violence. Hence, we split the sample into two sub-samples according to a threshold depending on the number of conflict deaths measured at the polygon level (*Fatalities*). We assume institutions are "good" when this number is below the sample median.[20] Protected areas reduce deforestation significantly only in polygons characterised by "good" institutional quality (Table A- 11 in Appendix: compared column 1 versus column 2; total effect). In addition, the impact of mines on deforestation is higher in polygons with "weak" institutions.

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[19] The Congo Basin countries are: Angola, Burundi, Central African Republic, Cameroon, Democratic Republic of Congo, Congo Republic, Gabon, Rwanda, Tanzania, and Zambia. The number of polygons is 537.

[20] The sample was also split on the basis of the mean of the variable *Fatalities*. The results are unchanged.

We also studied the impact of mines according to mining status.[21] We consider the category of pre-operating mines as it concerns many polygons (163). The results are qualitatively unchanged (Table A- 11 in Appendix: column 3, total effect). In particular, protected areas do not mitigate mining-driven deforestation. In addition, an additional pre-operating mine appears to lead to a forest loss of 202.4 km2. This effect is more important than the one obtained with all the mines regardless of their status (155.4 km2; Table 6, model 4). Therefore, during the pre-operating phase, mining activity appears to have the highest impact on land use in the area surrounding the mine.

Although the results favour the effectiveness of protected areas, these highlighted effects can also depend on the more or less strict character of the protected areas following the IUCN classification. We, therefore, break down protected areas into two groups. Both less stringent protected areas ($Lag\ Large\_PA$) and strictly protected areas ($Lag\ Strict\_PA$) preserve the forest from deforestation (Table A- 3 and Table A- 4 in Appendix). Nevertheless, it is not possible to highlight the greater effectiveness of strictly protected areas. Moreover, even when we decompose protected areas into two groups, the interactive variable is still non-significant.

[21] There are three mining status, namely (1) operating mines, (2) pre-operating mines and (2) closed mines. Pre-operated mines include mines in the feasibility study phase, mines under construction and mines awaiting commissioning.

6 Concluding remarks

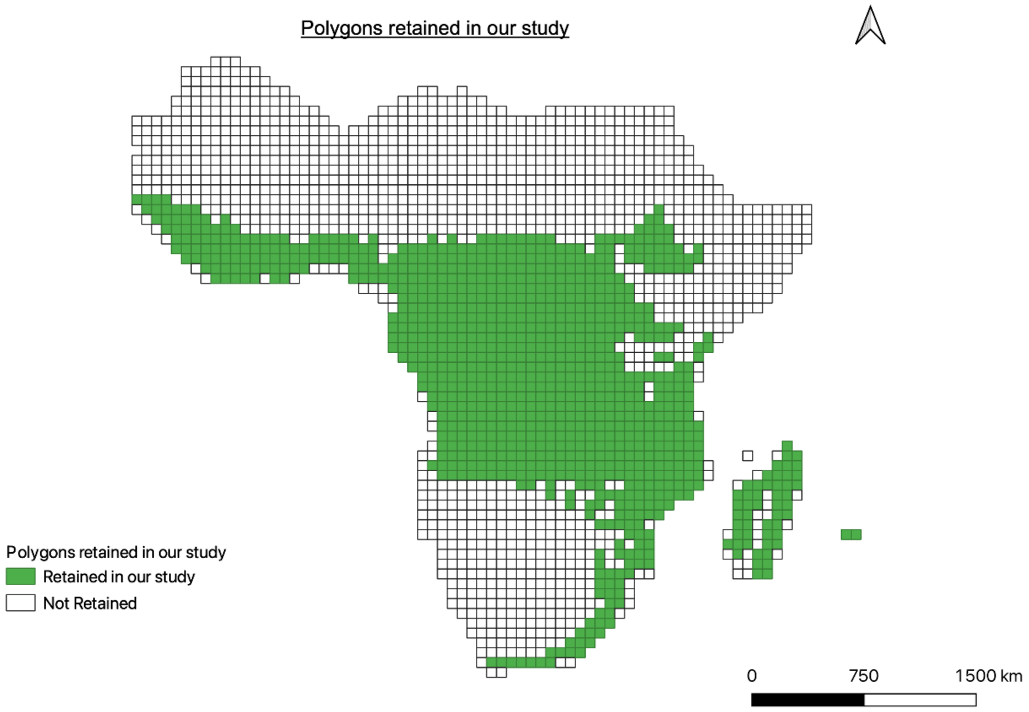
This article studies mining-driven deforestation using fine-scale data from 2001 to 2019. We run spatial panel models controlling for spatial interactions. Mining activities harm the forest, and protected areas allow for reduced deforestation. We also find that protected areas do not dampen the impact of mining activities on deforestation. The result is robust to several econometric specifications. In addition, spatial heterogeneity prevails: the lower the institutional quality of the polygon, the greater the impact of the mine on deforestation. Furthermore, the effectiveness of protected areas is lost in areas characterised by low institutional quality.

The interpretation of the results may raise several questions. First, satellite data does not distinguish forest loss resulting from human actions or natural disasters. We cope with this issue with temperature and rainfall variables. Second, the presence of endogenous variables on the right-hand side is a common occurrence in econometric work. In particular, including variables related to protected areas could lead to localisation bias (Joppa and Pfaff, 2009). Nevertheless, the panel structure with period and polygon fixed effects and the one-year lagged value of protected areas address the bias.

It is feared that the likely development of mining activities in Africa in the coming years will increase the pressure on the forest resource. Smart mining attracts increasing attention, but offsets' contribution to forest preservation depends on many factors, such as enabling institutions and support of local communities (Maddox *et al.*, 2019). It is not realistic to hope that protected areas alone will be able to preserve the forest from mining activities. The weight of mining activity must be contained by increased diversification, thus reducing the dependence on primary commodities. Lower dependence on natural resources and higher diversification is not only an economic imperative but also an environmental one.

7 Appendix

Figure A- 1. Polygons and the 926 forested polygons in 2001



Source: authors' calculations. Forested polygons have at least 10% of their surface under forest

Table A- 1. Variables description

Variable name	Description	Source
Forest_loss	Forest loss	Hansen's database
Mine	Number of industrial mines present in each cell	MinEx database
PA	Surface of protected area for each study unit.	World Database on Protected Areas and world database on other effective area- based conservation measures
Temp	Absolute deviation of the temperature	GISS Surface Temperature Analysis (GISTEMPv4) database
Rain	Rainfall	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)
Activity	Night-time luminosity	Defense Meteorological Program -Operational Line-Scan System (DMSP-OLS) dataset
Fatalities	Number of deaths due to conflicts	ACLED database
Pop	Population density	The Gridded Population of the World, Version 4 (GPWv4)

Table A- 2. Pairwise correlations

Variables	(1) $Forest\_loss$	(2) PA	(3) $Mine$	(4) $Temp$	(5) $Rain$	(6) $Activity$	(7) $Fatalities$	(8) Pop
(1) $Forest\_loss$	1.000							
(2) PA	-0.069***	1.000						
(3) $Mine$	0.167***	-0.057***	1.000					
(4) $Temp$	0.043***	0.050***	-0.011	1.000				
(5) $Rain$	0.210***	-0.055***	0.040**	0.172***	1.000			
(6) $Activity$	0.056***	-0.029*	0.058***	-0.026*	-0.109***	1.000		
(7) $Fatalities$	-0.028*	-0.018	0.006	-0.024	0.013	0.018	1.000	
(8) Pop	0.086***	-0.100***	0.079***	-0.067***	-0.074***	0.620***	0.072***	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A- 3. Marginal effects of covariates on deforestation for heterogeneity PA; spatial autoregressive model without common factors

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**	**Model9**	**Model10**
	Direct									
Lag_Strict_PA	-0,004 (0.005)	-0,018 (0.018)	-0.035** (0.019)	-0.029 (0.020)	-0.037 (0.025)	-0.043** (0.022)	-0.043** (0.024)	-0.044* (0.022)	-0.044** (0.024)	-0.044* (0.022)
Lag_Large_PA		-0,016 (0.021)	-0.034* (0.020)	-0.033* (0.021)	-0.042 (0.026)	-0.050** (0.023)	-0.050** (0.026)	-0.050* (0.023)	-0.050** (0.026)	-0.051* (0.024)
Mine			39.908*** (5.891)	41.890*** (5.972)	40.034*** (6.463)	39.009*** (6.550)	39.023*** (6.429)	38.961*** (7.412)	38.718*** (6.859)	38.626*** (6.787)
Lag_Strict_PA x Mine				-0.009 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)
Lag_Large_PA x Mine					0.002 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Activity						15.271*** (4.262)	15.211*** (4.468)	15.377*** (4.756)	15.304*** (4.459)	14.023*** (4.470)
Temp							0.628 (5.843)	0.687 (5.888)	0.657 (5.953)	0.890 (6.071)
Rain								-0.010 (0.009)	-0.010 (0.010)	-0.011 (0.010)
Fatalities									-0.008 (0.008)	-0.007 (0.008)
Pop										0.058 (0.077)
	Indirect									
Lag_Strict_PA	0,001 (0.001)	0,003 (0.004)	-0.103** (0.057)	-0.084 (0.059)	-0.106 (0.075)	-0.127* (0.068)	-0.126* (0.072)	-0.128* (0.066)	-0.128** (0.074)	-0.129* (0.068)
Lag_Large_PA		0,003 (0.004)	-0.100* (0.060)	-0.097* (0.061)	-0.121 (0.081)	-0.143** (0.073)	-0.143** (0.080)	-0.146* (0.069)	-0.145** (0.106)	-0.147* (0.074)
Mine			116.168*** (22.832)	121.996*** (22.236)	116.341*** (23.880)	114.058*** (23.904)	114.081*** (23.856)	113.150*** (25.787)	112.224*** (23.807)	112.003*** (23.787)
Lag_Strict_PA x Mine				-0.027 (0.020)	-0.024 (0.019)	-0.023 (0.021)	-0.023 (0.021)	-0.023 (0.021)	-0.023 (0.022)	-0.024 (0.020)
Lag_Large_PA x Mine					0.006 (0.011)	0.008 (0.011)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)
Activity						44.650*** (14.582)	44.468*** (14.526)	44.658*** (14.758)	44.359*** (14.174)	40.662*** (13.910)
Temp							1.837 (17.1888)	1.995 (17.675)	1.906 (17.398)	2.580 (18.039)
Rain								-0.030 (0.028)	-0.030 (0.031)	-0.0331 (0.029)
Fatalities									-0.024 (0.023)	-0.023 (0.022)
Pop										0.168 (0.232)
	Total									
Lag_Strict_PA	-0,003 (0.004)	-0,015 (0.015)	-0.139** (0.075)	-0.113 (0.079)	-0.143 (0.099)	-0.170* (0.089)	-0.170* (0.096)	-0.172* (0.088)	-0.172** (0.097)	-0.174* (0.090)
Lag_Large_PA		-0,013 (0.017)	-0.134* (0.079)	-0.130* (0.081)	-0.162 (0.107)	-0.193** (0.096)	-0.192** (0.106)	-0.196* (0.091)	-0.196** (0.106)	-0.198* (0.098)
Mine			156.076*** (28.041)	163.887*** (27.364)	156.376*** (29.638)	153.067*** (29.793)	153.105*** (29.708)	152.111*** (32.535)	150.942*** (29.963)	150.628*** (29.884)
Lag_Strict_PA x Mine				-0.036 (0.026)	-0.033 (0.026)	-0.031 (0.028)	-0.031 (0.028)	-0.031 (0.028)	-0.031 (0.029)	-0.032 (0.027)
Lag_Large_PA x Mine					0.001 (0.014)	0.010 (0.015)	0.010 (0.016)	0.011 (0.016)	0.011 (0.016)	0.011 (0.015)
Activity						59.921*** (18.629)	59.679*** (18.822)	60.036*** (19.334)	59.664*** (18.452)	54.685*** (18.200)
Temp							2.465 (23.008)	2.683 (23.538)	2.563 (23.326)	3.470 (24.083)
Rain								-0.040 (0.038)	-0.041 (0.041)	-0.045 (0.038)
Fatalities									-0.033 (0.030)	-0.030 (0.030)
Pop										0.226 (0.309)

*** p<0.001, ** p<0.01, * p<0.05; standard errors in parentheses

Table A- 4. Marginal effects of covariates on deforestation for heterogeneity PA; spatial autoregressive model with common factors

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10
	Direct									
Lag_Strict_PA	-0.004 (0.005)	-0.018 (0.018)	-0.036* (0.017)	-0.029 (0.019)	-0.037* (0.021)	-0.043** (0.023)	-0.043* (0.024)	-0.044** (0.021)	-0.044** (0.021)	-0.047* (0.025)
Lag_Large_PA		-0.016 (0.019)	-0.0345 (0.019)	-0.033* (0.019)	-0.041* (0.022)	-0.049** (0.026)	-0.049** (0.025)	-0.050** (0.023)	-0.050** (0.023)	-0.051** (0.025)
Mine			39.923*** (5.475)	41.914*** (6.455)	40.047*** (6.490)	39.045*** (6.699)	39.060*** (6.611)	38.998*** (6.381)	38.754*** (6.284)	38.661*** (6.486)
Lag_Strict_PAxMine				-0.009 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.006)	-0.008 (0.007)
Lag_Large_PAxMine					0.002 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Activity						15.288*** (4.071)	15.229*** (4.154)	15.393*** (4.294)	15.321*** (4.426)	14.042*** (4.609)
Temp							0.619` (5.854)	0.680 (6.162)	0.647 (6.181)	0.880 (6.037)
Rain								-0.010 (0.009)	-0.010 (0.009)	-0.011 (0.009)
Fatalities									-0.009 (0.007)	-0.008 (0.008)
Pop										0.058 (0.078)
	Indirect									
Lag_Strict_PA	0.001 (0.001)	0.004 (0.004)	-0.105* (0.053)	-0.086 (0.059)	-0.108* (0.065)	-0.128** (0.072)	-0.128* (0.075)	-0.130* (0.065)	-0.130* (0.064)	-0.131* (0.074)
Lag_Large_PA		0.003 (0.004)	-0.102 (0.058)	-0.098* (0.059)	-0.123* (0.069)	-0.146** (0.078)	-0.146* (0.078)	-0.150** (0.071)	-0.150** (0.070)	-0.150** (0.076)
Mine			117.600*** (20.877)	123.524*** (26.425)	117.779*** (23.912)	115.575*** (25.354)	115.598*** (24.723)	114.654*** (23.318)	113.722*** (24.504)	113.482*** (22.484)
Lag_Strict_PAxMine				-0.027 (0.021)	-0.025 (0.022)	-0.024 (0.021)	-0.024 (0.021)	-0.024 (0.022)	-0.024 (0.020)	-0.024 (0.020)
Lag_Large_PAxMine					0.007 (0.011)	0.008 (0.013)	0.008 (0.012)	0.008 (0.012)	0.008 (0.012)	0.008 (0.011)
Activity						45.253*** (13.473)	45.071*** (14.078)	45.257*** (14.290)	44.959*** (13.976)	41.217*** (15.346)
Temp							1.832 (17.469)	1.990 (18.417)	1.899 (18.026)	2.582 (18.158)
Rain								-0.029 (0.027)	-0.030 (0.027)	-0.033 (0.029)
Fatalities									-0.025 (0.021)	-0.023 (0.024)
Pop										0.170 (0.234)
	Total									
Lag_Strict_PA	-0.003 (0.004)	-0.015 (0.014)	-0.140* (0.070)	-0.115 (0.078)	-0.145* (0.085)	-0.172** (0.095)	-0.172* (0.098)	-0.174** (0.086)	-0.174* (0.085)	-0.176* (0.098)
Lag_Large_PA		-0.013 (0.015)	-0.136 (0.076)	-0.132* (0.078)	-0.166* (0.090)	-0.195** (0.104)	-0.195* (0.103)	-0.198** (0.094)	-0.198* (0.093)	-0.201** (0.101)
Mine			157.523*** (25.689)	165.438*** (32.244)	157.826*** (29.687)	154.620*** (31.345)	154.658*** (30.625)	153.651*** (29.061)	152.476*** (30.195)	152.143*** (28.296)
Lag_Strict_PAxMine				-0.037 (0.085)	-0.033 (0.030)	-0.032 (0.028)	-0.032 (0.028)	-0.032 (0.029)	-0.032 (0.026)	-0.032 (0.027)
Lag_Large_PAxMine					0.009 (0.015)	0.010 (0.017)	0.010 (0.016)	0.010 (0.016)	0.011 (0.016)	0.011 (0.015)
Activity						60.542*** (17.323)	60.300*** (17.999)	60.650*** (18.285)	60.280*** (18.180)	55.259*** (19.828)
Temp							2.451 (23.306)	2.667 (24.551)	2.546 (24.180)	3.461 (24.171)
Rain								-0.039 (0.036)	-0.041 (0.036)	-0.044 (0.038)
Fatalities									-0.033 (0.028)	-0.031 (0.031)
Pop										0.228 (0.312)

*** p<0.001, ** p<0.01, * p<0.05; standard errors in parentheses

Table A- 5. Regression of error terms of Table 6 on the explanatory variables.

	error1	error2	error3	error4	error5	error6	error7	error8
Lag_PA	0.004 (0.010)	0.003 (0.010)	0.005 (0.011)	0.005 (0.011)	0.006 (0.011)	0.007 (0.011)	0.007 (0.011)	0.006 (0.011)
$Mine$		0.940 (4.682)	2.202 (5.428)	1.455 (5.425)	1.483 (5.425)	1.562 (5.425)	1.578 (5.426)	1.595 (5.430)
$Activity$				2.052 (3.893)	2.474 (3.910)	2.274 (3.913)	2.269 (3.914)	1.755 (4.206)
$Temp$					-6.435 (5.853)	-6.548 (5.854)	-6.562 (5.854)	-6.531 (5.860)
$Rain$						0.012 (0.009)	0.012 (0.009)	0.011 (0.009)
$Fatalities$							0.0001 (0.006)	0.0003 (0.006)
Pop								0.024 (0.072)
$Lag\_PA \times Mine$			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)

Standard errors in parentheses; *p< 0.1; **p<0.05; ***p<0.01

Table A- 6. Standard tests in spatial panel models

	Statistics	Df
LM_lag	3906.8***	1
LM_error	3502.4***	1
Robust LM_lag	410.32***	1
Robust LM_error	5.9003**	1
Hausman	290.45***	16

*** p<0.01, ** p<0.05, * p<0.10

Table A- 7. Estimation results for the spatial Durbin model with additive PA

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ρ	0.799*** (0.019)	0.791*** (0.019)	0.792*** (0.019)	0.792*** (0.019)	0.791*** (0.019)	0.794*** (0.019)	0.793*** (0.019)	0.794*** (0.019)
λ	-0.229*** (0.050)	-0.229*** (0.050)	-0.231*** (0.050)	-0.231*** (0.050)	-0.230*** (0.050)	-0.236*** (0.049)	-0.234*** (0.049)	-0.239*** (0.049)
Lag_PA	-0.011 (0.009)	-0.015 (0.009)	-0.014 (0.010)	-0.015 (0.010)	-0.015 (0.010)	-0.021** (0.010)	-0.021** (0.010)	-0.021** (0.010)
Mine		31.429*** (4.458)	32.500*** (5.225)	32.513*** (5.226)	32.529*** (5.228)	31.894*** (5.206)	31.715*** (5.210)	31.514*** (5.203)
Temp				4.600 (5.559)	4.835 (5.572)	3.167 (5.554)	3.042 (5.563)	2.586 (5.545)
Rain					-0.008 (0.008)	-0.008 (0.008)	-0.009 (0.008)	-0.009 (0.008)
Activity						12.857*** (3.609)	12.786*** (3.612)	12.593*** (3.869)
Fatalities							-0.006 (0.006)	-0.006 (0.006)
Pop								0.009 (0.064)
SlagW_Lag_PA	0.0002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
SlagW_Mine		3.928 (3.771)	3.914 (5.055)	4.052 (5.058)	3.968 (5.060)	3.389 (5.044)	3.461 (5.046)	3.115 (5.041)
SlagW_Temp				5.250 (16.210)	5.898 (16.240)	4.659 (16.166)	4.100 (16.195)	1.942 (16.176)
SlagW_Rain					-0.002 (0.009)	0.004 (0.009)	0.004 (0.009)	0.004 (0.009)
SlagW_Activity						7.638** (3.477)	7.607** (3.477)	15.105*** (4.447)
SlagW_Fatalities							0.008 (0.014)	0.008 (0.014)
SlagW_Pop								-0.132*** (0.049)
Lag_PA x Mine			-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
SlagW_Lag_PAxMine			-0.0001 (0.003)	-0.0002 (0.003)	-0.0001 (0.003)	-0.00002 (0.003)	-0.0001 (0.003)	0.0001 (0.003)

*** p<0.01, ** p<0.05, * p<0.1; standard errors in parentheses

Table A- 8. Estimation results for the spatial Durbin model with heterogeneity PA

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
ρ	0.799*** (0.019)	0.799*** (0.019)	0.794*** (0.019)	0.794*** (0.019)	0.794*** (0.019)	0.796*** (0.019)	0.796*** (0.019)	0.795*** (0.019)	0.795*** (0.019)	0.796*** (0.019)
λ	-0.229*** (0.050)	-0.229*** (0.050)	-0.232*** (0.050)	-0.234*** (0.050)	-0.230*** (0.050)	-0.236*** (0.049)	-0.236*** (0.049)	-0.234*** (0.049)	-0.232*** (0.049)	-0.238*** (0.049)
Lag_Strict_PA	-0.004 (0.005)	-0.018 (0.018)	-0.028* (0.015)	-0.023 (0.015)	-0.030 (0.019)	-0.034* (0.019)	-0.034* (0.019)	-0.035* (0.019)	-0.036* (0.019)	-0.035* (0.019)
Lag_Large_PA		-0.015 (0.020)	-0.027* (0.016)	-0.026 (0.016)	-0.034* (0.020)	-0.039** (0.020)	-0.039** (0.020)	-0.040** (0.020)	-0.040** (0.020)	-0.040** (0.020)
Mine			32.021*** (4.494)	33.644*** (4.633)	31.874*** (5.306)	31.290*** (5.287)	31.321*** (5.288)	31.281*** (5.290)	31.090*** (5.294)	30.983*** (5.288)
Activity						11.915*** (3.533)	11.827*** (3.562)	12.102*** (3.577)	12.049*** (3.580)	11.535*** (3.824)
Temp							1.565 (5.514)	1.616 (5.524)	1.493 (5.534)	1.076 (5.511)
Rain								-0.008 (0.008)	-0.008 (0.008)	-0.008 (0.008)
Fatalities									-0.007 (0.006)	-0.007 (0.006)
Pop										0.024 (0.065)
Slag_Lag_Strict_PA	0.001 (0.002)	0.001 (0.002)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.001 (0.003)
Slag_Lag_Large_PA		-0.002 (0.002)	0.0001 (0.003)	-0.0001 (0.003)	-0.0001 (0.003)	0.0002 (0.003)	0.0002 (0.003)	0.0002 (0.003)	0.0002 (0.003)	-0.001 (0.003)
Slag_Mine			3.561 (4.992)	3.476 (4.991)	3.747 (5.006)	3.074 (4.993)	3.110 (4.994)	3.060 (4.995)	3.103 (4.996)	2.688 (4.991)
Slag_Activity						7.415** (3.437)	7.422** (3.444)	7.611** (3.482)	7.575** (3.482)	14.986*** (4.449)
Slag_Temp							3.407 (16.162)	3.773 (16.189)	3.153 (16.219)	0.838 (16.194)
Slag_Rain								0.004 (0.009)	0.004 (0.009)	0.004 (0.009)
Slag_Fatalities									0.007 (0.014)	0.007 (0.014)
Slag_Pop										-0.131*** (0.049)
Lag_Strict_Pa x Mine				-0.008 (0.005)	-0.007 (0.005)	-0.007 (0.005)	-0.006 (0.005)	-0.006 (0.005)	-0.006 (0.005)	-0.007 (0.005)
Lag_Large_PA x Mine					0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
Slag_Lag_Strict_PA x Slag_Mine			-0.00005 (0.003)	-0.00002 (0.003)	-0.0001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.0004 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Slag_Lag_Large_PA x Slag_Mine			0.0005 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)

*** p<0.001, ** p<0.01, * p<0.05; standard errors in parentheses

Table A- 9. Akaike's information criterion (AIC) and Bayes' information criterion (BIC) : Comparison tests for models with and without spatially explanatory variables

Criteria	Model without spatially lagged independent variables	Model with spatially lagged independent variables
Loglik	-23671.29	-23664.48
AIC	49 222.58	49 224.96
BIC	55 066.72	55 118.84

Table A- 10. Marginal effects of covariates on deforestation focusing on Congo Basin countries; spatial autoregressive model without common factors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Direct		.	.	.	.	.	.	.
Lag_PA	-0.099 (0.134)	-0.094 (0.129)	-0.092 (0.126)	-0.079 (0.143)	-0.081 (0.130)	-0.089 (0.129)	-0.086 (0.128)	-0.086 (0.138)
Mine		14.734*** (5.617)	12.633** (5.869)	12.182* (6.064)	11.882** (6.298)	11.842** (6.032)	11.699** (5.511)	11.650* (6.663)
Lag_PAxMine			0.00291 (0.0036)	0.00293 (0.0040)	0.00299 (0.0035)	0.00297 (0.0035)	0.00286 (0.0036)	0.00286 (0.0034)
Activity				9.976 (7.569)	9.689 (7.163)	9.584 (7.110)	8.810 (7.615)	8.203 (7.884)
Temp					35.936* (20.353)	36.351* (19.726)	36.341* (20.502)	36.527* (19.347)
Rain						-0.0182 (0.0189)	-0.0180 (0.0170)	-0.0178 (0.0166)
Fatalities							-0.009 (0.0059)	-0.009 (0.0058)
Pop								0.035 (0.099)
Indirect		.	.	.	.	.	.	.
Lag_PA	-0.029 (0.0788)	-0.023 (0.0456)	-0.022 (0.047)	-0.020 (0.052)	-0.020 (0.053)	-0.024 (0.063)	-0.022 (0.053)	-0.022 (0.055)
Mine		3.550 (4.034)	2.987 (3.6413)	3.047 (3.415)	2.964 (3.826)	3.139 (4.013)	3.046 (3.689)	3.007 (3.284)
Lag_PAxMine			0.00068 (0.0013)	0.00073 (0.0017)	0.00074 (0.0013)	0.00079 (0.0017)	0.00075 (0.0015)	0.00074 (0.0015)
Activity				2.495 (3.604)	2.417 (3.854)	2.541 (4.044)	2.294 (3.8259)	2.117 (4.146)
Temp					8.964 (11.875)	9.637 (12.469)	9.462 (10.637)	9.426 (10.537)
Rain						-0.0048 (0.0089)	-0.0047 (0.0072)	-0.0046 (0.0071)
Fatalities							-0.0024 (0.0029)	-0.0024 (0.00313)
Pop								0.009 (0.041)
Total		.	.	.	.	.	.	.
Lag_PA	-0.128 (0.195)	-0.116 (0.165)	-0.114 (0.162)	-0.099 (0.187)	-0.10 (0.172)	-0.112 (0.177)	-0.109 (0.173)	-0.108 (0.183)
Mine		18.285** (8.132)	15.620* (8.193)	15.229* (8.351)	14.846* (8.962)	14.981* (8.661)	14.745* (8.0512)	14.657* (8.821)
Lag_PAxMine			0.0036 (0.0046)	0.0037 (0.0054)	0.0037 (0.0045)	0.0038 (0.0048)	0.0036 (0.0049)	0.0036 (0.0045)
Activity				12.472 (10.347)	12.106 (9.882)	12.125 (10.025)	11.104 (10.422)	10.320 (11.171)
Temp					44.901 (28.975)	45.99* (27.71)	45.803* (26.759)	45.954* (26.529)
Rain						-0.023 (0.0258)	-0.023 (0.0223)	-0.022 (0.0221)
Fatalities							-0.012 (0.0079)	-0.0116 (0.008)
Pop								0.0439 (0.134)

*** p<0.01, ** p<0.05, * p<0.10; standard errors in parentheses

Table A- 11. Marginal effects of covariates on deforestation, Heterogeneities; spatial autoregressive model without common factors

	Quality of institutions (Fatalities)		**Status of mines**
	Weak (1)	**Strong**	
	(1)	(2)	(3)
	Direct		
Lag_PA	-0.022 (0.018)	-0.023* (0.014)	-0.022* (0.012)
Mine	64.261*** (9.737)	42.238*** (6.719)	
Activity	12.0342** (5.511)	18.092*** (5.994)	15,075*** (4.854)
Temp	1.225 (8.267)	2.754 (6.477)	2,229 (5,976)
Rain	-0.0226 (0.014)	-0.00428 (0.010)	-0.011 (0.009)
Pop	0.040 (0.093)	-0.035 (0.113)	0.040 (0.079)
Lag_PA x Mine	-0.00112 (0.004)	-0.00117 (0.003)	
Pre_Operating Mine			52.182*** (7,531)
Fatalities			-0.009 (0.008)
Lag_PA×Pre_Operating mine			-0.0064 (0.004)
	Indirect		
Lag_PA	-0.064 (0.055)	-0.057* (0.035)	-0,063* (0.037)
Mine	189.263*** (38.570)	104.197*** (21.877)	.
Activity	35.444** (17.494)	44.631*** (16.094)	43.384*** (15.112)
Temp	3.607 (24.792)	6.793 (16.415)	6,415 -17,501
Rain	-0.067 (0.0439)	-0.010 (0.025)	-0.0308 (0.028)
Pop	0.118 (0.279)	-0.0872 (0.285)	0,115 (0.231)
Lag_PA×Mine	-0.0033 (0.0124)	-0.0029 (0.008)	.
Pre_Operating mine			150.177*** (28.404)
Fatalities			-0.026 (0.023)
Lag_PA×Pre_Operating mine			-0.0185 (0.012)
	Total		
Lag_PA	-0.085 (0.072)	-0.080* (0.049)	-0.084*** (0.049)
Mine	253.524*** (47.029)	146.434*** (27.74)	.
Activity	47.478** (22.868)	62.723*** (21.842)	58.459*** (19,792)
Temp	4.832 (33.022)	9.5461 (22.857)	8.644 (23,454)
Rain	-0.0892 (0.058)	-0.0146 (0.035)	-0,042 (0.037)
Pop	0.158 (0.371)	-0.123 (0.397)	0,155 (0.310)
Lag_PA x Mine	-0.0044 (0.0165)	-0.0041 (0.0115)	.
Pre_Operating mines			202,359*** (35,029)
Fatalities			-0.035 (0.030)
Lag_PA x Pre_Operating mines			-0.0133162 (0.016)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses

8 References

Adu, G. and Dramani, J.B. (2018) *Africa's mineral economies : breaking their dependence on mining*. Nordiska Afrikainstitutet. Available at: http://urn.kb.se/resolve?urn=urn:nbn:se:nai:diva-2217 (Accessed: 30 January 2023).

Aleman, J.C., Jarzyna, M.A. and Staver, A.C. (2018) 'Forest extent and deforestation in tropical Africa since 1900', *Nature Ecology & Evolution*, 2(1), pp. 26–33. Available at: https://doi.org/10.1038/s41559-017-0406-1.

Alvarez-Berríos, N.L. and Aide, T.M. (2015) 'Global demand for gold is another threat for tropical forests', *Environmental Research Letters*, 10(1), p. 014006. Available at: https://doi.org/10.1088/1748-9326/10/1/014006.

Amin, A. *et al.* (2019) 'Neighborhood effects in the Brazilian Amazônia: Protected areas and deforestation', *Journal of Environmental Economics and Management*, 93, pp. 272–288. Available at: https://doi.org/10.1016/j.jeem.2018.11.006.

Andam, K.S. *et al.* (2008) 'Measuring the effectiveness of protected area networks in reducing deforestation', *Proceedings of the National Academy of Sciences*, 105(42), pp. 16089–16094. Available at: https://doi.org/10.1073/pnas.0800437105.

Angelsen, A. (2001) 'Playing games in the forest: State-local conflicts of land appropriation', *Land Economics*, 77(2), pp. 285–299.

Austin, K.G. *et al.* (2019) 'What causes deforestation in Indonesia?', *Environmental Research Letters*, 14(2), p. 024007. Available at: https://doi.org/10.1088/1748-9326/aaf6db.

Azomahou, T.T. and Ouédraogo, M. (2021) *Strategic Environmental Commitment and Climate Change in Africa: Evidence on Mining and Deforestation*. African Economic Research Consortium. Available at: http://publication.aercafricalibrary.org/handle/123456789/2774 (Accessed: 30 January 2023).

Baltagi, B.H. (2021) *Econometric Analysis of Panel Data*. 6th edn. Cham: Springer International Publishing (Springer Texts in Business and Economics). Available at: https://doi.org/10.1007/978-3-030-53953-5.

Berman, N. *et al.* (2017) 'This Mine Is Mine! How Minerals Fuel Conflicts in Africa', *American Economic Review*, 107(6), pp. 1564–1610. Available at: https://doi.org/10.1257/aer.20150774.

Bouayad Agha, S., Le Gallo, J. and Védrine, L. (2018) 'Chapter 7 - Spatial econometrics on panel data', in *Handbook of spatial analysis: Theory and practical application with R*. INSEE & Eurostat, pp. 179–203. Available at: https://www.insee.fr/en/information/3635545.

Bowker, J.N. *et al.* (2017) 'Effectiveness of Africa's tropical protected areas for maintaining forest cover', *Conservation Biology*, 31(3), pp. 559–569. Available at: https://doi.org/10.1111/cobi.12851.

Brambor, T., Clark, W.R. and Golder, M. (2006) 'Understanding Interaction Models: Improving Empirical Analyses', *Political Analysis*, 14(1), pp. 63–82. Available at: https://doi.org/10.1093/pan/mpi014.

Brandt, J.S., Nolte, C. and Agrawal, A. (2016) ‘Deforestation and timber production in Congo after implementation of sustainable forest management policy’, *Land Use Policy*, 52, pp. 15–22. Available at: https://doi.org/10.1016/j.landusepol.2015.11.028.

Brandt, J.S., Nolte, C. and Agrawal, A. (2018) ‘Deforestation and timber production in Congo after implementation of sustainable management policy: A response to Karsenty et al. (2017)’, *Land Use Policy*, 77, pp. 375–378. Available at: https://doi.org/10.1016/j.landusepol.2018.04.056.

Bray, D.B. *et al.* (2008) ‘Tropical deforestation, community forests, and protected areas in the Maya Forest’, *Ecology and Society*, 13(2), p. 56.

Brueckner, J.K. (2003) ‘Strategic Interaction Among Governments: An Overview of Empirical Studies’, *International Regional Science Review*, 26(2), pp. 175–188. Available at: https://doi.org/10.1177/0160017602250974.

Brueckner, J.K. and Saavedra, L.A. (2001) ‘Do Local Governments Engage in Strategic Property—Tax Competition?’, *National Tax Journal*, 54(2), pp. 203–229. Available at: https://doi.org/10.17310/ntj.2001.2.02.

Busch, J. and Ferretti-Gallon, K. (2017) ‘What Drives Deforestation and What Stops It? A Meta-Analysis’, *Review of Environmental Economics and Policy*, 11(1), pp. 3–23. Available at: https://doi.org/10.1093/reep/rew013.

Butsic, V. *et al.* (2015) ‘Conservation and conflict in the Democratic Republic of Congo: The impacts of warfare, mining, and protected areas on deforestation’, *Biological Conservation*, 191, pp. 266–273. Available at: https://doi.org/10.1016/j.biocon.2015.06.037.

Buys, P. *et al.* (2009) ‘Determinants of a Digital Divide in Sub-Saharan Africa: A Spatial Econometric Analysis of Cell Phone Coverage’, *World Development*, 37(9), pp. 1494–1505. Available at: https://doi.org/10.1016/j.worlddev.2009.01.011.

Caballero Espejo, J. *et al.* (2018) ‘Deforestation and Forest Degradation Due to Gold Mining in the Peruvian Amazon: A 34-Year Perspective’, *Remote Sensing*, 10(12), p. 1903. Available at: https://doi.org/10.3390/rs10121903.

Chape, S. *et al.* (2005) ‘Measuring the extent and effectiveness of protected areas as an indicator for meeting global biodiversity targets’, *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1454), pp. 443–455. Available at: https://doi.org/10.1098/rstb.2004.1592.

Chen, X. and Nordhaus, W.D. (2011) ‘Using luminosity data as a proxy for economic statistics’, *Proceedings of the National Academy of Sciences*, 108(21), pp. 8589–8594. Available at: https://doi.org/10.1073/pnas.1017031108.

Chudik, A., Pesaran, M.H. and Tosetti, E. (2011) ‘Weak and strong cross-section dependence and estimation of large panels’, *The Econometrics Journal*, 14(1), pp. C45–C90. Available at: https://doi.org/10.1111/j.1368-423X.2010.00330.x.

Corrado, L. and Fingleton, B. (2012) ‘Where Is the Economics in Spatial Econometrics?’, *Journal of Regional Science*, 52(2), pp. 210–239. Available at: https://doi.org/10.1111/j.1467-9787.2011.00726.x.

Cropper, M., Puri, J. and Griffiths, C. (2001) ‘Predicting the Location of Deforestation: The Role of Roads and Protected Areas in North Thailand’, *Land Economics*, 77(2), pp. 172–186. Available at: https://doi.org/10.2307/3147088.

Edwards, D.P. *et al.* (2014) ‘Mining and the African Environment’, *Conservation Letters*, 7(3), pp. 302–311. Available at: https://doi.org/10.1111/conl.12076.

Eisler, R. (2004) ‘Mercury Hazards from Gold Mining to Humans, Plants, and Animals’, in *Reviews of Environmental Contamination and Toxicology*. New York, NY: Springer (Reviews of Environmental Contamination and Toxicology), pp. 139–198. Available at: https://doi.org/10.1007/0-387-21733-9_4.

Eisler, R. and Wiemeyer, S.N. (2004) ‘Cyanide Hazards to Plants and Animals from Gold Mining and Related Water Issues’, in G.W. Ware (ed.) *Reviews of Environmental Contamination and Toxicology*. New York, NY: Springer (Reviews of Environmental Contamination and Toxicology), pp. 21–54. Available at: https://doi.org/10.1007/978-1-4419-9100-3_2.

Elhorst, J.P. (2010) ‘Applied Spatial Econometrics: Raising the Bar’, *Spatial Economic Analysis*, 5(1), pp. 9–28. Available at: https://doi.org/10.1080/17421770903541772.

Fingleton, B. and Le Gallo, J. (2010) ‘Endogeneity in a Spatial Context: Properties of Estimators’, in A. Páez et al. (eds) *Progress in Spatial Analysis: Methods and Applications*. Berlin, Heidelberg: Springer (Advances in Spatial Science), pp. 59–73. Available at: https://doi.org/10.1007/978-3-642-03326-1_4.

Gabriel, K.R. and Sokal, R.R. (1969) ‘A New Statistical Approach to Geographic Variation Analysis’, *Systematic Biology*, 18(3), pp. 259–278. Available at: https://doi.org/10.2307/2412323.

Gaveau, D.L.A. *et al.* (2009) ‘Evaluating whether protected areas reduce tropical deforestation in Sumatra’, *Journal of Biogeography*, 36(11), pp. 2165–2175. Available at: https://doi.org/10.1111/j.1365-2699.2009.02147.x.

Geist, H.J. and Lambin, E.F. (2002) ‘Proximate causes and underlying driving forces of tropical deforestation’, *BioScience*, 52(2), pp. 143–150.

Gibbons, S. and Overman, H.G. (2012) ‘Mostly Pointless Spatial Econometrics?*’, *Journal of Regional Science*, 52(2), pp. 172–191. Available at: https://doi.org/10.1111/j.1467-9787.2012.00760.x.

Giljum, S. *et al.* (2022) ‘A pantropical assessment of deforestation caused by industrial mining’, *Proceedings of the National Academy of Sciences*, 119(38), p. e2118273119. Available at: https://doi.org/10.1073/pnas.2118273119.

González-González, A., Clerici, N. and Quesada, B. (2021) ‘Growing mining contribution to Colombian deforestation’, *Environmental Research Letters*, 16(6), p. 064046. Available at: https://doi.org/10.1088/1748-9326/abfcf8.

Hansen, M.C. *et al.* (2013) ‘High-Resolution Global Maps of 21st-Century Forest Cover Change’, *Science*, 342(6160), pp. 850–853. Available at: https://doi.org/10.1126/science.1244693.

Herrera, D., Pfaff, A. and Robalino, J. (2019) ‘Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian

Amazon', *Proceedings of the National Academy of Sciences*, 116(30), pp. 14916–14925. Available at: https://doi.org/10.1073/pnas.1802877116.

Heß, S., Jaimovich, D. and Schündeln, M. (2021) 'Environmental effects of development programs: Experimental evidence from West African dryland forests', *Journal of Development Economics*, 153, p. 102737. Available at: https://doi.org/10.1016/j.jdeveco.2021.102737.

Joppa, L.N. and Pfaff, A. (2010) 'Global protected area impacts', *Proceedings of the Royal Society of London B: Biological Sciences*, p. rspb20101713. Available at: https://doi.org/10.1098/rspb.2010.1713.

Joppa, L.N. and Pfaff, A.S.P. (2009) 'High and Far: Biases in the Location of Protected Areas', *PLoS ONE*, 4(12), p. e8273. Available at: https://doi.org/10.1371/journal.pone.0008273.

Karsenty, A. *et al.* (2008) 'Regulating industrial forest concessions in Central Africa and South America', *Forest Ecology and Management*, 256(7), pp. 1498–1508. Available at: https://doi.org/10.1016/j.foreco.2008.07.001.

Karsenty, A. *et al.* (2017) 'Deforestation and timber production in Congo after implementation of sustainable management policy: A reaction to the article by J.S. Brandt, C. Nolte and A. Agrawal (Land Use Policy 52:15–22)', *Land Use Policy*, 65(Supplement C), pp. 62–65. Available at: https://doi.org/10.1016/j.landusepol.2017.02.032.

Kéré, E.N. *et al.* (2017) 'Addressing Contextual and Location Biases in the Assessment of Protected Areas Effectiveness on Deforestation in the Brazilian Amazônia', *Ecological Economics*, 136, pp. 148–158. Available at: https://doi.org/10.1016/j.ecolecon.2017.02.018.

Knutsen, C.H. *et al.* (2017) 'Mining and Local Corruption in Africa', *American Journal of Political Science*, 61(2), pp. 320–334. Available at: https://doi.org/10.1111/ajps.12268.

Kotsadam, A. and Tolonen, A. (2016) 'African Mining, Gender, and Local Employment', *World Development*, 83, pp. 325–339. Available at: https://doi.org/10.1016/j.worlddev.2016.01.007.

LeSage, J. and Pace, R.K. (2009) *Introduction to Spatial Econometrics*. Boca Raton, FL: CRC Press Taylor & Francis (Statistics: Textbooks and Monographs).

Leuenberger, A. *et al.* (2021) 'Health impacts of industrial mining on surrounding communities: Local perspectives from three sub-Saharan African countries', *PLOS ONE*, 16(6), p. e0252433. Available at: https://doi.org/10.1371/journal.pone.0252433.

Maddox, T. *et al.* (2019) *Forest-Smart Mining. Identifying Factors Associated with the Impacts of Large-Scale Mining on Forests*. Washington D.C.: The World Bank. Available at: http://hdl.handle.net/10986/32025 (Accessed: 16 March 2023).

Mansourian, S. and Berrahmouni, N. (2021) *Review of Forest and Landscape Restoration in Africa 2021*. Accra: The Food and Agriculture Organization of the United Nations & the African Union Development Agency-NEPAD, p. 84. Available at: https://www.fao.org/documents/card/en?details=2d309fca-89be-481f-859e-72b27a3ea5dc/ (Accessed: 30 January 2023).

McGuirk, E.F. and Nunn, N. (2020) *Nomadic Pastoralism, Climate Change, and Conflict in Africa*. w28243. National Bureau of Economic Research. Available at: https://doi.org/10.3386/w28243.

McMillen, D.P. (2010) 'Issues in Spatial Data Analysis', *Journal of Regional Science*, 50(1), pp. 119–141. Available at: https://doi.org/10.1111/j.1467-9787.2009.00656.x.

Ndiaye, Y. (2018) 'Road tax interactions among local governments: a spatial panel data analysis of the French case over the period 1984–2000', *Applied Economics*, 50(38), pp. 4182–4196. Available at: https://doi.org/10.1080/00036846.2018.1441518.

Nelson, A. and Chomitz, K.M. (2011) 'Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods', *PLoS ONE*, 6(8), p. e22722. Available at: https://doi.org/10.1371/journal.pone.0022722.

Nolte, C. *et al.* (2013) 'Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon', *Proceedings of the National Academy of Sciences*, 110(13), pp. 4956–4961. Available at: https://doi.org/10.1073/pnas.1214786110.

Oliveira, P.J.C. *et al.* (2007) 'Land-Use Allocation Protects the Peruvian Amazon', *Science*, 317(5842), pp. 1233–1236. Available at: https://doi.org/10.1126/science.1146324.

Pesaran, M.H. (2006) 'Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure', *Econometrica*, 74(4), pp. 967–1012. Available at: https://doi.org/10.1111/j.1468-0262.2006.00692.x.

Pesaran, M.H. (2015) 'Testing Weak Cross-Sectional Dependence in Large Panels', *Econometric Reviews*, 34(6–10), pp. 1089–1117. Available at: https://doi.org/10.1080/07474938.2014.956623.

Peterson, G.D. and Heemskerk, M. (2001) 'Deforestation and forest regeneration following small-scale gold mining in the Amazon: the case of Suriname', *Environmental Conservation*, 28(2), pp. 117–126. Available at: https://doi.org/10.1017/S0376892901000121.

Pfaff, A. *et al.* (2014) 'Governance, Location and Avoided Deforestation from Protected Areas: Greater Restrictions Can Have Lower Impact, Due to Differences in Location', *World Development*, 55, pp. 7–20. Available at: https://doi.org/10.1016/j.worlddev.2013.01.011.

Pfaff, A. *et al.* (2015) 'Protected area types, strategies and impacts in Brazil's Amazon: public protected area strategies do not yield a consistent ranking of protected area types by impact', *Phil. Trans. R. Soc. B*, 370(1681), p. 20140273. Available at: https://doi.org/10.1098/rstb.2014.0273.

Pfaff, A.S.P. *et al.* (2009) 'Park Location Affects Forest Protection: Land Characteristics Cause Differences in Park Impacts across Costa Rica', *The B.E. Journal of Economic Analysis & Policy*, 9(2). Available at: https://doi.org/10.2202/1935-1682.1990.

Prem, M., Saavedra, S. and Vargas, J.F. (2020) 'End-of-conflict deforestation: Evidence from Colombia's peace agreement', *World Development*, 129, p. 104852. Available at: https://doi.org/10.1016/j.worlddev.2019.104852.

Ranjan, R. (2019) 'Assessing the impact of mining on deforestation in India', *Resources Policy*, 60, pp. 23–35. Available at: https://doi.org/10.1016/j.resourpol.2018.11.022.

Ritchie, H., Spooner, F. and Roser, M. (2022) *Biodiversity*, *Our World in Data*. Available at: https://ourworldindata.org/biodiversity (Accessed: 30 January 2023).

Robalino, J. *et al.* (2015) 'Evaluating Interactions of Forest Conservation Policies on Avoided Deforestation', *PLoS ONE*, 10(4), p. e0124910. Available at: https://doi.org/10.1371/journal.pone.0124910.

Robalino, J., Pfaff, A. and Villalobos, L. (2017) 'Heterogeneous Local Spillovers from Protected Areas in Costa Rica', *Journal of the Association of Environmental and Resource Economists*, 4(3), pp. 795–820. Available at: https://doi.org/10.1086/692089.

Rudel, T.K. (2013) 'The national determinants of deforestation in sub-Saharan Africa', *Phil. Trans. R. Soc. B*, 368(1625), p. 20120405. Available at: https://doi.org/10.1098/rstb.2012.0405.

Schwartz, S. *et al.* (2022) 'Optimal protected area implementation under spillover effects', *Resource and Energy Economics*, 68, p. 101284. Available at: https://doi.org/10.1016/j.reseneeco.2022.101284.

Shi, W. and Lee, L. (2018) 'A spatial panel data model with time varying endogenous weights matrices and common factors', *Regional Science and Urban Economics*, 72, pp. 6–34.

Siqueira-Gay, J. and Sánchez, L.E. (2021) 'The outbreak of illegal gold mining in the Brazilian Amazon boosts deforestation', *Regional Environmental Change*, 21(2), p. 28. Available at: https://doi.org/10.1007/s10113-021-01761-7.

Solé Ollé, A. (2003) 'Electoral accountability and tax mimicking: the effects of electoral margins, coalition government, and ideology', *European Journal of Political Economy*, 19(4), pp. 685–713. Available at: https://doi.org/10.1016/S0176-2680(03)00023-5.

Sonter, L.J. *et al.* (2017) 'Mining drives extensive deforestation in the Brazilian Amazon', *Nature Communications*, 8(1), p. 1013. Available at: https://doi.org/10.1038/s41467-017-00557-w.

Swenson, J.J. *et al.* (2011) 'Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports', *PLOS ONE*, 6(4), p. e18875. Available at: https://doi.org/10.1371/journal.pone.0018875.

Tritsch, I. *et al.* (2020) 'Do forest-management plans and FSC certification help avoid deforestation in the Congo Basin?', *Ecological Economics*, 175, p. 106660. Available at: https://doi.org/10.1016/j.ecolecon.2020.106660.

Weisse, M.J. and Naughton-Treves, L.C. (2016) 'Conservation Beyond Park Boundaries: The Impact of Buffer Zones on Deforestation and Mining Concessions in the Peruvian Amazon', *Environmental Management*, 58(2), pp. 297–311. Available at: https://doi.org/10.1007/s00267-016-0709-z.