Global Development Policy Center

GCI WORKING PAPER 036 • 05/2024

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Direct Impacts and Spatial Spillovers

THE IMPACT OF CHINESE INFRASTRUCTURE PROJECTS ON ECONOMIC ACTIVITIES IN SUB-SAHARAN AFRICA

BY YAN WANG AND YINYIN XU

ABSTRACT

This working paper focuses on the impact of Chinese infrastructure projects on economic activities in local jurisdictions in sub-Saharan Africa (SSA). Our theoretical framework is based on theories of economic geography and public economics. Chinese infrastructure projects are defined as infrastructure projects in the recipient countries that are financed by China's two major development financial institutions, the China Development Bank and Export-Import Bank of China, in the sectors of power, transportation, telecommunications, water and wastewater. We use satellite-collected spatial distribution of nighttime light as a proxy for economic activity at the second subnational level. A panel dataset of 4,385 second-order administrative regions (municipalities equivalent) in 48 SSA countries from 2008-2021 has been compiled using spatial analysis tools in ArcGIS Pro. The aspatial and

Acknowledgments: The authors are grateful to Kevin Gallagher, Bill Kring, Rebecca Ray, Hongbo Yang, John Carruthers, Ding Fei and colleagues at the Boston University Global Development Policy for comments and suggestions, and to Yanze Yang for research assistance at an early stage. Any errors or omissions are entirely the responsibility of the authors.

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spatial econometrics analysis reports that the existence of Chinese infrastructure projects leads to increased economic activities proxied by nighttime luminosity and notable positive spillovers in neighboring jurisdictions. The existence of at least one Chinese infrastructure project in a second sub-national region (or an equivalent administrative region) in SSA is associated with a roughly 5 percentage point direct increase in nighttime luminosity and about 10-15 percentage increase in nighttime luminosity as the indirect impact in the region. These impacts are statistically positive and significant after controlling for multiple factors, whereas World Bank projects in the region do not show a significant association with the nighttime luminosity increase in the micro-regions.

Keywords: Chinese infrastructure investments, sub-Saharan Africa, nighttime luminosity, spatial spillovers

INTRODUCTION

Amid a weak and uneven economic recovery in the Global South, regional development and infrastructure investment seem to be critical to sustainable development. In particular, infrastructure provision is seen as an "unmissable driver for development" in the sub-Saharan Africa (SSA) region (World Bank, 2019). Aside from institutional reasons, physical infrastructure is critical in facilitating market integration and freeing the lagged regions from the poverty trap (Sachs, 2003). Thus, in many SSA countries, regional development goals are often associated with the public infrastructure provision to benefit the lagged regions by increasing productivity and promoting welfare. Due to inadequate savings in these low-income countries, most infrastructure in the region is co-financed by multilateral or bilateral development finance institutions (DFIs).

Over the past 20 years, China has grown to be the largest financier and constructor of infrastructure in SSA. An International Monetary Fund (IMF) report recognized that Chinese loans to SSA, mostly to finance public infrastructure projects, have risen rapidly in the region over the past two decades (IMF, 2023). However, China's involvement in SSA is often associated with controversies and misconceptions, as the design and delivery of Chinese overseas infrastructure projects differs from those of Western donors and multilateral development banks (MDBs). China is often criticized by the West for creating a "debt traps" for recipient countries and for being "profit-seeking" given the mega-scale of the committed projects.

Until recently, however, spatial analysis on the footprints and impacts of these infrastructure investments has been limited largely to low transparency on detailed project-level data. Two newly published geolocated evidence-based datasets on China's overseas development finance provide the basis for spatial analysis of the Chinese overseas infrastructure investment footprints: the Boston University Global Development Policy Center's China's Overseas Development Finance (CODF) Database[1] and AidData's Global Chinese Development Finance Dataset at the College of William & Mary. Comparatively, the CODF Database provides more credibility, while the AidData database suffers from a lack of double verification. The double verification is necessary in the context of China's overseas development finance because of the "ambiguous classification" of the nation's overseas actors[2] and the over-counting rooted in the low transparency in information disclosure. (Brautigam,

[1] The periods covered by the two geocoded databases are different. The AidData geolocated database covers 2000-2014, while the CODF Database covers 2008-2021.

[2] Usually, these include state-owned enterprises, provincial-supported enterprises and private firms. Such classification does not fit within the conventional definition and system of development finance established by Western donors.

2011; Xu, 2023) Given the unavailability of official data, only limited research has examined the empirical impact of the Chinese infrastructure projects that have been committed. The majority of the studies focused on the allocation patterns compared to the Western donors (see Horn et al., 2021 for an example).

This working paper focuses on the impact of Chinese infrastructure projects on economic activity in local jurisdictions in SSA using aspatial and spatial econometrics models. Our theoretical framework is based on theories of economic geography and public economics. Based on the CODF Database dataset, Chinese infrastructure projects are defined as infrastructure projects in the recipient countries that are financed by China's two major DFIs, the China Development Bank (CDB) and the Export-Import Bank of China (CHEXIM), in the sectors of power, transportation, telecommunications, water and wastewater. We compiled a large panel dataset of 4,385 second-order administrative regions (ADM2, which is equivalent to municipalities) in 48 SSA countries from 2008-2021 using spatial analyst tools in ArcGIS Pro.

After our previous study examined the question of whether these investment projects have addressed infrastructure bottlenecks in relevant host countries (Wang and Xu 2023), we ask two questions here: have the geocoded investment projects directly impacted the local economic activities in SSA? Are there spatial spillover effects from those infrastructure projects across regional borders?

This working paper contributes to existing research in three aspects. First, it provides empirical evidence on the direct impacts of Chinese infrastructure investment on economic activities at the second-subnational level in the SSA region. Second, based on spatial modeling, we account for the spatial spillovers of such micro-regional impacts. Third, this study uses the geocoded project with double-verification, which enhances the credibility of the results. In addition, the impact of mega projects committed during the Belt and Road Initiative (BRI) decade is also examined empirically.

Following a brief review of the literature, we discuss a conceptual framework linking the home region and non-home regions by drawing on the New Economic Geography. The third section provides a description of data and methodology, a review of methodology-related literature, and a descriptive analysis; while the fourth section discusses the empirical strategy to identify the direct impacts and spatial spillovers and estimate the magnitudes of such impacts. The fifth section presents the results from the aspatial analysis and the spatial econometrics modeling, while the sixth section summarizes the empirical results and provides policy implications.

LITERATURE REVIEW AND THE CONCEPTUAL FRAMEWORK

At the national level, Chinese development cooperation projects from 2000-2014 are found to improve recipient countries' economic performance in the region. Given that the CODF Database dataset was released recently, most past studies have used the AidData dataset for empirical analysis, despite its potential shortcomings. Most studies focused on the overall impact of China's development cooperation projects on economic development at the country level and provided positive estimated results (Dreher et al., 2021; Xu and Zhang, 2022). Another group of researchers attempted to understand the underlying mechanism by investigating the intertwined relationship between trade, aid, employment and foreign investments from the perspective of structural transformation (Zafar, 2017; Guo et al., 2022). None of these papers, however, have studied the spatial impact at the micro-regional levels, i.e., administrative levels below the national level.

The impact of these investments at the local, i.e., sub-national or lower levels, is less studied. The Africa's Urbanisation Dynamics report recognized that "urbanisation in Africa contributes to better economic outcomes and higher standards of living" (AfDB, 2022). Does the existence of Chinese infrastructures increase economic activities at the local level in the region? Unlike most studies that focus on estimating the overall impact at the national level in recipient countries, this working paper is primarily interested in the distributive effects at the second sub-national level. For comparability[3], we arbitrarily use the second-order administrative (ADM2) regions as the spatial unit of the baseline analysis. Except for the theoretical reasons to be discussed in the next section, we use the second sub-national region as the spatial unit for the following technical reasons.

The spatial precision level of the geocoded Chinese projects is based on administrative divisions. Based on the methodological guidebook of the CODF Database dataset (Ray et al., 2021), the precision level of the location data is based on administrative divisions (sub-national and second sub-national levels). The highest level of spatial precision is the exact project footprint, and the next level of precision is potentially suffering from the mislocating error within a 25 kilometer (km) radius. The second-order administrative division stands for the level-3 precision. Table 1 displays the various spatial precision levels of geolocated Chinese infrastructure projects. If we use the cell or hexagonal grid as the spatial unit, we will have to omit all the other projects except those with the exact locations documented (223 of 295 projects). Omitting 25 percent of the projects could lead to serious omitted variable bias in the empirical testing.

Table 1: Precision Levels of Geolocated Chinese Infrastructure Projects

Precision Level Code	Spatial Precision Description
1	Exact
2	Within 25 km
3	Second-order administrative division
4	First-order administrative division
5	Spanning multiple first-order administrative divisions
6	Country
7	Unknown

Source: Authors, based on Ray et al., 2021.

For the purpose of this study, the satellite-collected spatial distribution of nighttime light is used as a proxy for economic activity at the second sub-national level, following Henderson et al. (2012). The original purpose of utilizing the nighttime light intensity data by many researchers was to measure the income level for regions with weak statistical capacity (Sutton et al., 2007; Henderson et al., 2012, 2018). However, considering the recent finding that the nighttime luminosity growth elasticities concerning many socio-economic variables are low and unstable in within-country analysis (Addison and Stewart, 2015), we see the nighttime luminosity as a proxy for the distribution of economic activities rather than evidence for economic development.[4]

The second sub-national region is a suitable geographical unit to capture the effects on economic activity using remote-sensing data. The key dependent variable, the nighttime light intensity index, is suggested to be used at the second sub-national level or above in economics studies. Some scholars in remote sensing have noted that there could be an endogenous "bottom coding" problem with

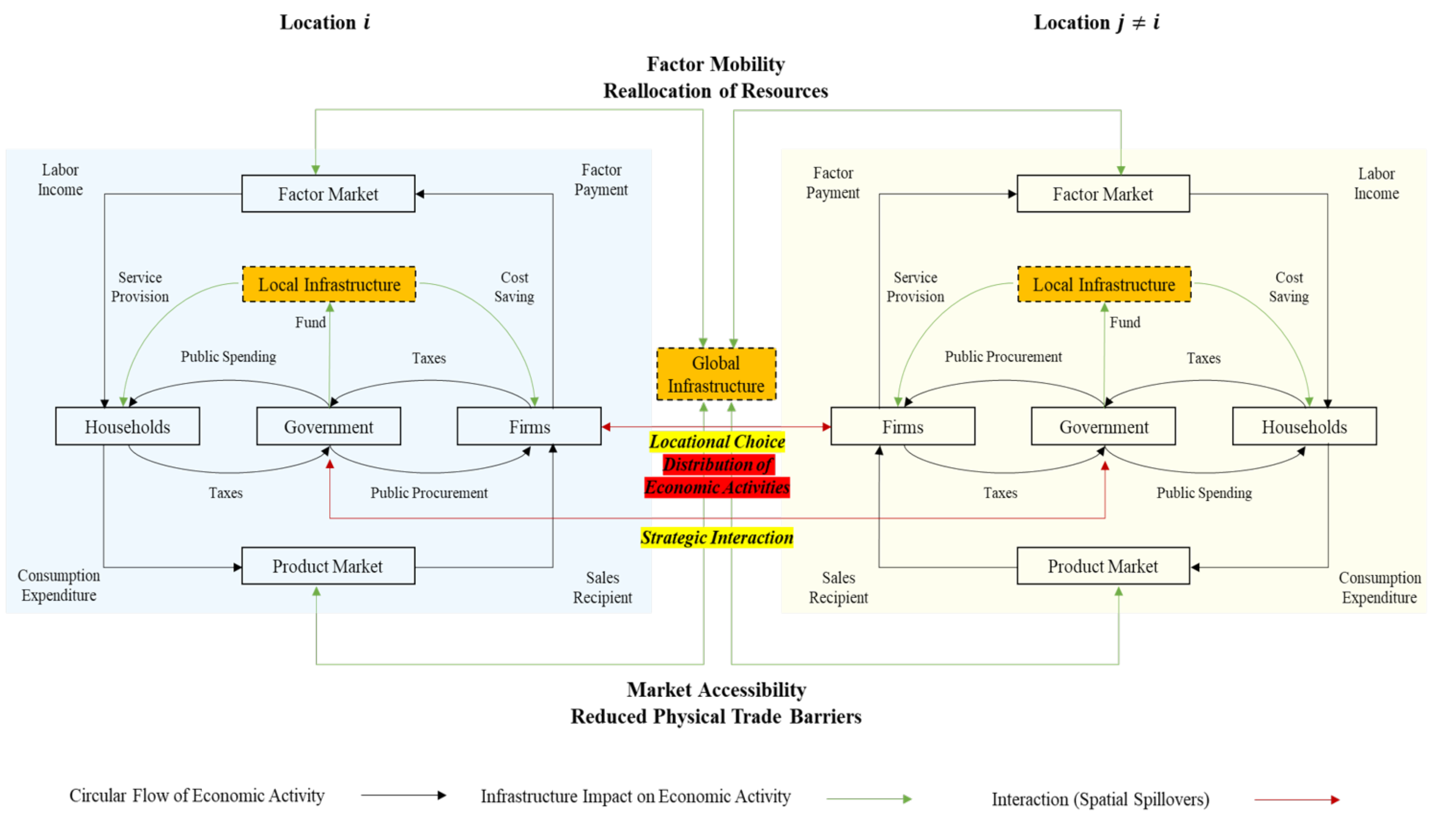
[3] The national definitions of urban vs. rural areas differ significantly from each other, which hinders the comparability of the analysis. Also, the same level of administrative level may account for the homogeneity in public goods or services provision, i.e., infrastructure.

[4] The intuition behind our empirical design is similar to that of Bluhm et al. (2020), who focused on the dispersion of economic activities within the ADM1 regions as a result of the existence of Chinese transportation infrastructure projects.

the nighttime light intensity data (particularly for the satellite-collected data). The "bottom coding" problem results in emitting or weak luminosity signals as the geographical units decrease. Such "measurement error" could be even worse in cross-sectional analyses (Chen and Nordhaus, 2015; Gibson et al., 2021). However, this is not yet widely recognized by economists. Also, it is more difficult to control for the other confounding factors at the even higher spatial resolution level, as it requires high-resolution spatial data by nature. Also, most conventional socio-economic indicators have been collected through the Census, for which the spatial unit is based on jurisdictions.

Attempting to examine the direct and indirect impacts on micro-regional economic activity distribution, we develop the theoretical model based on the New Economy Geography (NEG) (Krugman 1991a and b), as illustrated in Figure 1. According to the NEG, the accessibility to spatially dispersed markets drives the locational choices of households (consumers) and firms. Such accessibility is measured by the costs faced by the economic agents in the exchange process (Fujita and Thisse, 2002, 2009). Contrary to neoclassical models, the cost to access the spatially dispersed markets is inevitable, given the fact that the economic activities are not perfectly divisible. Thus, the spaces are ultimately heterogeneous, and the agglomeration is observable (Starrett, 1978). Fujita and Thisse (2009, p.109) summarized that "the emergence of economic agglomeration is naturally associated with the emergence of inequalities across locations."

Figure 1: Illustration of the Direct Impacts and Spatial Spillovers in a Two-locality Scenario



Source: Authors' elaboration, inspired by Behrens et al., 2007.

The infrastructures increase the agglomeration of economic activities at the local level through two channels in terms of the firms' locational choices for production: cost-saving and market-seeking (Krugman, 1998). The infrastructure can benefit a region by increasing its attractiveness and accessibility to firms. For example, transportation infrastructure facilitates factor mobility for production (i.e., labor and capital), reducing transportation costs, promoting trade and market integration, and increasing economic activities (Rietveld, 1999). Thus, changes in infrastructure improve the market potential of a particular region so that it can attract economic activities. Meanwhile, the relationship between infrastructure and regional development is a multi-dimensional phenomenon. Improved infrastructure provisions do not guarantee that the region will become more attractive, as network externalities can be negative due to the loss of markets amid increasing competition. Also, in real-world settings, different types of infrastructures often co-exist as a system and bring synergetic effects. The resulting equilibrium distribution of firms across regions arises from a balancing of agglomeration and dispersion forces, which is affected by the provision of infrastructure.

Local governments play a critical role in promoting infrastructure financing. Infrastructure investment is one form of public spending, and the local government retains the ownership of infrastructure assets. Infrastructure is critical for providing local public goods. Meanwhile, infrastructure projects are expensive assets to "purchase" and build, and local governments must be careful to balance such borrowing with their attendant fiscal responsibilities. Despite the emerging trend of "integrated construction and operation" in Chinese overseas infrastructure project delivery for risk-bearing concerns (Zhang, 2023), local governments own these infrastructure projects. The location choice of Chinese infrastructure projects can be a bottom-up merger by the local government or top-down strategic planning by the central government. Most projects have been committed through "sovereign guarantee" loans[5] or open competition in the recipient country.

The strategic interactions among local governments also promote "cross-border" spillovers. According to the public spending theory, strategic interactions among local governments occur because the market environment in which local policy decisions are made is affected by the actions of other local governments. In other words, policy choices are interdependent and local governments often compete with and learn from each other. Empirical work has generally proved the existence of such strategic interactions from the perspective of tax competition, welfare competition, and benefit spillovers. (Brueckner, 1998, 2003) In terms of our research interest in infrastructure, local governments' decisions in funding infrastructures can directly affect the welfare of residents in neighboring jurisdictions, as well as expenditures on public goods and services whose benefits transcend borders.

DATA DESCRIPTION

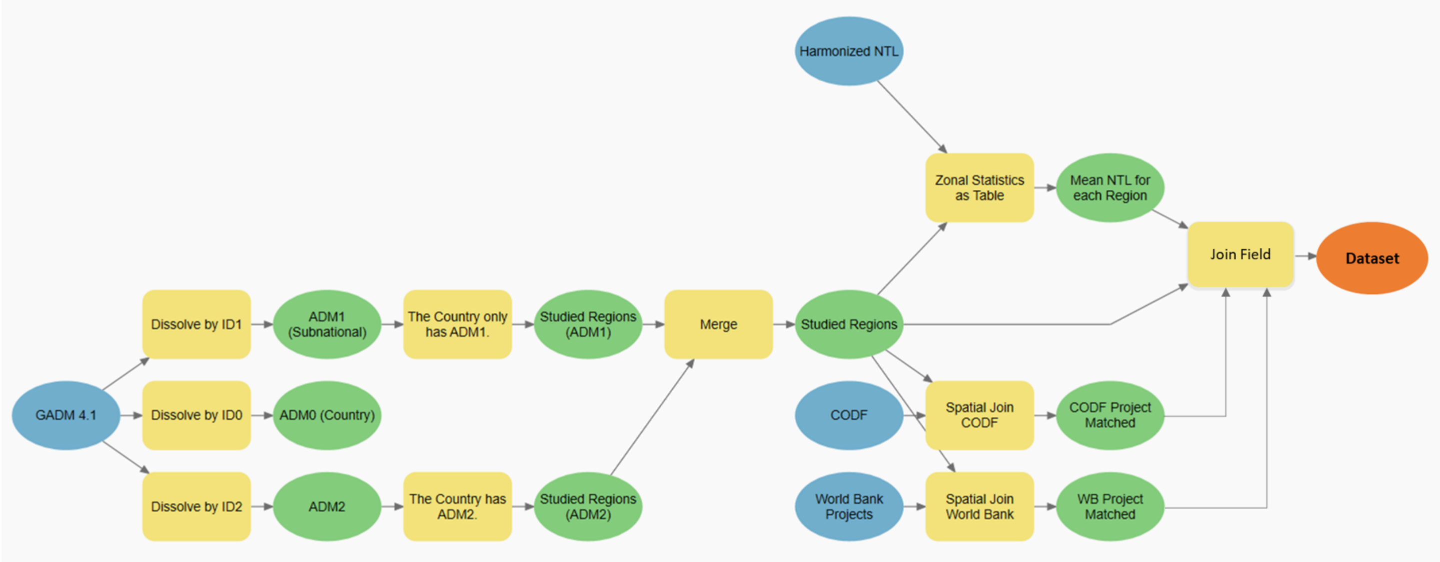
Three geoprocessing steps have been taken to formalize a panel dataset covering 2008-2021. The first step was determining the study's spatial unit and formalizing a base shapefile for analysis. The second step was transforming the satellite-collected raster data, the key dependent variable, nighttime light intensity, into computable numeric data for each studied region. The last step was to match Chinese infrastructure projects to the pre-determined studied regions. Additional data is collected for geocoded World Bank-financed development projects and other variables for future research purposes and robustness checks. All the map projections are set to World Geodetic System 1984 by default. The geospatial methodology is illustrated in Figure 2[6].

Spatial Units. The spatial unit in this study is the second-order administrative (ADM2) regions in 48 SSA countries, i.e., two levels below the national level, equivalent to municipalities or cities in most developing countries (or US county equivalent). The spatial scope of the research is indicated in Figure A1. The raw data of the administrative region boundaries is obtained from the Database

[5] The "sovereign guarantee" loans usually happen when the recepient country has a infrastructure project to be funded and a Chinese company offers to build the project with a Chinese bank providing financing for the project. The process is similar to the Design-Build-Finance (DBF) model of project delivery.

[6] The spatial correlation is not included in the illustration but tested for spatial modeling preparation. In addition, the one-to-one spatial join was used because many projects are co-located in various regions.

Figure 2: Geoprocessing Steps, Simplified



Source: Authors' elaboration, developed using ArcGIS Pro ModelBuilder and minor edits for illustration purposes.

of Global Administrative Areas (GADM) vector dataset (version 4.1) released on July 16, 2022, the latest version at the time of this empirical analysis. Each data record in the raw dataset of GADM is at the lowest administrative level available in each country. By dissolving, the country level (ADM0), sub-national level (ADM1) and second-order administrative level (ADM2) shapefiles were obtained for analysis. In addition, GADM only includes the ADM1 level boundary data for five countries (Cabo Verde, Comoros, Lesotho, Mauritius and Seychelles)[7], and this study follows Dreher et al. (2019) to use ADM1 regions for these countries instead. The combined boundary shapefile covers 4,358 studied regions in 708 ADM1 regions in 48 SSA countries.

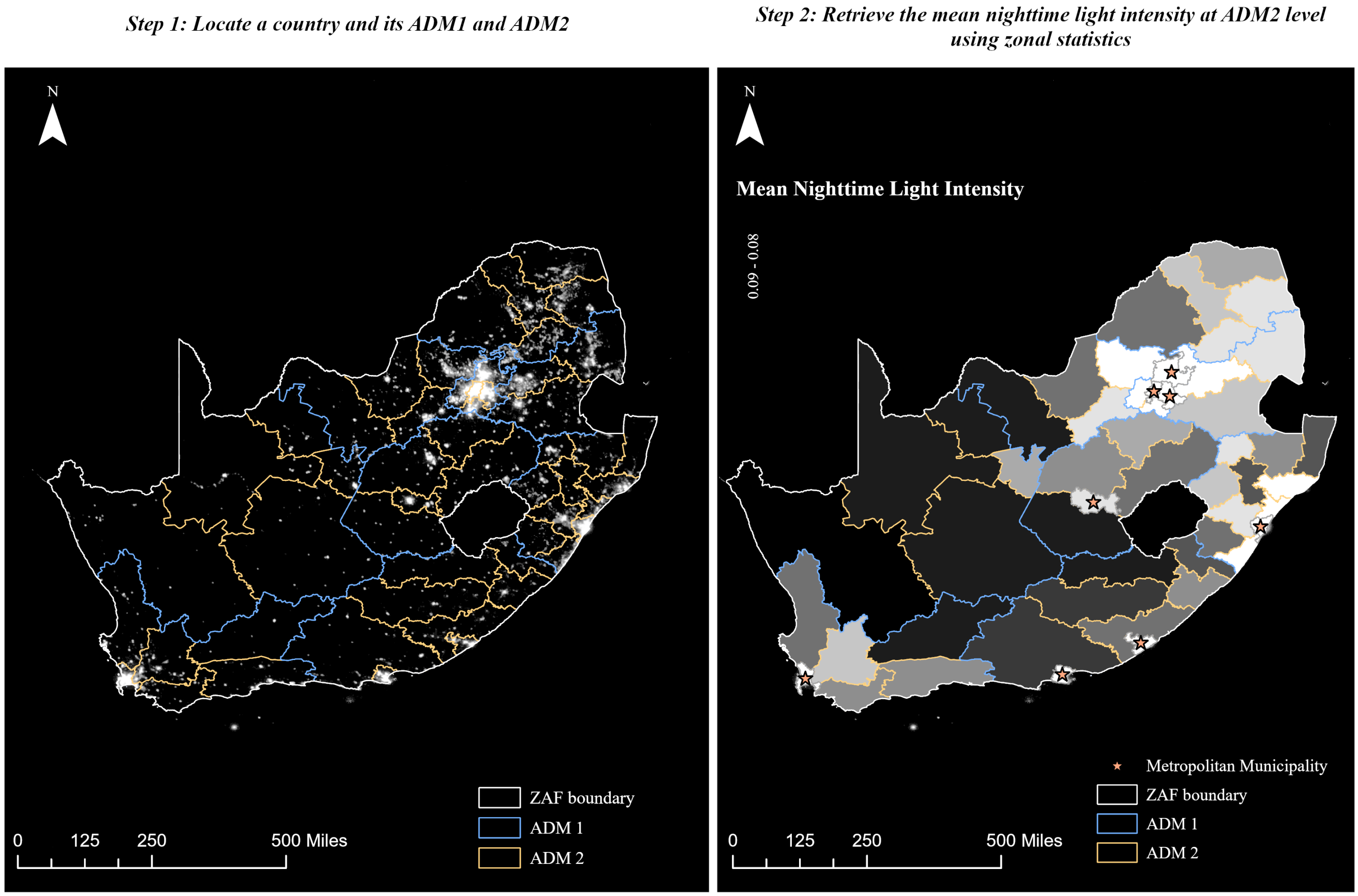
Dependent Variable. This study uses the nighttime light intensity as a proxy for local economic activity. The data is from the harmonized global nighttime light dataset by Li et al. (2020) and the most updated version, 8.0, archived in the online repository. The harmonized dataset was generated with data from the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership satellite. Their dataset has a comprehensive annual coverage from 1992-2021 with a 30 arc-second resolution, composited from monthly observations after eliminating the noises caused by aurora and temporal lights. However, researchers also noted that this data lacks a comprehensive means of ground-truthing (Ru et al., 2022). The data generation process uses ArcGIS Pro software with the spatial analyst tool "Zonal Statistics." The mean statistic is used following Henderson et al. (2018). Thus, the nighttime light intensity statistic (nighttime luminosity hereafter) calculated for each studied region $\boldsymbol{i}$ is a product of population distribution and nighttime light per capita, i.e.,

$$luminosity = \frac{Nighttime\ light\ intensity_i}{Area_i} = \frac{Population_i}{Area_i} \times \frac{Nighttime\ light\ intensity_i}{Population_i}.$$

See Figure 3 for an example of the geoprocessing of South Africa in 2000 and Figure A5 for an example of nighttime luminosity for the studied regions in selected years.

[7] No earlier literature merges shapefiles from other sources. Usually, researchers choose to omit these countries in the analysis.

Figure 3: Utilizing Zonal Statistics to Quantify the Nighttime Luminosity: South Africa 2000



Source: Authors' elaboration, based on Li et al. (2020) and GADM 4.1. The projection is World Geodetic System 1984.

The distribution of the economic activities in the region, proxied by the nighttime luminosity, has gradually changed over the past two decades. In the first period from 2000 -2010, Southern Africa was home to the most significant economic activities. The spatial distribution became comparatively more dispersed in the second period from 2011-2020, with more "lighter" areas detectable in Western and Eastern Africa.

Explanatory Variable. The key explanatory variable of concern is the Chinese infrastructure projects in SSA countries. This study utilizes the geocoded CODF Database dataset for tracking Chinese infrastructure projects in SSA. Only projects with geolocation at a precision level of 1-3, i.e., the geocoding error not exceeding the second-level administrative areas (ADM2), are included for the empirical analysis, which is also the spatial unit of this study (See Ray et al., 2021 for technical documentation of this dataset). A total of 295 infrastructure projects were committed in 36 SSA countries in the sectors of power, telecommunication, transport, and water and wastewater, between 2008-2020, as displayed in Table 2 and Figure 3. These infrastructure projects had a total committed loan amount of over $67 billion. The spatial distribution of these projects is shown in Figure A2, and the distribution by sector is shown in Figure A3.

Table 2: Chinese Infrastructure Projects in SSA with Precision Level 1-3, by Sector

Sector	No. of Projects	Loan Amount ($ Million)
Power[8]	76	25764.82
Telecom	23	2560.60
Transportation	165	35460.02
Water and Wastewater	31	3760.40
Total	295	67545.84

Source: Authors' elaboration, based on Decomposition Analysis of the CODF Database, version 2.0.

All projects are then matched to the boundary shapefile of 4,358 studied regions with the analysis tool "Spatial Join." It is important to note that some Chinese infrastructure projects are co-located in various regions, and some regions have received more than one project during the observed period. These 295 committed projects span 929 studied regions over the observed period. Given that a time lag of three years is adopted to account for the difference between the commitment year and the completion year empirically (to be discussed in detail in the following section, the econometrics analysis is only able to examine the impact of 258 projects from 2008-2017 spanning 272 studied regions. These 258 projects include 69 power projects, 18 telecommunication projects, 143 transportation projects and 28 water and wastewater projects, spanning 727 studied regions over the observed period, as seen in Table 3.

Table 3: Chinese Infrastructure Projects in SSA with Precision Level 1-3, Impact Analyzed, by Sector

Sector	No. of Projects	Loan Amount ($ Million)
Power	69	22298.82
Telecom	18	1689.6
Transportation	143	31649.02
Water and Wastewater	28	3129.4
Total	258	58766.84

Source: Authors' elaboration, based on Decomposition Analysis of the CODF Database, version 2.0.

World Bank Projects Pre-existence. China is not the only development cooperation partner in SSA's regional development. Scholars have found that there is interaction between Chinese donors and traditional Western donors in locating the development cooperation projects at the aggregated national level (Kilama, 2016; Hernandez, 2017; Zeitz, 2021). Regardless of the nature of these interactions, competing or collaborating, it is necessary to account for the activities of the traditional donors in the region. Given that the geolocation for projects by individual Western donors is not available, the geocoded World Bank projects are used considering the representative and similar aid eligibility criteria. A similar geoprocessing was done for the World Bank projects (Yang et al., 2023)[9] as the CODF Database dataset infrastructure projects, for which the spatial distribution is shown in Figure A4.

[8] One project in Rwanda, "Nyabarongo 2 Hydropower Plant (43.5MW); Transmission Line (110kV)," has been mistakenly geocoded in the current 2.0 of CODF, thus not included in the analysis.

[9] We thank Hongbo Yang for sharing World Bank project data.

Spatial Weighting. Inspired by LeSage (2014) on identification problems for parameterized decay, this study uses sparse weight matrices, i.e., the k-nearest neighbors, when defining the spatial weighting matrices. First, the internal point of each studied region is generated along with the coordinates using the World Geodetic System 1984 as the spatial reference system. Second, the arc distances in kilometers are calculated for each studied region pair. Third, the k-nearest neighbors are identified based on the closest distances. The spatial weights matrix used in this study is $N \times N$ matrix, $W_{ij} = 1$ if i and j are defined as neighbors, and 0 otherwise. $W_{ii} = 0$ since one spatial unit cannot be its own neighbor.

The descriptive statistics are provided in Table 4.

Table 4: Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Observations
$\boldsymbol{Nighttime\ Light\ Intensity}$	4.733	9.950	0	63	61,012
$\Delta \ln (NTL_{ist} + 0.01)$	0.217	1.034	-6.8	6.7	61,012
$CHN_{ijs,t-3}$	0.305	1.276	0	10	61,012
$\Delta CHN_{is,t-3}$	0.073	0.260	0	1	61,012
$WB_{ijs,t-4}$	0.599	1.681	0	9	61,012
$\Delta WB_{is,t-4}$	0.152	0.359	0	1	61,012
$\Delta Power_{is,t-3}$	0.014	0.118	0	1	61,012
$\Delta Telecom_{is,t-3}$	0.039	0.194	0	1	61,012
$\Delta Transport_{is,t-3}$	0.022	0.147	0	1	61,012
$\Delta Water_{is,t-3}$	0.006	0.079	0	1	61,012

Source: Authors' elaboration.

EMPIRICAL STRATEGY

Step 1: Generalized Difference-in-Difference

In order to answer the question of whether Chinese infrastructure projects increase economic activities in SSA's second sub-national level regions, a generalized difference-in-difference (DID) model has been developed. The empirical model is given as follows:

Equation 1:

$$\ln(NTL_{ist} + 0.01) = \alpha\, CHN_{is,t-3} + \beta\, WB_{is,t-4} + \theta_i + \vartheta_p \times T + \delta_i \times T + \omega_{st} + \varepsilon_{ist} \qquad (1)$$

Where NTL_{ist} is the nighttime luminosity in the studied region i in subnational region p in county s at time t. We added 0.01 to NTL_{ist} before the logarithm transformation for interpretation convenience and the fact that the luminosity index can possibly be 0 empirically. $CHN_{is,t-3}$ is the number of elapsed years in which there is at least one Chinese infrastructure project committed by $t-3$. The three-year time lag accounts for the difference between the project completion year and the commitment year. The CODF Database dataset does not provide information on the completion year, and the average difference between the project completion and commitment year of infrastructure projects during the observed period of 2008-2020 is three and a half years using AidData's Global

Chinese Development Finance Dataset, Version 3.0. Similarly, $WB_{is,t-4}$ is the number of elapsed years in which there is at least one World Bank project committed by $t-4$. The four-year time lag is to account for the difference between the project completion year and the commitment year, which is determined based on the sub-sample average of four and a half years with the available completion year documented. The inclusions of $WB_{is,t-4}$ is to control for the potential impact of Western donors' development cooperation activities in the studied regions. θ_i is the studied region fixed effect. $\boldsymbol{T}$ is the linear time trend, and $\vartheta_p \times T$ and $\delta_i \times T$ are the sub-national level and studied region-specific linear time trends, respectively. ω_{st} is the country-year fixed effect which accounts for the shock to all the regions in a country in a particular year. ε_{ist} is the error term.

In order to estimate the parameters of interest in a panel setting, the following first difference model (Eq.2) is used for analysis:

$$\Delta CHN_{is,t-3} = CHN_{is,t-3} - CHN_{is,t-4}\,,$$

which is thus a binary variable indicating the existence of at least one committed project in region $\boldsymbol{i}$ in year $t-3$. The interpretation is the same for the World Bank project existence, $\Delta WB_{is,t-4}$ equal to 1 if there is at least one committed project in region $\boldsymbol{i}$ in year $t-4$. However, given the lack of information on the size of each project, i.e., the targeted beneficiary population, the model cannot identify the heterogeneous impact of different projects of various sizes.

Equation 2:

$$\boldsymbol{\Delta \ln (NTL_{ist} + 0.01) = \alpha\, \Delta CHN_{is,t-3} + \beta\, \Delta WB_{is,t-4} + \vartheta_p + \delta_i + \omega_{st} + \tilde{\varepsilon}_{ist}} \quad (2)$$

The studied region fixed effect θ_{ijs} is differenced out in the first differences. $\vartheta_p = \vartheta_p \times T - \vartheta_p \times (T-1)$ and $\delta_i = \delta_i \times T - \delta_i \times (T-1)$, now capture the sub-national level fixed effect and the studied region fixed effect, respectively. $\widetilde{\omega}_{st} = \omega_{st} - \omega_{st-1}$ is the new set of country-year fixed effect.

The expected sign for α is positive and statistically significant if the hypothesis that the existence of Chinese infrastructure projects increases economic activities in SSA second sub-national level regions holds.

Additionally, another set of models is estimated to study the sector-specific impact of Chinese infrastructure projects on economic activity. The first differences model for the sectoral heterogeneity study is as follows:

Equation 3:

$$\boldsymbol{\Delta \ln(NTL_{ist} + 0.01) = \alpha_s\, \Delta Sector_{is,t-3} + \alpha_o\, \Delta Other_{is,t-3} + \beta\, \Delta WB_{is,t-4} + \vartheta_p + \delta_i + \tilde{\omega}_{st} + \tilde{\varepsilon}_{ist}} \quad (3)$$

Where $\Delta Sector_{is,t-3}$ is a binary variable indicating the existence of at least one committed project in a particular sector in the studied region $\boldsymbol{i}$ in year $t-3$. $\Delta Other_{is,t-3}$ accounts for the pre-existence of projects in other sectors. The sectors considered are power, telecommunications, water and wastewater, and transport.

Step 2: Spatial Spillovers: A Spatial Econometrics Model

The study first examines whether there are spatial spillover effects not captured by the aspatial model. Two sets of tests are conducted to validate the existence of spatial spillovers (see Chi and Zhu, 2008). First, Moran's Index (Eq.4) is computed for the outcome variable from 2008-2021 based on the predefined neighbor rules, i.e., k-nearest neighbors. The statistically significant Moran's Index signifies the existence of spatial autocorrelation of the dependent variable. Second, the residuals of the first-difference model (Eq.3) are obtained after the statistical analysis. Moran's Index is computed for the residuals. Similarly, suppose the Moran's Index for the residuals is statistically significant. In that case, the aspatial model fails to capture the spatial spillovers in the model, which could result in bias in the estimation because of the omitted variables.

Equation 4:

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \text{ where } S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \text{ and } z_i = x_i - \bar{X} \quad (4)$$

Given that the study is particularly interested in the spatial spillover effects of Chinese infrastructure investment, the spatial Durbin Linear model (spatially lagged X, SLX) has been adopted for empirical analysis (see Rüttenauer, 2022 for a technical reason):

Equation 5:

$$\Delta \ln(NTL_{ist} + 0.01) = \alpha\,\Delta CHN_{is,t-3} + \alpha_s \sum_{J\neq I}^{N} W_{ij} \times \Delta CHN_{is,t-3} + \beta_s \sum_{J\neq I}^{N} W_{ij} \times \Delta WB_{is,t-4} + \vartheta_p + \delta_i + \widetilde{\omega}_{st} + \tilde{\varepsilon}_{ist} \quad (5)$$

The expected sign for α_s is positive and statistically significant if the hypothesis holds that Chinese infrastructure projects have positive spatial spillover effects on economic activities in SSA second sub-national level regions.

RESULTS

Aspatial DID model

Table 5 reports the ordinary least squares (OLS) estimated baseline results on the relationship between Chinese infrastructure projects and economic activities in SSA countries. Column 1 reports all-project results, while columns 2-5 report the sectoral heterogenous impacts. In the baseline analysis, the standard errors are clustered at the country level to allow for spatial and temporal correlation among different studied regions within a country.

Table 5: Estimated Results for Eq. (2) and (3)

		Sectoral Heterogeneity			
	(1) All	(2) Power	(3) Telecom	(4) Transport	(5) Water
Chinese Project	0.063** (0.025)	0.019 (0.038)	0.095*** (0.027)	0.066** (0.033)	0.133*** (0.040)
World Bank Project	-0.003 (0.014)	-0.001 (0.014)	-0.002 (0.014)	-0.001 (0.014)	0.000 (0.014)
Other Sector Controlled	-	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y
Subnational level FE	Y	Y	Y	Y	Y
Studied Region FE	Y	Y	Y	Y	Y
Adjusted R^2	0.385	0.385	0.385	0.385	0.385
Observations	61012	61012	61012	61012	61012

Source: Authors' elaboration.

Note: *** p<.01, ** p<;.05, * p<;.1; standard errors clustered at country level, reported in parentheses.

In summary, the existence of Chinese infrastructure projects led to increased economic activities proxied by the nighttime luminosity. The existence of at least one Chinese infrastructure project in a second sub-national region (or an equivalent administrative region) in SSA is associated with a 6.3 percentage point increase in nighttime luminosity. However, it is essential to note that the coefficient estimated with the aspatial model can be ultimately biased due to omitted variables controlling for indirect spatial spillovers.

There is sectoral heterogeneity in the magnitude of the impact. The power projects have a relatively limited impact compared to the projects in other sectors. This could be partly due to the fact that among the 69 power projects examined in the empirical analysis, 27 were transmission projects. In addition, the renewable energy plants might be located in non-residential or less populated areas with favorable geographical attributes. The water projects have the most significant impact compared to other sectors. Such a significant impact could be caused by the water scarcity in the region and the pressing need for water-related projects at the local level. The existence of at least one water and wastewater project in an SSA second sub-national region is associated with a 13.3 percentage points increase in its nighttime luminosity. The existence of at least one telecommunication and transport project in an SSA second national level region is associated with 9.5 and 6.6 percentage points increase in its nighttime luminosity, respectively .

Spatial Spillover

Indentification of the Spatial Spillover. In the baseline model specification, the standard errors are clustered at the country level to allow for the spatial correlation within the country. However, the global Moran's Index calculated for the nighttime luminosity using the different spatial relationship specifications provides evidence for spatial correlation of the dependent variable. In addition, the reported statistically significant and positive Moran's Index of the baseline aspatial model residuals indicates that the aspatial model suffers from the omitted variable bias (Table 6), i.e., not taking the spatial spillovers into account.

The magnitude of the Spatial Spillover. Table 7 reports the estimation result of the SLX, i.e., Eq. 5, with different spatial model specifications. Two neighbor rules are used, i.e., five nearest neighbors (columns 2 in Table 7) and 10 nearest neighbors (columns 3 in Table 7), identified by the distance of internal points of each studied region. The coefficient for the spatially weighted Chinese infrastructure projects is statistically significant and positive. The estimation is robust using different neighbor rules and various SDM specifications. The empirical results validate the hypothesis that Chinese infrastructure projects have positive spillovers in second sub-national jurisdictions in the SSA region. The empirical estimation does not provide enough evidence to conclude the spatial spillover effects of the World Bank-funded projects. The existence of at least one Chinese infrastructure project in a second sub-national region (or an equivalent administrative region) in SSA is associated with a roughly 5 percentage point direct increase in nighttime luminosity and about 10-15 percentage increase in nighttime luminosity as the indirect impact in the region.

Table 6: Moran's Index of the Dependent variable and Baseline Aspatial Model Residuals, Various Neighbor Rules Specified, Estimation Method: Eq.4

Year	Neighbor Rule: Nearest 5 neighbors		Neighbor Rule: Nearest 10 neighbors	
	NTL	Residuals	NTL	Residuals
2008	0.7776***	0.1061***	0.6505***	0.0908***
2009	0.7781***	0.0999***	0.6548***	0.0919***
2010	0.7758***	0.0977***	0.6501***	0.0984***
2011	0.7800***	0.0810***	0.6575***	0.0765***
2012	0.7828***	0.0836***	0.6613***	0.0739***
2013	0.7821***	0.0772***	0.6607***	0.0772***
2014	0.7702***	0.1520***	0.6519***	0.1288***
2015	0.7694***	0.0644***	0.6510***	0.0587***
2016	0.7735***	0.0473***	0.6550***	0.0439***
2017	0.7796***	0.0678***	0.6669***	0.0544***
2018	0.7816***	0.0935***	0.6740***	0.0803***
2019	0.7691***	0.1332***	0.6630***	0.0952***
2020	0.7677***	0.0817***	0.6618***	0.0596***
2021	0.7670***	0.0421***	0.6660***	0.0361***

Source: Authors' elaboration. Calculated with GeoDa.

Note: p-value is calculated from 999 permutations with the Monte Carlo method for each specified neighbor rule scenario. Distances are calculated using the census-reported internal points in the provided shapefile. The distance matric is set as Arc Distance (km) as the layer is projected in WGS 1984. Residuals used are obtained from the baseline aspatial model using robust standard errors. *** p<.01, ** p<;.05, * p<;.1.

Table 7: Estimated Results for Eq. (2) and (5)

	Aspatial	Spatial Durbin Linear model	
	(1)	(2)	(3)
Chinese Project	0.063** (0.025)	0.048*** (0.012)	0.048*** (0.012)
World Bank Project	-0.003 (0.014)	-0.003 (0.011)	-0.003 (0.011)
Spatially Weighted Chinese Project	-	0.107*** (0.025)	0.146*** (0.033)
Spatially Weighted World Bank Project	-	-0.018 (0.022)	-0.019 (0.028)
Country-Year FE	Y	Y	Y
Subnational level FE	Y	Y	Y
Studied Region FE	Y	Y	Y
Adjusted R^2	0.385	0.424	0.424
Observations	61012	61012	61012
Neighbor Rule	-	5 nearest	10 nearest

Source: Authors' elaboration.

Note: *** p<.01, ** p<;.05, * p<;.1; standard errors clustered at country level for aspatial model and robust standard errors for spatial model specifications, reported in parentheses. Column 1 reports the aspatial model, columns 2-3 report the spatial model using the five nearest neighbors as the neighbor rule, and columns 4-5 using the 10 nearest neighbors as the neighbor rule. The spatial weight is row-standardized.

CONCLUSION AND POLICY RECOMMENDATIONS

Our empirical results provide evidence that Chinese infrastructure projects increase economic activities in the second sub-national level regions in SSA through both direct impacts and spatial spillovers. After controlling for World Bank projects' existence, country, sub-national region and time effects, these effects are positive and statistically significant. The quantitative results are consistent with the reality that the region faces serious infrastructure gaps. Chinese infrastructure projects play a critical role in narrowing the gaps, which further facilitates urban development, unlocks the development potential and sustains economic growth in the long term. Necessary infrastructure is an important public good and is critical in reducing firms' production and transaction costs, which simultaneously support local employment.

To accurately gauge the impact of Chinese infrastructure projects in recipient countries, it is crucial to consider spatial spillovers. Empirical findings confirm that such spillover effects in various spatial model specifications while controlling for the Western donors' behaviors in the region, rigorous fixed effects, etc. Previous studies that failed to include the spatial factors in the empirical estimation models may have underestimated the total impacts.

A limitation is that this study only focuses on one aspect of economic activities measured by night-time luminosity; it cannot replace detailed project-by-project monitoring and evaluation using other indicators at completion and the impact evaluation five years after completion. To ensure an optimal balance of high quality and efficiency, monitoring and evaluation of these projects are crucial, with mandatory ex-post, mid-term and impact assessments for mega-projects in infrastructure. Other socio-environmental indicators can be used in future studies. It is worth noting that infrastructure projects have both local and "cross-border" effects, which must be kept in mind. It is not our intention to test the hypothesis of whether these projects help the agglomeration or dispersion of economic activities, which is clearly beyond the scope of this study.

Admittedly, as a development partner, China is still on an upward learning curve to deliver high-quality development cooperation projects, and its institutions need to be established and its capacity strengthened. As a responsible development partner and financier, China should fully utilize its resources and build capacity in high-quality cooperative project management. The Chinese government and DFIs need to work with established MDBs on monitoring and evaluation, and build awareness and technical capacity in independent evaluation.

Considering the Forum on China-Africa Cooperation planned for later this year, it is high time to recognize the direct and spillover impact of infrastructure investment. The stakeholders have the incentives to bring the issue of promoting results-based project management to the agenda, completing the project supply chains with quality control and strengthening accountability. From a practical perspective, we recommend promoting the international consultancy sector, which can be established as a measure of creating a new engine of high-quality growth for the BRI, generating jobs for educated youth in China and Africa, and serving the global development agenda for a green and sustainable future.

REFERENCES

AfDB. 2022. *Africa's Urbanisation Dynamics 2022—The economic power of Africa's cities*. African Development Bank Group. Available at: https://www.afdb.org/en/documents/africas-urbanisation-dynamics-2022-economic-power-africas-cities.

AidData. 2023. *Global Chinese Development Finance Dataset, Version 3.0*. Retrieved from https://www.aiddata.org/data/aiddatas-global-chinese-development-finance-dataset-version-3-0.

Behrens, K., Ottaviano, G.I.P., Mion, G., 2007. Industry Reallocations in a Globalizing Economy. *SSRN CORE Discussion Paper #2007/12*.

Boston University Global Development Policy Center. 2023. *China's Overseas Development Finance Database*. Retrieved from http://www.bu.edu/gdp/chinas-overseas-development-finance/.

Brautigam, D. 2010. *The Dragon's Gift: The Real Story of China in Africa*. Oxford University Press.

Brueckner, J.K., 2003. Strategic Interaction Among Governments: An Overview of Empirical Studies. *International Regional Science Review*, 26, 175–188.

Brueckner, J.K., 1998. Testing for Strategic Interaction Among Local Governments: The Case of Growth Controls. *Journal of Urban Economics*, 44, 438–467.

Chen, X., & Nordhaus, W. 2015. A Test of the New VIIRS Lights Data Set: Population and Economic Output in Africa. *Remote Sensing*, 7(4), Article 4.

Chi, G., Zhu, J., 2008. Spatial Regression Models for Demographic Analysis. *Population Research and Policy Review*, 27, 17–42.

Dreher, A., Fuchs, A., Hodler, R., Parks, B. C., Raschky, P. A., & Tierney, M. J. 2019. African leaders and the geography of China's foreign assistance. *Journal of Development Economics*, 140, 44–71.

Dreher, A., Fuchs, A., Parks, B., Strange, A., & Tierney, M. J. 2021. Aid, China, and Growth: Evidence from a New Global Development Finance Dataset. *American Economic Journal: Economic Policy*, 13(2), 135–174.

Fujita, M., Thisse, J.-F., 2009. New Economic Geography: An appraisal on the occasion of Paul Krugman's 2008 Nobel Prize in Economic Sciences. *Regional Science and Urban Economics*, 39, 109–119.

Fujita, M., Thisse, J.-F., 2002. *Economics of Agglomeration: Cities, Industrial Location, and Regional Growth*. Cambridge University Press.

Gibson, J., Olivia, S., Boe-Gibson, G., & Li, C. 2021. Which Night Lights Data Should We Use in Economics, and Where? *Journal of Development Economics*, 149, 102602.

Guo, S., An, J., & Jiang, H. 2022. Chinese Aid and Local Employment in Africa. *SSRN 3718578*.

Henderson, J. V., Squires, T., Storeygard, A., & Weil, D. 2018. The Global Distribution of Economic Activity: Nature, History, and the Role of Trade1. *The Quarterly Journal of Economics*, 133(1), 357–406.

Henderson, J. V., Storeygard, A., & Weil, D. N. 2012. Measuring Economic Growth from Outer Space. *American Economic Review*, 102(2), 994–1028.

IMF. 2023. *Regional Economic Outlook*. IMF. Retrieved 8 December, 2023, available at: https://www.imf.org/en/Publications/REO.

Krugman, P. 1991a. *Geography and Trade*. Cambridge: MIT Press.

Krugman, P. 1991b. Increasing Returns and Economic Geography. *Journal of Political Economy*, 99, 483-499.

Krugman, P., 1998. What's new about the new economic geography? *Oxford Review of Economic Policy*, 14, 7–17.

LeSage, J.P., 2014. What Regional Scientists Need to Know About Spatial Econometrics. *SSRN 2420725*.

Li, X., Zhou, Y., Zhao, M., & Zhao, X. 2020. A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, 7(1), Article 1.

Ray, R., Gallagher, K. P., Kring, W., Pitts, J., & Simmons, B. A. 2021. Geolocated dataset of Chinese overseas development finance. *Scientific Data*, 8(1), Article 1.

Rietveld, P. 1989. Infrastructure and regional development. *The Annals of Regional Science*, 23(4), 255–274.

Ru, Y., Haile, B., & Carruthers, J. I. 2022. Urbanization and child growth failure in Sub-Saharan Africa: A geographical analysis. *Journal of Geographical Systems*, 24(3), 441–473.

Rüttenauer, T., 2022. Spatial Regression Models: A Systematic Comparison of Different Model Specifications Using Monte Carlo Experiments. *Sociological Methods & Research*, 51, 728–759.

Xu, Z., & Zhang, Y. 2022. Lightening up Africa: The effects of Chinese aid on the economic development in Africa. *China Economic Quarterly International*, 2(3), 178–189.

Xu, Y. 2017. *China, Africa and Responsible International Engagement*. Routledge.

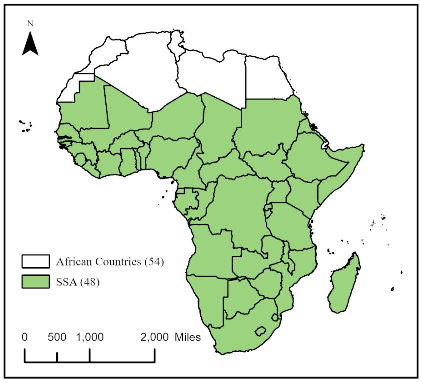
Yang, H., Simmons, B. A., Ray, R., Nolte, C., Gopal, S., Ma, Y., Ma, X., & Gallagher, K. P. 2021. Risks to global biodiversity and Indigenous lands from China's overseas development finance. *Nature Ecology & Evolution*, 5(11), Article 11.

Zafar, A. 2007. The Growing Relationship Between China and Sub-Saharan Africa: Macroeconomic, Trade, Investment, and Aid Links. *The World Bank Research Observer*, 22(1), 103–130.

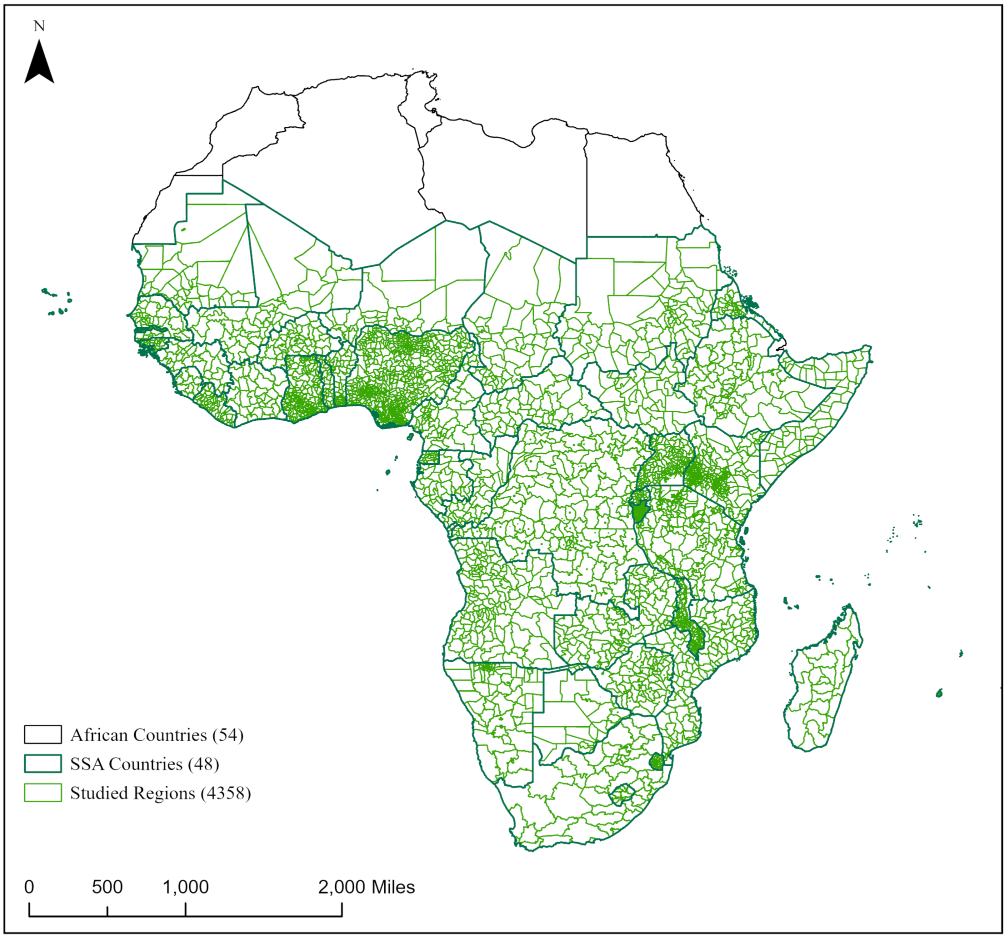
Zhang, Z. 2023. From Contractors to Investors? Evolving Engagement of Chinese State Capital in Global Infrastructure Development and the Case of Lekki Port in Nigeria. *Working Paper No. 2023/53*. China Africa Research Initiative, School of Advanced International Studies, Johns Hopkins University, Washington, DC. Available at: http://www.sais-cari.org/publications.

APPENDIX

Figure A1: Spatial Scope of the Study: Studied Regions in Sub-Saharan Africa Countries

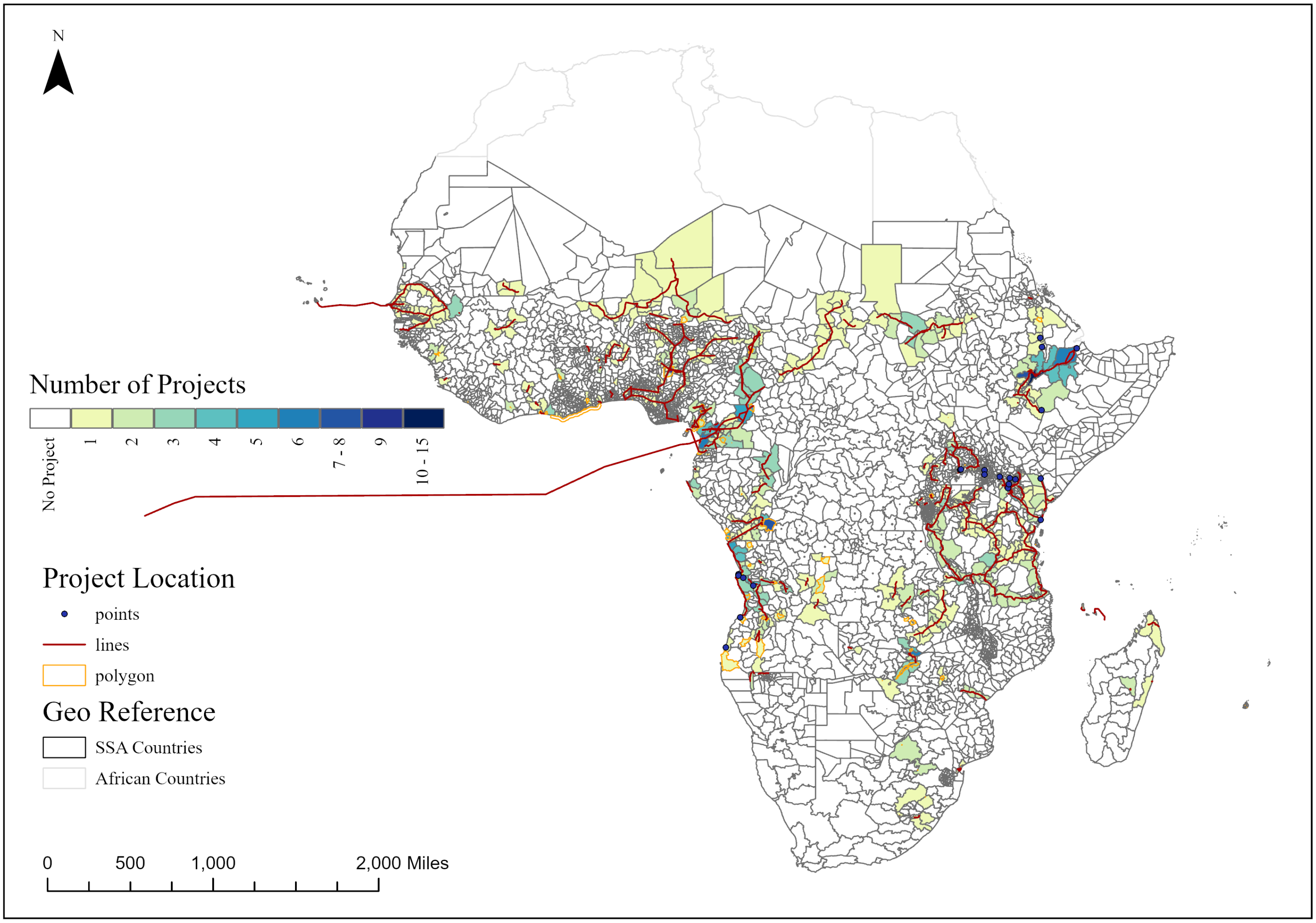


Note:
We followed the World Bank definitions that Djibouti is not included in Sub-Saharan Africa, as it is handled administratively as part of the Middle East and North Africa. Western Sahara is not recognized as a sovereign state.
Number of observations is provided in the parentheses.



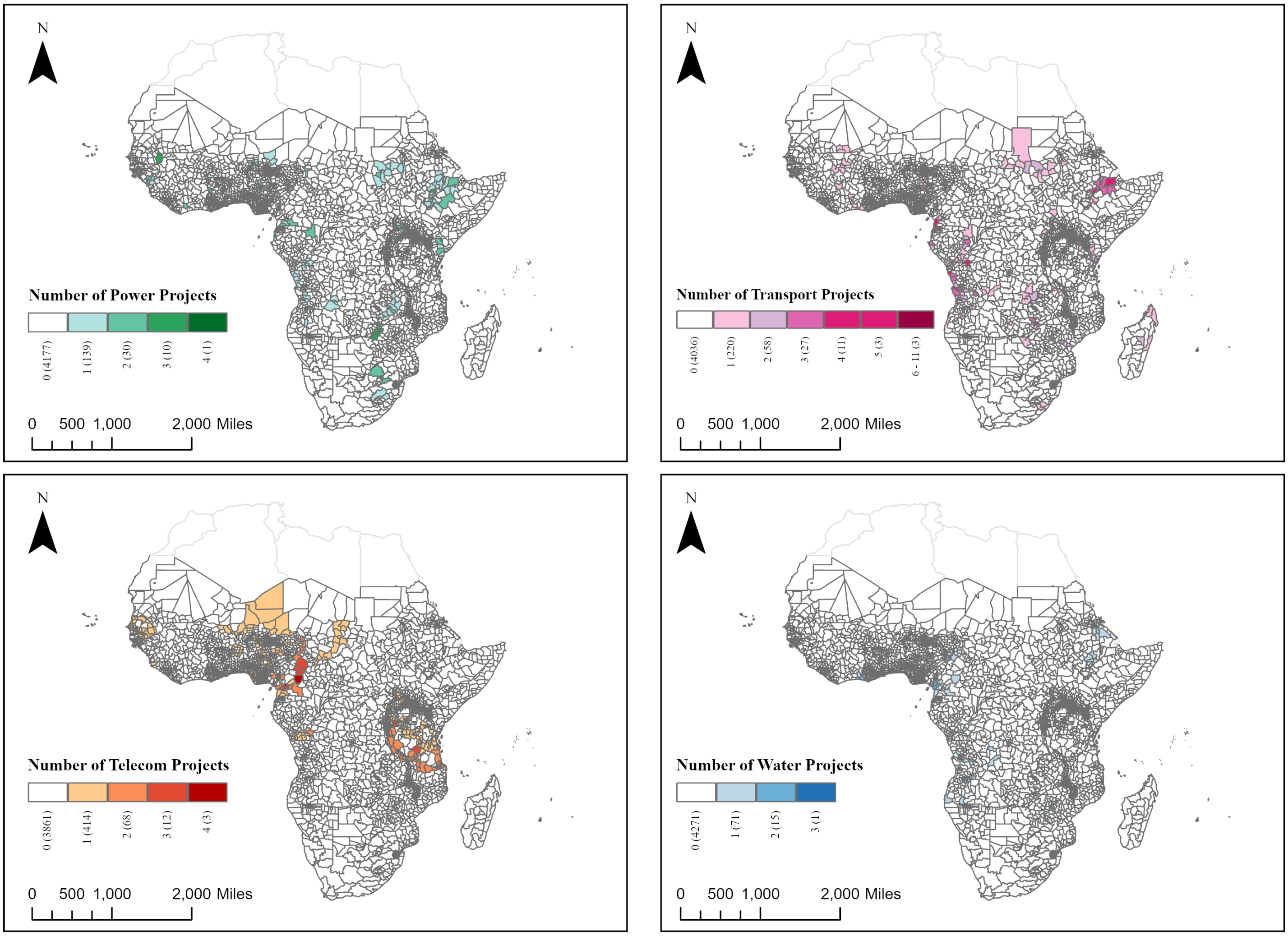
Source: Authors' elaboration, GADM version 4.1. The projection is World Geodetic System 1984.

Figure A2: Existence of CODF Hard Infrastructure Projects with Precision Level of 1-3 in SSA Countries



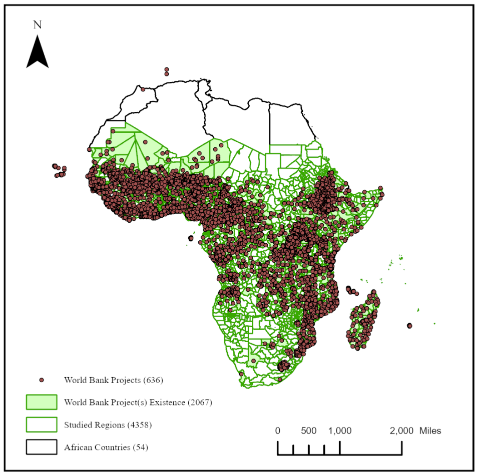
Source: Authors' elaboration, GADM version 4.1, CODF version 2.0. The projection is World Geodetic System 1984.

Figure A3: Existence of CODF Hard Infrastructure Projects in SSA Countries, by Sector

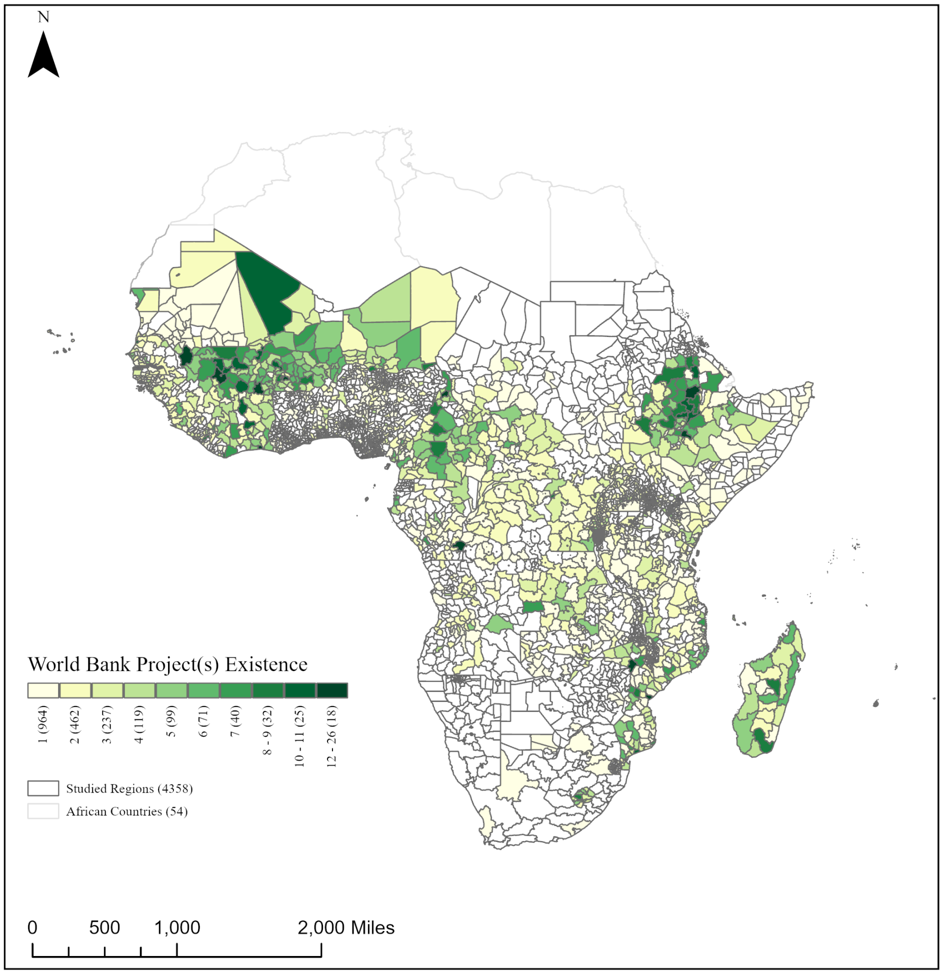


Source: Authors' elaboration, GADM version 4.1, CODF version 2.0. The projection is World Geodetic System 1984.

Figure A4: Existence of World Bank Projects in SSA Countries

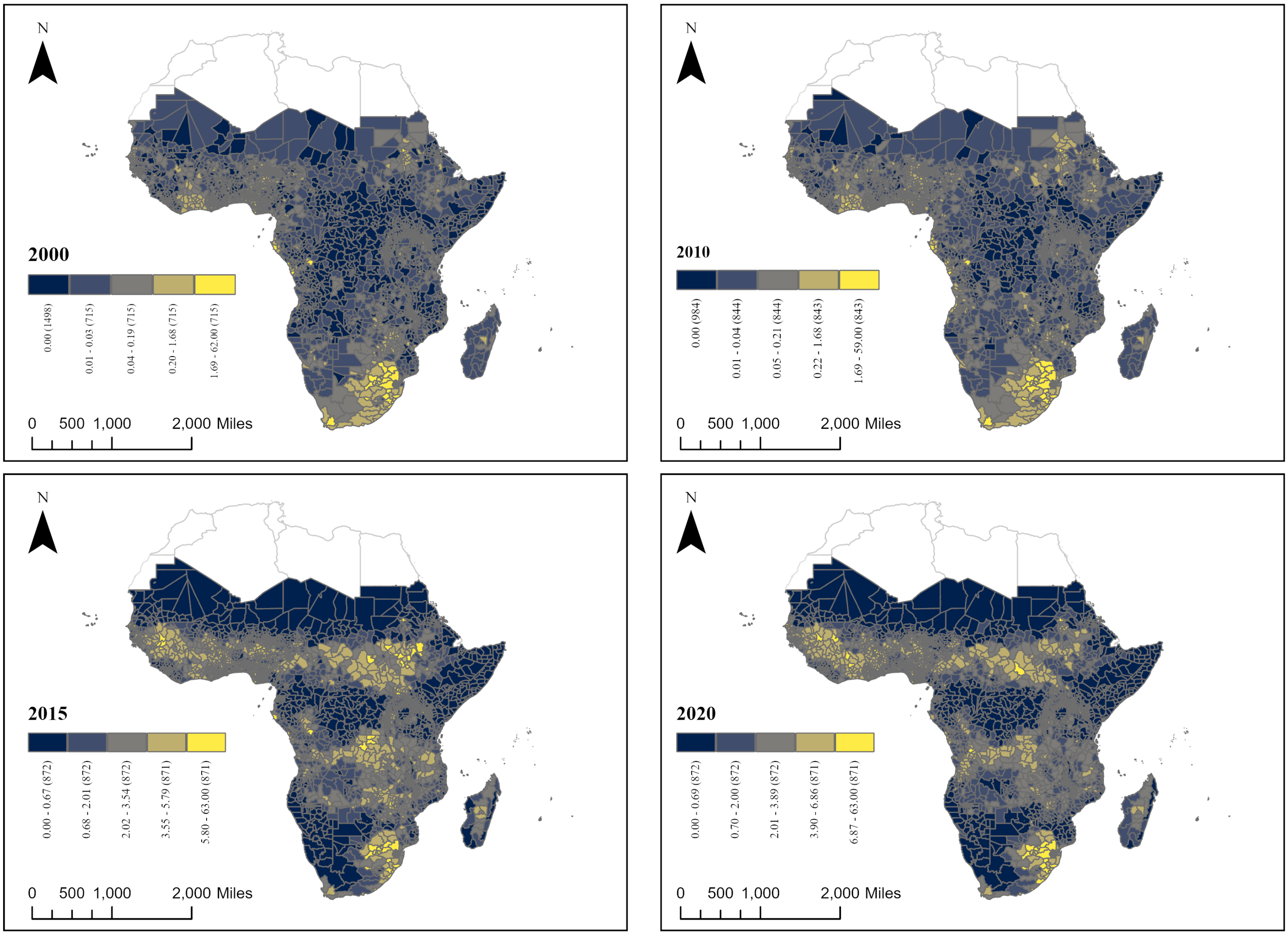


Note:
Multiple projects co-locate in various studied regions. On average, the projects co-locate in 8 regions. This means that one single project might be geo-coded to more than one region.
The approval year of these projects is between the observed period of 2008-2019. 1/4 of the projects are without the close year information. The average project duration of projects with both approval year and close year information is 4.4 years.
Most of the regions are home to more than 1 World Bank project during the observed period, and some have received more than 1 project in one particular year.
Number of observations is provided in the parentheses.



Source: Authors' elaboration, GADM version 4.1; World Bank projects gathered by Yang et al., 2021. The projection is World Geodetic System 1984.

Figure A5: Nighttime Luminosity in SSA Countries, Studied Regions, Selected Years



Source: Authors' elaboration, GADM version 4.1; Nighttime luminosity calculated based on Li et al. (2020) and version 8.0 archived in the online repository. The projection is World Geodetic System 1984.

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