

Towards unlocking sustainable land consumption in sub-Saharan Africa: Analysing spatio-temporal variation of built-up land footprint and its determinants

Yacouba Kassouri^a, Andrew Adewale Alola^{b,c,d,*}

^a Department of Economics and Finance, Nisantasi University, Istanbul, Turkey

^b Department of Economics, School of Accounting and Finance, University of Vaasa, 65101 Vaasa, Finland

^c Vaasa Energy Business Innovation Centre, University of Vaasa, 65101 Vaasa, Finland

^d Department of Economics and Finance, South Ural State University, Chelyabinsk, Russian Federation

ARTICLE INFO

Keywords:

Built-up land footprints
Biocapacity
Globalization
Convergence
Sub-Saharan Africa

ABSTRACT

A systematic understanding of the dynamics of land consumption is extremely important for human well-being and especially vital for the ecological balance of the sub-Saharan Africa (SSA) region. Remarkable land use/land cover changes due to climate change, urbanization, and food demand have affected the spatio-temporal dynamics of built-up land footprints (BLFs) in SSA. By using spatial econometric techniques, this study investigates the spatio-temporal evolution and key drivers of built-up land footprints in 28 SSA countries from 2000 to 2017. Our results show how an appropriate consideration of the role of spatial effects can shed new insights into the convergence process of built-up land footprints. Foremost, the study reveals significant evidence of both absolute and conditional β convergence in BLFs over the experimental period. Additionally, the estimation indicates that biocapacity plays an important role in cutting built-up land footprints in SSA countries as there was a faster conditional convergence in countries with higher biocapacity. Moreover, the study outlined that the promotion of globalization and urbanization draws more pressure on the built-up environment and makes it challenging to reduce BLFs in SSA. In addition, this study found evidence for an inverted U-shaped nexus between per capita built-up land footprints and per capita gross domestic product (GDP), supporting the prediction of the environmental Kuznets curve (EKC) hypothesis.

1. Introduction

Over the past decades, the sub-Saharan Africa (SSA) has been considered a dynamic and rapidly developing region with significant biophysical and socioeconomic changes (Brink and Eva, 2009). At the global level, approximately 50% of the expansion of urban land consumption outpaces population growth, which is expected to add 1.2 million km² of new urban built-up land to the world over the three decades (World Cities Report, 2020). Such sprawl increases concerns about the rate and extent of land cover change in the global research agenda, particularly with the growing awareness of the critical role of land cover in the climate system (Mahmood et al., 2010; Rounsevell and

Reay, 2009). Driven by rapid urban expansion (demand aspect), the human impact has exceeded natural biocapacity (supply aspect) such that the majority of the resource stocks bear the human footprint (Borucke et al., 2012, 2013; Herrmann et al., 2020). In the African context, the fragmented and disorderly expansion of urban space has put severe pressures on built-up area requirements with subsequent consequences on natural vegetation cover, biodiversity, socioeconomic stability, food security, and hydrological processes (Côté-Roy and Moser, 2019; Erb et al., 2007; Foley et al., 2005). Thus, this raises new questions about the temporal and spatial dynamics of the built-up land footprint per capita to monitor a reasonable and rational development of built-up land of the SSA region.

Abbreviations: Bio, Biocapacity; BLF, Built-up land footprints; EAP, Environmental Action Plan; ECOWAS, Economic Community of West African States; EKC, Environmental Kuznets curve; GDP, Gross domestic product; GLO, Globalization; Indus, Industrial structure; Ln, Natural logarithm function; MEP, Monitoring and evaluation plan; POP, Population; SAM, Spatial autoregression model; SDM, Spatial Durbin model; SDG, Sustainable development goal; SEM, Spatial error model; SSA, Sub-Saharan Africa; STIRPAT, Stochastic impacts by regression on population, affluence, and technology.

* Corresponding author at: Department of Economics, School of Accounting and Finance, University of Vaasa, 65101 Vaasa, Finland.

E-mail addresses: yacouba.kassouri@idiv.de, yahacoubk@gmail.com (Y. Kassouri), andrew.alola@uwasa.fi (A.A. Alola).

<https://doi.org/10.1016/j.landusepol.2022.106291>

Received 10 March 2022; Received in revised form 22 July 2022; Accepted 24 July 2022

Available online 4 August 2022

0264-8377/© 2022 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Built-up land footprints, originally derived from the concept of ecological footprint, captures the amount of land needed for infrastructures, such as houses and buildings, bridges, roads, car-parks, and manufacturing activities (Rees and Wackernagel, 2008), that is the areas designed for urban facilities. The built land footprint has witnessed the highest average growth rates among the subcomponents of the ecological footprint (Ke et al., 2018; Solarin et al., 2021). It has expanded from 81 million global hectares (gha) in 1961 to about 473 million gha in 2016, which poses a severe threat to ecological security (Global Footprint Network, 2020). In the African context, urban land acquisitions are increasingly occurring at the expense of agricultural and grazing land, resulting in a significant decrease in the amount of available farm land to the extent that food production can be significantly affected for a long time (FAOSTAT, 2001; Pham et al., 2013).

Consequently, built-up area expansion may drive unsustainable environmental change and increase the risk of food insecurity. Given these consequences, studies have extensively presented the influencing factors of built-up land footprints (Clancy, 2008; Fan et al., 2021; Lai et al., 2021; Lu et al., 2019; Lyu et al., 2021; Sanchez and Leakey, 1997; Shao et al., 2020; Uisso and Tanrivermiş, 2021). Several studies highlight urban development as one of the critical drivers of built-up land footprints. Other determinants of the built-up land footprints may include demographic changes, income, and technological factors (Junliang et al., 2010; Lai et al., 2021; Marquart-Pyatt, 2010; Sajjad and Iqbal, 2012; Zhao et al., 2018). While existing literature acknowledge that globalization, population aspect, and economic-related activities as drivers ecological footprints (Rudolph and Figge, 2017; Alola et al., 2021a, 2021b), these factors especially globalization and biocapacity has been overlooked in the study of built-up land footprints. Moreover, the transactions of land known as "land grabbing" (i.e., the appropriation of productive land by foreign investors) have played an essential role in the development of land footprint in Africa (Cain, 2014; Coscieme et al., 2018, 2016; Watson, 2014). As documented by Coscieme et al. (2016), having higher biologically productive land (biocapacity) like most SSA countries can increase land grabbing and cause severe environmental damage to the built-up environment, especially in the age of globalization of the land market. The question that arises is how the expansion of globalization and biocapacity have affected built-up land footprints in the SSA countries.

Another strand of the literature focused on the degree of persistence and non-stationarity in ecological footprints (Kassouri, 2021a; Solarin et al., 2021; Solarin and Bello, 2018; Ulucak et al., 2020; Ulucak and Apergis, 2018; Yilanci et al., 2019). These studies examine the stochastic convergence characteristics of ecological footprints based on panel and/or time series unit root tests. Technically, a stationary property of ecological footprint implies that the ecological footprint per capita series displays mean-reverting property, and shocks are short-lived; otherwise, the effects are permanent in the long run. In a more comprehensive study, Solarin et al. (2021) examine the degree of persistence of shocks to built-up land footprints. The authors conclude that there is heterogeneity in the persistence of the built-up land footprint across 89 countries. However, the authors conclude that shocks to built-up land footprints are momentary, and there is no need to intervene when the built-up land footprint departs from its trend path. The rationale behind this narrative is that built-up land footprint displays some degree of stochastic convergence in the long term.

This paper contributes to the attendant literature in three significant ways. Firstly, this is one of the rare studies to test the convergence characteristics of built-up land footprints in 28 SSA countries over 2000–2017. This study is one of the rare studies to test the convergence characteristics of built-up land footprints in SSA countries. The SSA region is selected for the study because the urban landscape is constantly experiencing spatial and temporal changes stemming from the rapid urban development of the region. In this context, pressure will mount on urban managers to effectively monitor and manage these changes in cities. Our study contributes to the existing literature by providing one

of the first evidence-based insights into the spatio-temporal dynamics of built-up land footprints in order to raise awareness and concern for better policies and planning built-up land development and urban growth in the SSA region. Secondly, the field of research is enriched by identifying the triggers of built-up land footprints, including per capita biocapacity, per capita GDP, population density, globalization, industrial structure, and urbanization in shaping the convergence process. The consideration of these key drivers significantly increases the policy relevance of our study, which will help policymakers and academicians in the decision-making process. Thirdly, the spatial dependence effect is included in the analysis to examine how the interactions between SSA countries influence the path of convergence of built-up land footprints.

This study proceeds as follows. In the following section, we discuss previous studies and the theoretical background of our study. The underlying data and methods used are presented in Section 3. Section 4 introduces the empirical findings based on the different methods used. Section 5 provides a thorough discussion of the empirical findings. Finally, the conclusion the policy implications of our analysis are presented in Section 6.

2. Theoretical underpinnings of convergence

Initially, convergence was used in the neoclassical growth theory model to decrease capital accumulation returns (Solow, 1956). This elucidates the probability of a catch-up mechanism between capital-abundant countries and developing countries over a duration of time. Therefore, developing countries are anticipated to grow faster than rich ones, leading to convergence. The concept has progressed through the years, and the convergence hypothesis has aroused the interests of environmental science researchers to investigate the convergence in pressure on the environment (Salvati and Zitti, 2008).

Convergence in environmental indicators provides adequate information for guiding policies related to a complex system characterized by the interactions of ecological and socioeconomic factors. The convergence analysis allows countries to balance economic and environmental outcomes within a region based on the equal pollutant intensity rule. Thus, countries with lower levels of pollutant emission intensity have a greater right to pollute and countries with a greater pollutant emission intensity should control their emissions at a certain level (Aldy, 2006). This mechanism clearly illustrates the convergence process in environmental pressure across different countries.

2.1. Empirical literature review

Following this theoretical framework, several studies have intensively explored the convergence characteristics of various environmental and ecological pollutants. Table 1 summarizes the existing studies on the convergence of environmental pressures.

A survey of the existing literature shows that a significant strand of literature examines the convergence property of various pollutants, including carbon dioxide emissions (CO₂), Sulphur dioxide (SO₂), Nitrogen dioxide (NO₂). This wave of studies is highlighted in Panel A (Table 1). Recently, the analysis of convergence based on pollutant emissions has been criticized by several studies and the use of more comprehensive indicators plays an increasing role in the convergence literature. Thus, the ecological footprint has been considered as a meaningful indicator to capture the complex dynamic to measure environmental and ecological sustainability (Dietz et al., 2007; Galli et al., 2014; Galli et al., 2012). In this light, emerging literature tests the convergence hypothesis using footprint items and other ecological indicators (Panel B). The emerging literature focuses only on ecological footprints and ignores its other sub-components. However, as recently pointed out by (Solarin et al., 2021), the expanding footprints of built-up areas deserve further attention given the great interconnection between built-up environment and human well-being. Additionally, the realization of the sustainable management of built-up land is essential to build

Table 1
Previous studies.

Author (s)	Country	Data	Variables used	Method (s)	Conclusion
<i>Panel A: Pollutant emissions</i>					
(Strazlich and List, 2003)	21 industrial countries	1960–1997	Per capita CO ₂ emissions	Stochastic and conditional convergence	Convergence
(Aldy, 2006)	100 countries	1960–2000	Per capita CO ₂ emissions	Non-parametric techniques	Convergence for OECD and mixed results for 88 countries
(Huang and Meng, 2013)	30 Chinese provinces	1985–2008	CO ₂ emissions	Spatio-temporal techniques	Convergence
(Hao et al, 2015)	29 Chinese provinces	1995–2011	CO ₂ emissions	Stochastic and β convergence techniques	Convergence
(Brännlund and Karimu, 2018)	94 countries	1971–2008	Environmental performance index	β convergence model	Mixed results
(Awaworyi Churchill et al., 2018)	44 developed countries	1900–2014	CO ₂ emissions	Stochastic convergence approach	Convergence
(Erdogan and Acaravci, 2019)	28 OECD countries	1960–2014	CO ₂ emissions	Stochastic convergence approach	Convergence
(Solarin and Tiwari, 2020)	32 OECD countries	1850–2005	SO ₂ emissions	Stochastic convergence	Convergence
(Payne and Apergis, 2021)	65 countries	1972–2014	CO ₂ emissions	Stochastic and club convergence methods	Mixed evidence
(Zhang and Hao, 2020)	Chinese province	2000–2014	SO ₂ and chemical oxygen demand	β convergence model	Conditional β convergence
(Tiwari et al. 2021)	USA	1976–2014	CO ₂ emissions	Stochastic and club convergence methods	Convergence
(Cui et al., 2021)	China	2005–2012	NO ₂ pollution	Spatial econometrics	Convergence
<i>Panel B: footprint items and ecological indicators</i>					
(Salvati and Zitti, 2008)	3 spatial aggregation of the Italian peninsula	1990–2000	Land degradation index	Non-parametric techniques	Nonlinear convergence across provinces
(Jiang et al., 2019)	Central Asia	1992–2015	Desertification risks	Spatial metrics	Divergence patterns from 1992 to 2000 and Convergence pattern for 2008–2015
(Ulucak et al. 2020b)	23 SSA countries	1961–2014	Ecological footprint	Club convergence	Convergence
(Erdogan and Okumus, 2021)	89 countries	1961–2016	Ecological footprint per capita	Panel KPSS and club convergence	Divergence with several convergent clubs

sustainable cities and plays an essential role in the sustainable development goal (SDG 11) (UN, 2016). Consequently, built-up land footprints are beginning to take central stage in discussions on sustainable development, especially in SSA.

3. Methods and data

3.1. Spatial correlation analysis

Prior to the analysis of convergence, we estimate whether spatial effects of the built-up land footprints are in the SSA countries. Thus, the Moran's I statistic developed by Moran (1948) is computed to examine the spatial correlation of built-up land footprints.

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (z_i - \bar{z})(z_j - \bar{z})}{s^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad \forall i = 1, \dots, n \quad \wedge \quad \forall j = 1, \dots, n \tag{1}$$

where,

$$\bar{z} = \frac{1}{N} \sum_{i=1}^n z_i, \quad s^2 = \frac{1}{N} \sum_{i=1}^n (z_i - \bar{z})^2 \tag{2}$$

where z_i represents the annual of built-up land footprints in the country i . \bar{z} denotes the average value of the built-up land footprints. W_{ij} represents the spatial weight matrix between country i and j . Generally, the spatial weight matrix is between 0 and 1. $W_{ij} = 1$ when country i and j share a common border and $W_{ij} = 0$, otherwise. Hence, the larger the absolute Moran's I value, the stronger the spatial autocorrelation. s^2 denotes the variance of the sample. In addition, Moran's I statistic ranges between - 1 and 1, suggesting positive and negative correlation, respectively.

3.1.1. The σ convergence method

The sigma (σ) convergence method captures the decline in dispersion across panel members. Sigma convergence is measured as the development of the standard deviation over time and the formula can be expressed as follows:

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i - \bar{z})^2} \tag{3}$$

The sigma-convergence approach has been extensively used in different fields (Rey and Dev, 2006; Rey and Montouri, 2010).

3.1.2. β convergence method

The β convergence method can be divided into conditional and absolute β convergence. The β convergence assumes that built-up land footprints of the SSA countries will converge to a common steady-state. At the same time, the former refers to that built-up land footprints converge to different steady states for all countries that are conditional on country-specific characteristics. By taking the spatial structure into account in the analysis, the spatial autoregression model, spatial error model, and the spatial Durbin model are all estimated.

(1) Spatial absolute (unconditional) β convergence model

$$\text{Spatial autoregression model(SAM)} : \ln\left(\frac{z_{it}}{z_{it-1}}\right) = \rho W \ln\left(\frac{z_{it}}{z_{it-1}}\right) + \beta \ln(z_{it-1}) + v_{it} \tag{4}$$

$$\text{Spatial error model(SEM)} : \ln\left(\frac{z_{it}}{z_{it-1}}\right) = \beta \ln(z_{it-1}) + \eta_{it} \text{ and } \eta_{it} = \lambda W \eta_{it} + e_{it} \tag{5}$$

$$\begin{aligned} \text{Spatial Durbin model(SDM)} : \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) \\ = \rho W \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) + \beta \ln(Z_{it-1}) + \delta W \ln(Z_{it-1}) + u_{it} \end{aligned} \tag{6}$$

Principally, a panel setting is considered for the analysis with Z_{it} , $i = 1, \dots, N$, $t = 1, \dots, T$, where N (number of countries under investigation) and T (the period under investigation) denote panel members and periods, respectively. W represents the row-standardized spatial weight matrix, ρ , δ and λ represent the respective coefficients of spatial autoregressive model and spatial autocorrelation model, v_{it} , e_{it} , and u_{it} are the disturbance terms, β represents the convergence coefficient, which will indicate the existence of absolute (unconditional convergence) if its value is negative and statistically significant.

The concept of beta – convergence is derived from the traditional neoclassical growth models presented in the Solow-Swan model. To estimate beta – convergence, the Eqs. 4, 5, and 6 are estimated, where the growth rate of built-up land footprint per capita ($\frac{Z_{it}}{Z_{it-1}}$) is presented as a function of the initial level of built-up land footprint per capita (Z_{it-1}). A negative sign on the coefficient associated with (Z_{it-1}) corresponds to an implied rate of convergence in built-up land footprints.

(2) Spatial condition β convergence model

$$\begin{aligned} \text{Spatial autoregression model(SAM)} : \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) \\ = \rho W \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) + \beta \ln(Z_{it-1}) + \phi \ln x_{it} + v_{it} \end{aligned} \tag{4'}$$

$$\begin{aligned} \text{Spatial error model(SEM)} : \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) = \beta \ln(Z_{it-1}) + \phi \ln x_{it} + \eta_{it} \text{ and } \eta_{it} \\ = \lambda W \eta_{it} + e_{it} \end{aligned} \tag{5'}$$

$$\text{Spatial Durbin model(SDM)} : \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) = \rho W \ln\left(\frac{Z_{it}}{Z_{it-1}}\right) + \beta \ln(Z_{it-1}) + \delta W \ln(Z_{it-1}) + \phi \ln x_{it} + u_{it} \tag{6'}$$

where, x_{it} represents the key drivers of built-up land footprints. In Equations (4)-(6)', the external factors that influence the convergence property of built-up land footprints are accounted for. Additionally, the LM procedure proposed by Anselin et al. (1996) is being followed to select the most appropriate model from the SDM, SEM, and SAM.

3.2. Data

3.2.1. Built-up land footprints

The built-up land Footprint is calculated based on the area of land covered by human infrastructure — transportation, housing, industrial structures, and reservoirs for hydro-power. Built-up land may occupy what would previously have been cropland. The per capita built-up land footprint calculator is based on national footprint accounts data for each country. This results in a matrix that uses a country’s average consumption profile to derive the level of footprint.

Consistent with recent empirical studies (Kassouri, 2021b; Solarin et al., 2021), annual dataset of built-up land footprint data from the Global Footprint Network database is employed. Our sample includes 28 SSA countries over the period 2000–2017. The countries included are Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Chad, Congo, Cote d’Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Malawi, Mali, Mozambique, Niger, Nigeria, Rwanda, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia, Zimbabwe. The

scope of the study concerning the choice countries and the sample period is mainly prompted by data availability.

Fig. 1 provides a general overview of the annual built-up land footprints per capita in 28 SSA countries from 2000 to 2017. Overall, the per capita built-up land footprint in 28 SSA countries increased over time because the mean of built-up land footprint increased by 38%, from 0.035 in 2000–0.048 in 2017, which coincides with the analysis of Solarin et al. (2021). The increase is possibly related to the African urbanism scheme, which is characterized by the domination of informal settlements and economic activity (Steel et al., 2017). During the study period, Lesotho has the lowest built-up land footprints, while Cote d’Ivoire is the country with the highest built-up land footprint. The latter country appears to be the third most urbanized country, behind Ghana and South Africa, posing challenges related to pollution and emissions and the unsustainable use of natural resources (World Bank, 2015). Notably, the per capita built-up land footprint from certain countries included Cameroon, Ghana, and South Africa, were initially small but increased relatively rapidly in 2017, which seems to confirm the prevalence of convergence ‘catches up’.

However, only a more formal analysis to test convergence will provide a clear picture of the convergence characteristics of built-up land footprints among SSA countries. Furthermore, consistent with our previous observations, there exists important cross-country difference within the SSA region as depicted in Fig. 2.

3.2.2. Drivers of BLF and definitions

To explore the sensitivity of the convergence rate to the drivers of BLFs, the role of biocapacity, globalization, urbanization, population density, per capita GDP, and the industrial structure are accounted for in the estimation. It is important to stress that this study follows the STIRPAT specification (Stochastic Impacts by Regression on Population, Affluence, and Technology) model as the reference theoretical and analytical framework to investigate the effects of different variables on

built-up land footprints (Ehrlich and Holdren, 1971; Dietz et al., 2007; York et al., 2003). Specifically, Ehrlich and Holdren (1971) had initially illustrated the environmental impact of population, affluence, and technology (IPAT) which has been further modified to include other associated factors that drives population such as urbanization, globalization, e. t.c. Moreover, the following variable has been considered in our analysis:

- (i) Per capita biocapacity can be defined as the biological capacity of the ecosystem to generate resources and absorb waste per person. Most SSA countries enjoy a relatively higher biological productive land (Global Footprint Network, 2020). It has been reported by Coscieme et al. (2016) that the abundance of biologically productive land in most of the African countries is an essential driver of the massive land acquisition in the continent. Thus, the favorable ecological condition of African countries leads them to seek short-term economic gains by sacrificing their environmental and ecological sustainability (Sumaila et al., 2015). This phenomenon may increase the footprint of built-up land and alter the ecological balance of the region. On the other hand, some analysts indicate that biocapacity is an imperative gauge for sustainability since a higher biological capacity increase the earth capacity to absorb waste and other harmful gases, therefore, alleviating the environmental stress in the areas designed for urban facilities (Majeed and Mazhar, 2020; Shujah-ur-Rahman

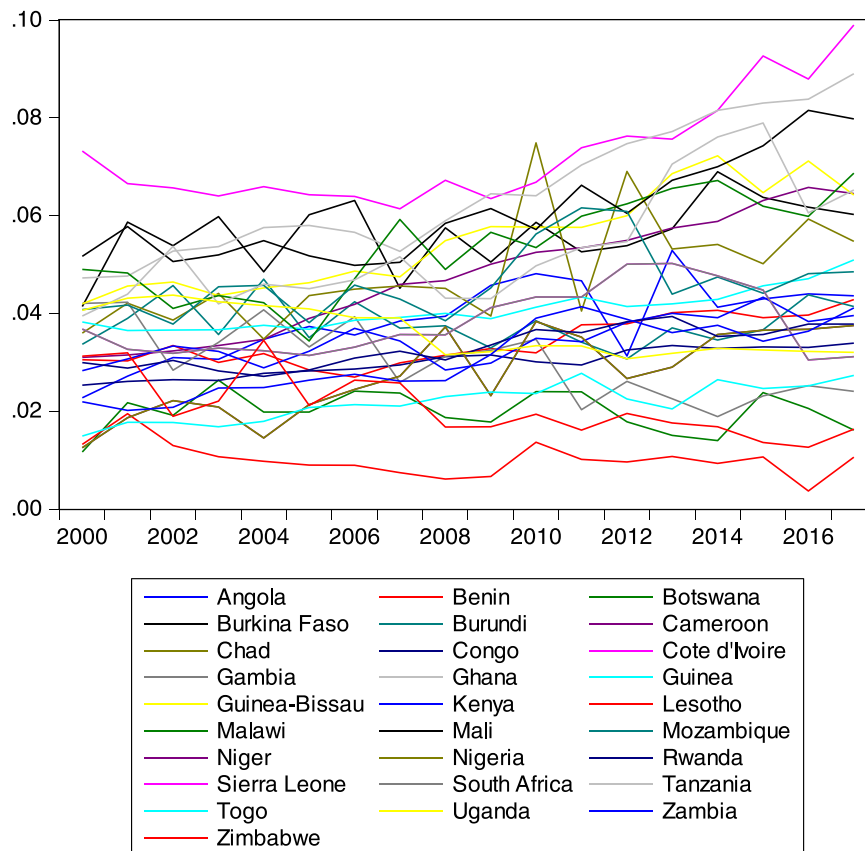


Fig. 1. Overview of built-up land footprints from 2000 to 2017.

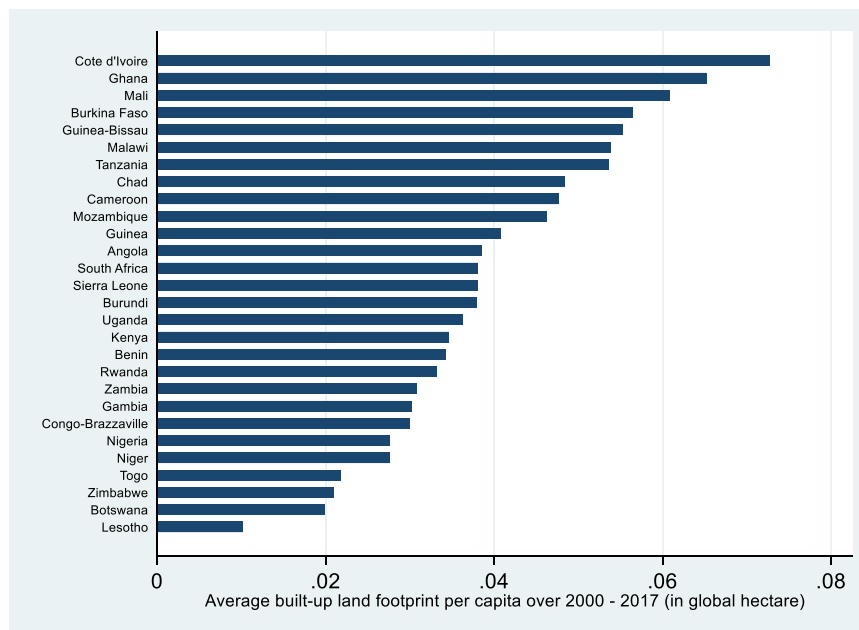


Fig. 2. Average built-up land footprints across SSA countries.

et al., 2019). Based on this narrative, one should expect bio-capacity to influence built-up land footprint reduction in SSA countries positively. However, in countries that are biologically rich a reverse effect is likely to occur, mainly because poor environmental legislations along with their dependence on natural capital may amplify the conversion of natural habitat into

built-up areas, which may generate a larger construction land footprint instead of reducing the footprint. From this perspective, one may argue that the levels of biological capacity can positively or negatively influence built-up land footprints, and only a formal analysis may enable us to elucidate this conflicting evidence.

- (ii) Globalization. The environmental implications of globalization have been extensively investigated (Akadiri et al., 2019; Erdoğan et al., 2021; Salahuddin et al., 2019; You and Lv, 2018), but the effects of globalization on land footprint has not been examined in the current literature. With the expansion of globalization, land use agents have changed, particularly in SSA countries. It has been reported that millions of hectares of farmland in Africa were leased to Chinese and other multinational investors from 2006 to 2012 (Meine and van, 2016). The rate at which land grabbing consumes large quantities of physical spaces in urban and rural areas destabilizes the land use and landscape dynamics with severe impacts on environmental sustainability (Carroccio et al., 2016; Lazarus, 2014). Estimates for 2004 indicate that globalization accounts for 24% of the global land footprints (Meyfroidt et al., 2013; Weinzettel et al., 2013). An important factor contributing to the expansion of this footprint has been the growth in agribusiness, high capitalized farm producing commodities for global markets. Based on these arguments, it is highly expected that globalization leads to the development of built-up land footprints in SSA countries.
- (iii) Per capita GDP. To date, there is extensive literature examining the environmental Kuznets Curve hypothesis using different footprint items. For instance, (Altıntaş and Kassouri, 2020) show that the Environmental Kuznets Curve (EKC) hypothesis is sensitive to the measure of environmental impact used. To depict the relationship between built-up land footprint and economic growth, the squared GDP is incorporated as an additional control variable. In this light, the existence or validity of the EKC hypothesis for built-up land footprints for SSA countries is investigated.
- (iv) Population density. It should be acknowledged that population density has been considered a significant indicator of changes in land patterns. It is well established that changes in a built-up area are the result of rapid population growth (Herrmann et al., 2020; Tan et al., 2016). As expected, the growing population in the SSA region is likely to exert considerable pressure on the land resources, leading to a significant increase in built-up land footprints.
- (v) Urbanization. Following the compact city and environmental transition theories, one might expect an increasing effect of urbanization on built-up land footprints as urbanization increases the demand for built-up land and infrastructures, resulting in higher built-up land footprints. However, the urban modernization theory holds that urbanization tends to decrease pressure on resource stocks through technological improvements, enforcement of environmental regulation, and advanced energy structure (Turok and McGranahan, 2013).
- (vi) Industrial structure, which is measured as the share of industry in GDP represents the industrial sector value-added expressed as a percentage of GDP. Although the industrial sector has been presented to be less land-intensive sectors, the agriculture-related manufacturing sectors that mainly rely on inter-industrial inputs from the forestry and farming sector can increase land footprints. Given the predominant role of the agriculture-related industrial sector in SSA countries, one may expect a positive influence of the industrial structure on built-up land footprints (Pang et al., 2019).

All the data were collected from the World Development Indicators (WDI) database with the exception of biocapacity and globalization, which have been gathered from the Global Footprint Network database and the Swiss Economic Institute website respectively. The summarized information and basic statistics of built-up land footprints and the variable sources are provided in Table 1.¹

4. Empirical results

4.1. Selection of the weight matrix

Table 2 reports the goodness of fit of 6 different row-standardized spatial weight matrices that illustrates the rejection of non-spatial over spatial lag and spatial error models. These weight matrices include inverse distance, K-nearest neighbors (KNN), Thiessen polygon, hybrids between inverse distance and KNN or Thiessen polygon matrices. It is quite impossible to perform the analysis for each weight matrix, one should select the most suitable weight matrix among possible candidates based on goodness of fit. Specifically, the stepwise approach is adopted by selecting the weight matrix with the smallest Akaike Information Criteria and the highest R-squared as suggested in Kim et al. (2014). Based on goodness of fit, the K= 3 nearest neighbor's weight matrix yields the smallest AIC and the highest R-squared, making it the preferred weight matrix of our analysis.

4.2. Spatial dependence

Following previous studies, the Moran's I statistic is used to measure spatial dependence of built-up land footprints among SSA countries. Table 2 reports the Moran's I statistic over the sample period. The Moran's I statistics are statistically significant over the sample period, suggesting that SSA countries' built-up land footprints are spatially autocorrelated. The existence of spatial autocorrelation in built-up land footprints is also supported by the scatter plot of Moran's I index (Fig. 3).

A visual inspection of the scatter plot of global Moran's I indicate the existence of positive spatial autocorrelation of built-up land footprints in our panel members (Fig. 3). This implies that changes in built-up land footprints come from a local country's built-up environment and depend on the development of built-up land in the surrounding countries. One possible explanation is the imitation of environmental policies among SSA countries since a similar land development scheme easily leads to similar development of built-up land footprints. This narrative is consistent with the geographic distribution of built-up land footprints depicted in Fig. 4.

We depict the geographic distribution of built-up land footprints in the 28 SSA countries in 2017 in Fig. 3. Dark brown denotes countries with higher built-up land footprints, while light brown indicates countries with small built-up land footprints. A positive spatial autocorrelation appears to exist for built-up land footprints because countries with higher built-up land footprints were clustered, and it was the same for countries with low built-up land footprints. Specifically, the per capita built-up land footprint is lower in Southern Africa (Botswana, South Africa, Lesotho, and Zimbabwe) than in Western Africa (Burkina Faso, Cote d'Ivoire, Ghana, Mali, Mauritania, and Guinea). This can be partly explained by the developmental stage of urbanization and differences in the vegetation coverage rate across regions (Coscieme et al., 2016). As discussed above, the clustering of countries with higher built-up land footprints can be explained by the joint environmental Action Plan

¹ It is important to stress that the variables have been log-transformed. In addition, the underlying variables considered in our analysis were subjected to multicollinearity tests before including them in the regression analysis. The variance inflation factor (VIF) results unravel that the data do not suffer from a high level of multicollinearity as the estimated VIF is well below the threshold of 10 (the results are available upon request).

Table 2
Descriptive Statistics.

Specific Indicator	Scale Unit	Source	Mean	Std. Dev.	Min.	Max.	Obs.
Per capita built-up land footprint	gha per capita	GFN	0.039	0.016	0.003	0.098	504
Real GDP per capita	Constant US dollar	WDI	1.421.438	1.651.356	214.139	7.864	504
Population density	persons/km2	WDI	2.100	2.900	12000	1.908	504
Urban population	% of total population	WDI	36.176	15.294	8.246	63	504
Economic globalization	Kof Index	SEI	46.942	7.917	23.612	70.793	504
Industrial structure	Percent of GDP	WDI	9.578	4.097	0.232	24.557	504
Biocapacity	gha per capita	GFN	1.114	1.4014	0.283	9.097	504

Note: gha stands for global hectares; GFN: Global Footprint Network database; WDI: World Development Indicators database; Std. Dev.: Standard Deviation; Min: Minimum; Max: Maximum; Obs: Observation. SEI: Swiss Economic Institutes. Spatial scale: Country-level analysis. Time period: annual data 2000 – 2017.

Table 3
Goodness of fit for selecting the weight matrix.

W matrix	R-squared	AIC
K nearest neighbor (KNN)		
k = 3	0.77	0.43
k = 5	0.61	0.43
k = 7	0.51	0.44
k = 9	0.65	1.03
Thiessen polygon	0.57	0.51
KNN × Inverse distance		
Thiessen polygon × Inverse distance	0.63	0.62

Note: AIC: Akaike Information criteria (lag selection process). W: row-standardized weight matrix

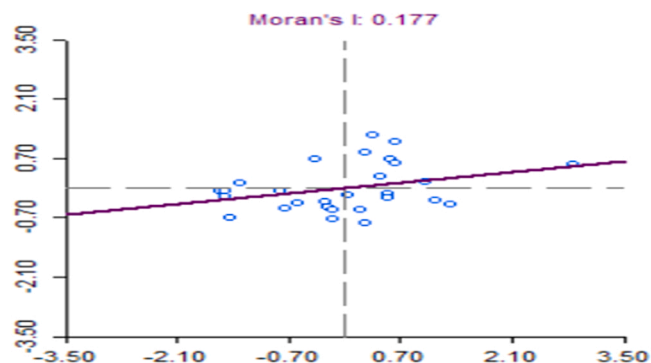


Fig. 3. Global Moran's I scatter plots of built-up land footprints in 2017.

(EAP) and associated Monitoring and Evaluation Plan (MEP) of the ECOWAS (Economic Community of West African States) Directorate of Environment and Natural Resources.² Such inter-regional policy reforms can significantly influence the spatial patterns of built-up land footprints in West Africa.

4.3. Sigma (σ) convergence

Fig. 5 displays the general trends of built-up land footprints and standard deviation (σ) between 2000 and 2016. Compared to Moran's I index trend; the standard deviation trend is less complicated and exhibits an overall decreasing trend over time. The significant decline in σ indicates that the deviations of built-up land footprints per capita across different countries gradually decreased. Intuitively, this reflects a potential tendency of convergence in built-up land footprints across countries. In other words, built-up land footprints (i.e per capita built-up land footprints as used) of different SSA countries may converge to a similar steady-state level.

² <https://www.wabicc.org/ecowas-ministers-adopt-strategic-documents-for-a-cleaner-sustainable-environment/>

4.4. Absolute and conditional β convergence

4.4.1. Model selection

Prior to the analysis of the spatial convergence of built-up land footprints, the Lagrange Multiplier (LM) test proposed by Anselin et al. (1996) is performed to choose the most appropriate model from the spatial error model, spatial autoregressive model, and spatial Durbin model. Table 2 displays the results of the model selection tests. Additionally, the LM test and Robust LM test are considered to evaluate whether spatial effects need to be considered. In both cases, the LM statistics are strongly significant at the 1% level of significance, indicating that spatial lag (autoregressive) and spatial error effects should be considered in our analysis. Then, the Wald test and the LR test are adopted to evaluate whether the spatial Durbin model can be simplified to the spatial autoregressive and spatial error model. It is observed that both the Wald test and LR test are highly significant suggesting that the spatial Durbin model is the optimal model to explore the convergence characteristics of built-up land footprints in SSA countries.

4.4.2. Spatial absolute β convergence

The spatial absolute β convergence estimation results are provided in Table 4 based on the SEM, SAM, and SDM models. Given the superiority of the spatial Durbin model relative to the SEM and SAM, only the discussion of the estimation results for the SDM is considered. Additionally, the coefficients of the first-lag of built-up land footprints are significantly negative in all three models, suggesting that there is strong evidence for the spatial absolute β convergence of built-up land footprints in SSA countries from 2000 to 2017. This implies that each country is able to converge to its respective steady states without any reference to other factors. In this case, a particular country would be facing significant pressure if surrounding countries met their projected built-up land footprint reduction targets. The absolute spatial convergence indicates that cutting built-up land footprints is faster in countries with the high initial built-up land footprints. However, in countries with lower initial footprints, the decrease of the built-up land footprint is slighter. Therefore, the annual decreasing rate in a specific country will also significantly affect the adjacent countries as the spatial spillover effects captured by ρ and λ are statistically significant. The higher absolute convergence rate in the SDM than in SAM and SEM indicates that the consideration of spillover effects from neighboring countries improves the convergence process of built-up land footprints. This is consistent with our preliminary tests reported in Table 4, suggesting that the SDM is more desirable.

4.4.3. Spatial condition β convergence

Table 5 presents the estimation results of the conditional convergence. The coefficient of the lagged dependent variable (β) is negative and statistically significant at a 1% level across all specifications. This confirms the existence of conditional β convergence of built-up land footprints after controlling for the key triggers of built-up land footprints. The result showed that the estimated convergence rates are higher than the absolute convergence rate reported in Table 5, although the saturated model with all the driving factors displayed in column 7

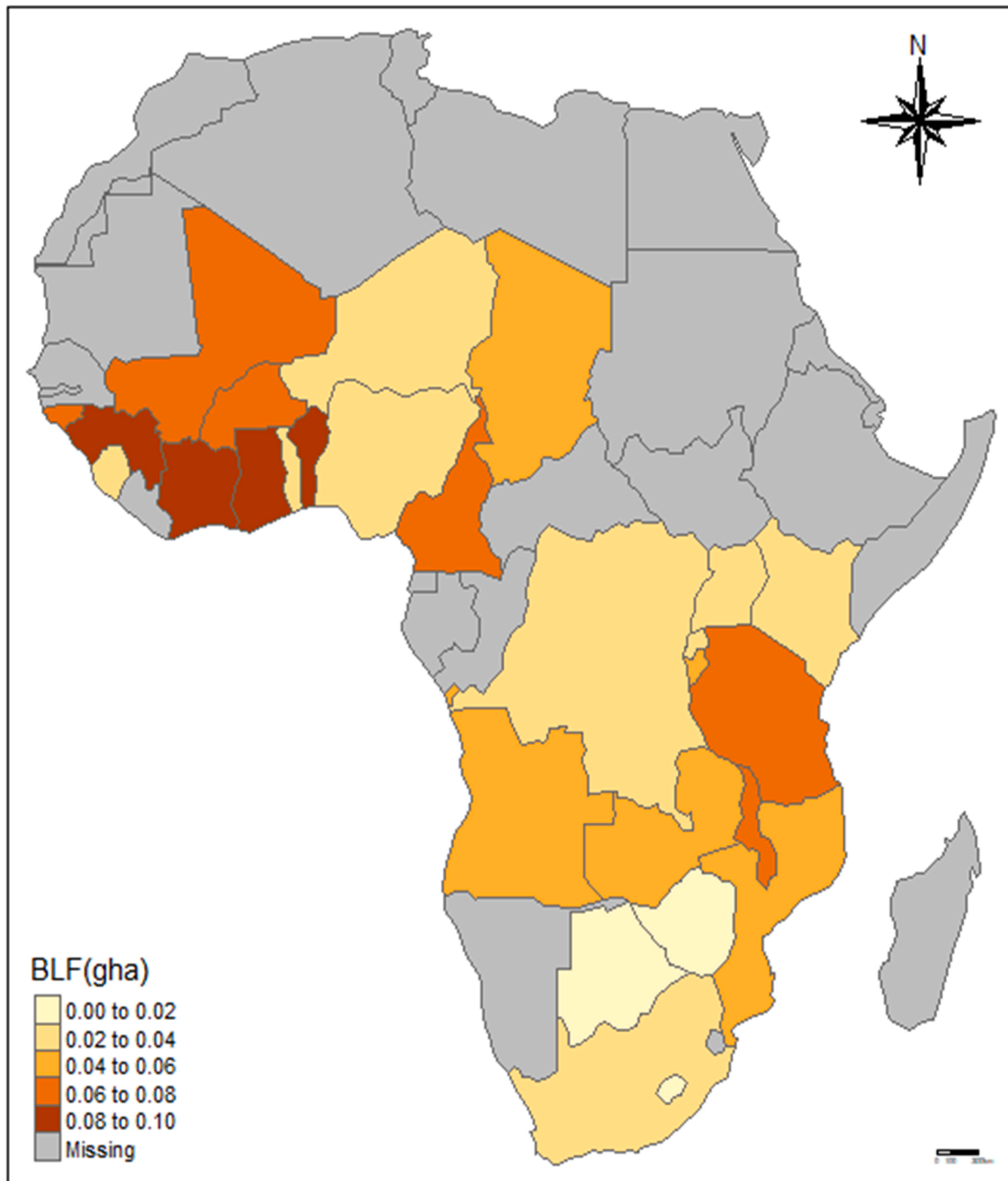


Fig. 4. Spatial distribution of per capita built-up land footprints in the SSA region.

yields an estimated convergence rate relatively small. This is indicative that the control variables considered in our analysis are an important driving force of the convergence process of built-up land footprints in SSA countries. The effects of the control variables on the convergence process can be summarized as follows.

- (i) By comparing the contribution of each variable to the convergence of built-up land footprint, result showed that the estimated convergence rate associated with biocapacity ($\ln Bio$) is the highest relative to other explanatory variables. One implication is that the availability of biologically productive land in SSA

- countries has significantly accelerated the convergence rates of built-up land footprints by reducing the development of built-up land footprints in countries with initially higher levels of footprints. This is in line with the negative and coefficient of biocapacity. For every increase in biocapacity by 1%, there is a significant reduction of the built-up land footprint by 0.216%. Thus, biocapacity conservation initiatives (such as protected areas, zero-deforestation, payment for ecosystem services) are essential to promote a sustainable built-up area development.
- (ii) It is found that both GDP ($\ln GDP$) and squared GDP ($\ln GDP^2$) are positive and negative, respectively. These two coefficients are

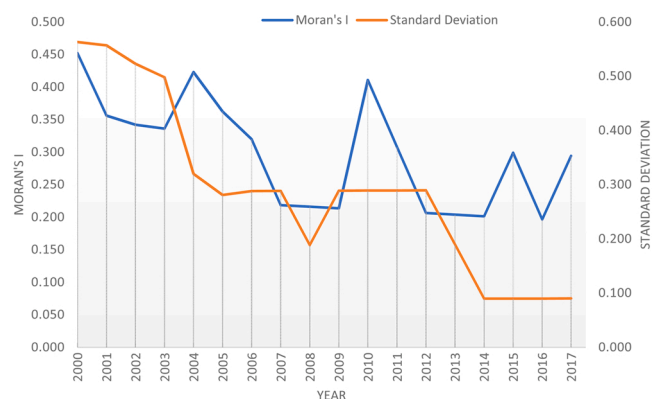


Fig. 5. Trends in standard deviations and Moran's I indices for built-up land footprints in 28 SSA countries, 2000–2017.

Table 4
Moran's I statistics for built-up land footprints.

Period	Z	P-values	Period	Z	P-value
2000	0.277 ^b	0.020	2009	0.155 ^c	0.086
2001	0.319 ^a	0.001	2010	0.113 ^c	0.095
2002	0.215 ^b	0.026	2011	0.120 ^c	0.090
2003	0.189 ^c	0.055	2012	0.541 ^a	0.000
2004	0.136 ^c	0.070	2013	0.240 ^b	0.015
2005	0.215 ^b	0.045	2014	0.175 ^c	0.062
2006	0.207 ^b	0.034	2015	0.167 ^c	0.079
2007	0.146 ^c	0.070	2016	0.240 ^b	0.034
2008	0.385 ^a	0.000	2017	0.177 ^c	0.066

Note: ^a, ^b and ^c represent significance level of 1%, 5%, and 10%, respectively

Table 5
Preliminary tests.

Tests	Statistics	Tests	Statistics
LM test no spatial lag	68.956 ^a	Wald spatial lag test	36.875 ^a
Robust LM test no spatial lag	10.563 ^a	Wald spatial error test	33.905 ^a
LM test no spatial error	57.149 ^a	LR spatial lag test	22.965 ^a
Robust LM test no spatial error	9.875 ^a	LR spatial error test	19.278 ^a

Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively.

Table 6
Regression results of the absolute spatial convergence.

Variables	Spatial autoregressive model	Spatial error model	Spatial Durbin Model
β	-0.110 ^a (0.000)	-0.158 ^a (0.000)	-0.261 ^a (0.000)
Convergence rate	0.116	0.171	0.302
ρ	0.225 ^a (0.000)		0.290 ^a (0.000)
λ		0.021 ^a (0.000)	
$W * \ln(z_{it-1})$			-0.521 ^a (0.000)
Log-likelihood	830.3973	232.5963	835.3791
Observation	504	504	504

Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively. The convergence rate (r) is computed as $r = -\ln(1 + \beta)$.

statistically significant at a 1% level. This indicates that there is an inverted U-shaped nexus between economic growth and built-up land footprints. Interestingly, the evidence of environmental Kuznets curve hypothesis is validated for built-up land footprint

as a measure of environmental pressure. Thus, built-up land footprints may decrease after a threshold level of per capita GDP, which corresponds to the peak of the built-up land footprint, is reached.

- (iii) Result also revealed that both population density (*lnpop*) and urbanization exert a positive and significant impact on built-up land footprints. It is well established that changes in a built-up area are the result of rapid population growth (Herrmann et al., 2020; Tan et al., 2016). Empirical evidence further revealed that urbanization has a detrimental impact on the built-up environment as it leads to the expansion of built-up land footprints. This finding is consistent with the compact city and environmental transition theories. These theories provide arguments in favor of urbanization's role in stimulating resources and ecological depletion. They are based on the premise that increasing urbanization leads to overcrowding, industrialization, and more transportation activities, resulting in severe ecological damages (Capello and Camagni, 2000; Poumanyong and Kaneko, 2010).
- (iv) Another important finding is that globalization (*lnglob*) significantly drives up built-up land footprints in SSA countries. Globalization allows a large variety of foreign actors to intervene directly or indirectly into the continent's urban land and built environment resulting in a significant imprint on the built-up landscape, especially with regard to changing land use and its environmental, ecological, and social consequences. This finding is in accordance with Amnon (2017), who found that current land market trends towards globalization are far from resulting in convergence among legal systems and constitute an important dilemma that land law faces. Again, the result revealed that industrial structure (*lnIndus*) has not a significant effect on built-up land footprints.

In order to show robust evidence of the above estimation results, series of sensitivity analyses are conducted by removing the urbanization and squared term of GDP over the sub-period 2008–2017. Furthermore, it is considered that the $K=5$ nearest weight matrix. The results are displayed in Table 7. It is observed that the results remain statistically unchanged and are well signed, suggesting that the convergence observed in built-up land footprint is not driven by the choice of the weight matrix. Consistent with our previous results reported in Table 5, the per capita biocapacity has the largest impact on the convergence rate, although the magnitudes of the estimated convergence are slightly lower.

5. Discussion of the findings

In the current academic literature, the question of built-up land is generally mentioned in the side-lines. The built-up land footprint question, which is at the very basis of transformation in human well-being, water resources, and food security, is rarely fully explored or taken as a central point in ecological sustainability debates. In this study, there is examination of the dynamics of the SSA region built-up land footprint with particular attention to the potential drivers of the built-up land expansion for 28 SSA countries over the period 2000–2017.

The highly significant global Moran's I index suggests the existence of spatial clustering patterns in built-up land footprints. In the investigation, it is illustrated that built-up land footprints are not randomly distributed within the SSA region and display two tendencies: moderate built-up land footprints in Southern Africa and high built-up land footprints Western African countries. This provides a piece of strong evidence that the distribution of built-up land footprint is not random but follows a significant spatial pattern. The report of the result shows that the imitation of environmental policies leads to a parallel development of built-up land footprints among SSA countries. A key implication of this finding is that a proper spatial arrangement can produce significant influences on the development of the built-up area (Msuya et al., 2021;

Table 7
Regression results of the spatial condition β convergence.

Variable	1	2	3	4	5	6	7
β	-0.458 ^a (0.000)	-0.369 ^a (0.000)	-0.250 ^a (0.001)	-0.310 ^a (0.000)	-0.396 ^a (0.000)	-0.382 ^a (0.022)	-0.116 ^c (0.077)
Convergence rate	0.612	0.460	0.287	0.371	0.504	0.481	0.123
lnBio	-0.216 ^a (0.000)						-0.145 ^b (0.041)
lnGDP		0.125 ^a (0.000)					0.256 ^a (0.000)
lnGDP ²		-1.937 ^a (0.001)					-1.204 ^b (0.000)
lnUrb			0.741 ^a (0.010)				0.314 (0.637)
lnpop				0.452 ^a (0.001)			0.336 (0.227)
lnIndus					1.089 (0.422)		0.965 (0.336)
lnglob						0.895 ^a (0.001)	0.729 ^a (0.000)
$W * \lnBio$	0.035 ^c (0.052)						0.063 ^c (0.078)
$W * \lnGDP$		0.096 ^a (0.001)					0.321 ^b (0.022)
$W * \lnpop$				0.005 ^c (0.097)			0.001 (0.123)
ρ	0.331 ^a (0.000)	0.456 ^a (0.050)	0.385 ^a (0.000)	0.812 ^a (0.000)	0.327 ^a (0.000)	0.410 ^a (0.000)	0.363 ^a (0.000)
Log-likelihood	855.2452	961.3605	743.1590	801.9673	963.1250	896.3284	635.2201
Observation	504	504	504	504	504	504	504

Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively. Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively. The convergence rate (r) is computed as $r = -\ln(1 + \beta)$. Values in parentheses denote p-values. In order to save space, the coefficients of other variables including $W * \lnUrb$, $W * \lnpop$, $W * \lnglob$, $W * \lnIndus$; are not reported. These coefficients are not statistically significant at the conventional levels of significance.

Table 8
Regression results of the spatial condition β convergence with K = 5 nearest weight matrix over the sub-period 2008 – 2017.

Variable	SDM	SDM	SDM	SDM	SDM
β	-0.371 ^a (0.000)	-0.201 ^a (0.000)	-0.218 ^a (0.000)	-0.335 ^a (0.000)	-0.227 ^a (0.022)
Convergence rate	0.463	0.241	0.245	0.407	0.257
lnBio	-0.016 ^a (0.000)				
lnGDP		0.010 ^a (0.000)			
lnpop			0.191 ^b (0.041)		
lnIndus				0.625 (0.100)	
lnglob					0.045 ^c (0.064)
$W * \lnBio$	0.001 ^a (0.002)				
$W * \lnGDP$		0.088 ^a (0.001)			
$W * \lnpop$			0.001 (0.197)		
ρ	0.224 ^a (0.000)	0.301 ^c (0.077)	0.307 ^a (0.000)	0.293 ^a (0.000)	0.291 ^a (0.000)
Log-likelihood	409.915	401.2101	441.0610	454.9591	428.0916
Observation	280	280	280	280	280

Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively. Notes: ^a, ^b, and ^c indicate significant levels at 1%, 5%, and 10%, respectively. The convergence rate (r) is computed as $r = -\ln(1 + \beta)$. Values in parentheses denote p-values. In order to save space, the coefficients of other variables including $W * \lnUrb$, $W * \lnpop$, $W * \lnglob$, $W * \lnIndus$; are not reported. These coefficients are not statistically significant at the conventional levels of significance.

Tu, 2011). As reported by Anselin et al. (1996) and Rey (2001), ignoring this spatial structure may lead to wrong inferences.

Based on the above finding, the spatial panel econometric techniques to investigate the spatial convergence features of built-up land footprints are employed. Accordingly, the investigation provides evidence for both spatial absolute and condition β convergence of built-up land footprints among SSA countries. One implication of this finding is that the differences in built-up land footprints among twenty-eight SSA countries were gradually being narrowed, and the built-up land footprints of each country will converge to the same steady state. Therefore, instead of following independent paths, the SSA countries gravitate towards a similar standard of built-up land patterns. One implication of the convergence hypothesis is that countries with higher land footprints tend to rapidly reduce the built-up land footprints compared to countries with lower built-up land footprints. The catching-up effect of convergence indicates that countries with initially higher land footprints must implement strict built-up land regulations to reduce land footprints because of the inherent hardship of shrinking footprints.

In contrast, countries with a low land footprint have more scope for allowing a reasonable development of their footprints. Interestingly, there is evidence that potential drivers of built-up land footprints increase the convergence rates relative to the convergence rate obtained from the absolute β convergence. Several previous studies of convergence have reached a similar conclusion (Hao and Peng, 2017; Yilanci et al., 2021).

Among the control variables, there is statistical evidence that biocapacity plays an important role in the convergence process, as it is associated with the highest rates of convergence of built-up land footprints. A key finding is that the availability of natural capital (biocapacity) improves the built-up environment by reducing footprints. This implies that the spatial optimization of biocapacity is essential for better resource patterns that reduce built-up land footprints. Several authors have reached similar findings such as (Guo et al., 2017; Wackernagel, 2014; Yue et al., 2011). Another significant result is that

globalization increases pressures on the built-up environment and delays the convergence process. As reported by some analysts, globalization harms the built-up area by the channel of land grabbing phenomenon observed in many SSA countries over the past decades. Indeed, globalization has been demonstrated to be strictly connected with the land grabbing phenomenon observed in many SSA countries, which has severe consequences for natural capital availability (Coscieme et al., 2018; Niccolucci et al., 2021). Our analysis shows that a higher degree of globalization and the resulting associated international transactions of land are detrimental for the built-up environment.

Because there is evidence for an inverted U-shaped nexus between built-up land footprints and per capita GDP, the increase in built-up land footprints may impede economic development in the SSA region. Due to the current level of economic development in many SSA countries, which is still considerably lower than the inflection points of the inverted U-shaped nexus, one may expect built-up land footprints to increase at least in the near future in the SSA countries. Since the process of the EKC does not take place immediately, the adoption of sustainable urban land management practices may result in a negative correlation between economic development and built-up resources. In the current literature, several studies have confirmed the EKC hypothesis for different environmental pollutants, such as CO₂ emissions (Armeanu et al., 2018; Bilgili et al., 2021; Markandya et al., 2006), ecological footprint (Erdoğan et al., 2021; Kassouri, 2021b; Kassouri and Altıntaş, 2020). Thus, the findings of this study open a new line of research regarding the examination of the EKC hypothesis based on different sub-components of ecological footprint.

Regarding the limitation of our study, it is important to stress that the lack of small-scale spatial data remains one of the key shortcomings of our study. A granular analysis to capture within country variation in built-up land footprints is quite relevant to identify place specific factors shaping land-use efficiency and long-term environmental sustainability. However, the authors believe that results can be improved as these data sets are developed and disseminated for SSA countries. Unlike the split-sample approach used in Rey and Montouri (2010), our data cover relatively small countries over a short period 2000 – 2017, which prevents us to estimate the convergence pattern over different subperiods. However, sensitivity analysis was performed by removing the squared terms of GDP and urbanization over the sub-period 2008 – 2017 based on the K= 5 nearest weight matrix. Thus, the sensitivity test revealed that the previous results remain statistically unchanged. One key implication is that the convergence observed in built-up land footprint is not driven by the choice of the weight matrix and consistent across different sub-periods (2000 – 2017 & 2008 – 2017).

6. Conclusion and policy implications

Several factors, including climate change, rapid urbanization, soil erosion, and population growth, have considerably affected the dynamics of built-up land footprints in Sub-Saharan African countries. In this study, the convergence characteristics of built-up land footprints in SSA countries is investigated over the period 2000–2017 by accounting for spatial effects. By utilizing spatial dependence to analyze the convergence process of built-up land footprints, and examining the drivers of the convergence, interesting results were revealed. Firstly, there is a significant spatial autocorrelation in the built-up land footprints of SSA countries. The implication is that ignoring this spatial structure may lead to wrong inferences. Secondly, the investigation found strong evidence for both spatial absolute and condition β convergence in BLF over the experimental period. This interprets that our data confirm the catching-up effect of convergence in built-up land footprint. Thirdly, the expansion of the biological capacity plays a significant role in accelerating the convergence rate as there is a negative impact of biocapacity on land footprints. Fourthly, besides the inclusion of globalization and urbanization, the employed STIRPAT model also revealed the effects of population density, GDP per capita, and the value-

added of industry in GDP on the convergence process. Specifically, statistical evidence found that all of these factors contribute to the expansion of land footprints, except the industrial structure, which does not significantly affect built-up land footprints.

6.1. Policy implications

The result from this study as implied above offers policy direction to decision makers and other stakeholders in both the environmental and economic sectors. Therefore, the following are relevant policy inference.

Spatial spillovers have played an important role in explaining built-up land trajectories in the SSA countries. More attention should be given to these countries because without rigorous ecological and environmental regulations the current pattern of built-up land footprints will not decrease in these countries but rather stay in self-reinforcing dynamics through spatial spillovers. The mutual influence of built-up land footprints between the adjacent countries should be considered in the formulation of sustainable built-up land policies.

Policymakers should set different built-up land targets according to locations. According to the spatial distribution characteristics, different trajectories of built-up land footprints and spatial autocorrelation patterns could help policymakers coordinate built-up and urban land reforms as well as proposing appropriate built-up area development accordingly.

Given the evidence of spatial convergence, one might suggest that narrowing the current level of built-up land footprint in countries with the relatively high footprint is more efficient as footprint intensity will decrease faster in these countries than in countries that have already cut built-up land footprints. Due to the existence of spatial spillover effects, the adjacent countries will benefit from the reduction of footprints.

It is established that biocapacity has played an important role in cutting built-up land footprints in SSA countries. In this light, biocapacity preservation policies (such as protected areas, payment of ecosystem services) should be encouraged through more targeted sustainable ecological policies. The government should coordinate its policies, especially for the preservation of biocapacity.

Lastly, there should be punitive actions against international investors, particularly those in international land transactions that are not environmentally conscious, to reduce the consequences of globalization on the expansion of built-up land footprints. The current framework of globalization in the SSA countries is detrimental to the built-up environment.

Although the estimation techniques and results are quite relevant and helpful to policymakers of other developing countries, the investigation could be replicated from different perspective. Future studies can investigate how land grabbing in SSA countries affects cross-national convergence of built-up land footprints which this study has not covered. The use of alternative analytical method(s) can also be considered as potential extension as observed in a related study of Jin et al. (2018) where 110 cities within the Yangtze River Economic Belt (YREB) were analyzed with the stochastic frontier analysis (SFA) and the use of the local indicators of spatial association (LISA) statistic.

Data availability

Data will be made available on request.

References

- Akadiri, S.Saint, Alola, A.A., Akadiri, A.C., 2019. The role of globalization, real income, tourism in environmental sustainability target. Evidence from Turkey. *Sci. Total Environ.* 687, 423–432. <https://doi.org/10.1016/j.scitotenv.2019.06.139>.
- Alola, A.A., Adebayo, T.S., Onifade, S.T., 2021a. Examining the dynamics of ecological footprint in China with spectral Granger causality and quantile-on-quantile approaches. *Int. J. Sustain. Dev. World Ecol.* 1–14.
- Alola, A.A., Eluwole, K.K., Lasisi, T.T., Alola, U.V., 2021b. Perspectives of globalization and tourism as drivers of ecological footprint in top 10 destination economies. *Environ. Sci. Pollut. Res.* 28 (24), 31607–31617.

- Altıntaş, H., Kassouri, Y., 2020. Is the environmental Kuznets Curve in Europe related to the per-capita ecological footprint or CO₂ emissions? *Ecol. Indic.* <https://doi.org/10.1016/j.ecolind.2020.106187>.
- Amnon, L., 2017. *Land Law in the Age of Globalization and Land Grabbing*. SSRN.
- Anselin, L., Bera, A.K., Florax, R., Yoon, M.J., 1996. Simple diagnostic tests for spatial dependence. *Reg. Sci. Urban Econ.* 26, 77–104. [https://doi.org/10.1016/0166-0462\(95\)02111-6](https://doi.org/10.1016/0166-0462(95)02111-6).
- Armeanu, D., Vintilă, G., Andrei, J.V., Gherghina, Ș.C., Drăgoi, M.C., Teodor, C., 2018. Exploring the link between environmental pollution and economic growth in EU-28 countries: Is there an environmental Kuznets curve? *e0195708–e0195708 PLoS One* 13. <https://doi.org/10.1371/journal.pone.0195708>.
- Bilgili, F., Nathaniel, S.P., Kuşkaya, S., Kassouri, Y., 2021. Environmental pollution and energy research and development: an Environmental Kuznets Curve model through quantile simulation approach. *Environ. Sci. Pollut. Res.* 2021 2838 (28), 53712–53727. <https://doi.org/10.1007/s11356-021-14506-0>.
- Borucke, M., Galli, A., Iha, K., Lazarus, E., Mattoon, S., Morales, J.C., Network, G.F., 2012. *The National Footprint Accounts, 2012 edition*. Global Footprint Network, Oakland, CA, USA.
- Borucke, M., Moore, D., Cranston, G., Gracey, K., Iha, K., Larson, J., Galli, A., 2013. Accounting for demand and supply of the biosphere's regenerative capacity: The National Footprint Accounts' underlying methodology and framework. *Ecol. Indic.* 24, 518–533.
- Brännlund, R., Karimu, A., 2018. Convergence in global environmental performance: assessing heterogeneity. *Environmental Economics and Policy Studies* 20 (3), 503–526. <https://doi.org/10.1007/s10018-017-0203-8>.
- Brink, A.B., Eva, H.D., 2009. Monitoring 25 years of land cover change dynamics in Africa: a sample based remote sensing approach. *Appl. Geogr.* 29, 501–512. <https://doi.org/10.1016/j.apgeog.2008.10.004>.
- Cain, A., 2014. African urban fantasies: past lessons and emerging realities. *Environ. Urban.* 26, 561–567. <https://doi.org/10.1177/0956247814526544>.
- Capello, R., Camagni, R., 2000. Beyond optimal city size: an evaluation of alternative urban growth patterns. *Urban Stud.* 37, 1479–1496. <https://doi.org/10.1080/00420980020080221>.
- Carroccio, A., Crescimanno, M., Galati, A., Tulone, A., 2016. The land grabbing in the international scenario: the role of the EU in land grabbing. *Agric. Food Econ.* 4, 1–9. <https://doi.org/10.1186/s40100-016-0056-7>.
- Churchill, S.A., Inekwe, J., Ivanovski, K., 2018. Conditional convergence in per capita carbon emissions since 1900. *Applied Energy* 228, 916–927. <https://doi.org/10.1016/j.apenergy.2018.06.132>.
- Clancy, J.S., 2008. Urban ecological footprints in Africa. *Afr. J. Ecol.* 46, 463–470. <https://doi.org/10.1111/j.1365-2028.2008.01041.x>.
- Coscieme, L., Niccolucci, V., Giannetti, B.F., Pulselli, F.M., Marchettini, N., Sutton, P.C., 2018. Implications of land-grabbing on the ecological balance of Brazil. *Resources* 7, 44. <https://doi.org/10.3390/resources7030044>.
- Coscieme, L., Pulselli, F.M., Niccolucci, V., Patrizi, N., Sutton, P.C., 2016. Accounting for “land-grabbing” from a biocapacity viewpoint. *Sci. Total Environ.* <https://doi.org/10.1016/j.scitotenv.2015.09.021>.
- Côté-Roy, L., Moser, S., 2019. ‘Does Africa not deserve shiny new cities?’ The power of seductive rhetoric around new cities in Africa. *Urban Stud.* 56, 2391–2407. <https://doi.org/10.1177/0042098018793032>.
- Dietz, T., Rosa, E.A., York, R., 2007. Driving the human ecological footprint. *Frontiers in Ecology and the Environment* 5 (1), 13–18. [https://doi.org/10.1890/1540-9295\(2007\)5\[13:DTHEF\]2.0.CO;2](https://doi.org/10.1890/1540-9295(2007)5[13:DTHEF]2.0.CO;2).
- Dietz, T., Rosa, E.A., York, R., 2007. Driving the human ecological footprint. *Front. Ecol. Environ.* 5, 13–18.
- Ehrlich, P.R., Holdren, J.P., 1971. Impact of population growth: complacency concerning this component of man's predicament is unjustified and counterproductive. *Science* 171 (3977), 1212–1217.
- Erb, K.H., Gaube, V., Krausmann, F., Plutzar, C., Bondeau, A., Haberl, H., 2007. A comprehensive global 5 min resolution land-use data set for the year 2000 consistent with national census data. *J. Land Use Sci.* 2, 191–224. <https://doi.org/10.1080/17474230701622981>.
- Erdogan, S., Acaravci, A., 2019. Revisiting the convergence of carbon emission phenomenon in OECD countries: new evidence from Fourier panel KPSS test. *Environmental Science and Pollution Research* 26 (4), 24758–24771.
- Erdogan, S., Çakar, N.D., Uluçak, R., Danış, Kassouri, Y., 2021. The role of natural resources abundance and dependence in achieving environmental sustainability: evidence from resource-based economies. *Sustain. Dev.* 29, 143–154. <https://doi.org/10.1002/sd.2137>.
- Erdogan, S., Okumus, I., 2021. Stochastic and club convergence of ecological footprint: an empirical analysis for different income group of countries. *Ecological Indicators* 121, 107123. <https://doi.org/10.1016/j.ecolind.2020.107123>.
- Fan, Y., Gan, L., Hong, C., Jessup, L.H., Jin, X., Pijanowski, B.C., Sun, Y., Lv, L., 2021. Spatial identification and determinants of trade-offs among multiple land use functions in Jiangsu Province, China. *Sci. Total Environ.* 772, 145022 <https://doi.org/10.1016/j.scitotenv.2021.145022>.
- FAOSTAT, 2001. A survey of indigenous land tenure: a report for the Land Tenure Service of the FAO.
- Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. *Sci.* (80-.). <https://doi.org/10.1126/science.1111772>.
- Galli, A., Kitzes, J., Niccolucci, V., Wackernagel, M., Wada, Y., Marchettini, N., 2012. Assessing the global environmental consequences of economic growth through the ecological footprint: a focus on China and India. *Ecological Indicators* 17, 99–107. <https://doi.org/10.1016/j.ecolind.2011.04.022>.
- Galli, A., Wackernagel, M., Iha, K., Lazarus, E., 2014. Ecological footprint: Implications for biodiversity. *Biological Conservation* 173, 121–132. <https://doi.org/10.1016/j.biocon.2013.10.019>.
- Global Footprint Network, 2020. *Ecol. Footpr. - Stat.*
- Guo, J., Yue, D., Li, K., Hui, C., 2017. Biocapacity optimization in regional planning. *Sci. Rep.* 7, 1–10. <https://doi.org/10.1038/srep41150>.
- Hao, Y., Peng, H., 2017. On the convergence in China's provincial per capita energy consumption: New evidence from a spatial econometric analysis. *Energy Econ.* 68, 31–43. <https://doi.org/10.1016/j.eneco.2017.09.008>.
- Herrmann, S.M., Brandt, M., Rasmussen, K., Fensholt, R., 2020. Accelerating land cover change in West Africa over four decades as population pressure increased. *Commun. Earth Environ.* 1, 1–10. <https://doi.org/10.1038/s43247-020-00053-y>.
- Huang, B., Meng, L., 2013. Convergence of per capita carbon dioxide emissions in urban China: a spatio-temporal perspective. *Applied Geography* 40, 21–29. <https://doi.org/10.1016/j.apgeog.2013.01.006>.
- Jin, G., Deng, X., Zhao, X., Guo, B., Yang, J., 2018. Spatiotemporal patterns in urban consumption: New evidence from the Yangtze River Economic Belt between 2005 and 2014. *J. Geogr. Sci.* 28 (8), 1113–1126.
- Junliang, D., Xiaolu, G., Shoushuai, D., 2010. Expansion of urban space and land use control in the process of urbanization: An overview. *Chin. J. Popul. Resour. Environ.* 8, 73–82. <https://doi.org/10.1080/10042857.2010.10684994>.
- Kassouri, Y., 2021a. Exploring the dynamics of fishing footprints in the Gulf of Guinea and Congo Basin region: Current status and future perspectives. *Mar. Policy* 133, 104739. <https://doi.org/10.1016/j.marpol.2021.104739>.
- Kassouri, Y., 2021b. Monitoring the spatial spillover effects of urbanization on water, built-up land and ecological footprints in sub-Saharan Africa. *J. Environ. Manag.* 300, 113690 <https://doi.org/10.1016/j.jenvman.2021.113690>.
- Kassouri, Y., Altıntaş, H., 2020. Human well-being versus ecological footprint in MENA countries: A trade-off? *J. Environ. Manag.* 263, 110405 <https://doi.org/10.1016/j.jenvman.2020.110405>.
- Ke, X., van Vliet, J., Zhou, T., Verburg, P.H., Zheng, W., Liu, X., 2018. Direct and indirect loss of natural habitat due to built-up area expansion: A model-based analysis for the city of Wuhan, China. *Land Use Policy* 74, 231–239. <https://doi.org/10.1016/j.landusepol.2017.12.048>.
- Kim, T., Cho, S.H., Larson, E.R., Armsworth, P.R., 2014. Protected area acquisition costs show economies of scale with area. *Ecol. Econ.* 107, 122–132. <https://doi.org/10.1016/j.ecolecon.2014.07.029>.
- Lai, Y., Tang, B., Chen, X., Zheng, X., 2021. Spatial determinants of land redevelopment in the urban renewal processes in Shenzhen, China. *Land Use Policy* 103, 105330. <https://doi.org/10.1016/j.landusepol.2021.105330>.
- Lazarus, E.D., 2014. Land grabbing as a driver of environmental change. <https://doi.org/10.1111/area.12072>.
- Lu, H., Xie, H., Lv, T., Yao, G., 2019. Determinants of cultivated land recuperation in ecologically damaged areas in China. *Land Use Policy* 81, 160–166. <https://doi.org/10.1016/j.landusepol.2018.10.052>.
- Lyu, R., Clarke, K.C., Zhang, J., Feng, J., Jia, X., Li, J., 2021. Dynamics of spatial relationships among ecosystem services and their determinants: Implications for land use system reform in Northwestern China. *Land Use Policy* 102, 105231. <https://doi.org/10.1016/j.landusepol.2020.105231>.
- Mahmood, R., Pielke, R.A., Hubbard, K.G., Niyogi, D., Bonan, G., Lawrence, P., McNider, R., McAlpine, C., Etter, A., Gameda, S., Qian, B., Carleton, A., Beltran-Przekurat, A., Chase, T., Quintanar, A.I., Adegoke, J.O., Vezhappambur, S., Conner, G., Asefi, S., Sertel, E., Legates, D.R., Wu, Y., Hale, R., Frauenfeld, O.W., Watts, A., Shepherd, M., Mitra, C., Anantharaj, V.G., Fall, S., Lund, R., Treviño, A., Blanken, P., Du, J., Chang, H.I., Leeper, R., Nair, U.S., Dobler, S., Deo, R., Syktus, J., 2010. Impacts of land use/land cover change on climate and future research priorities. *Bull. Am. Meteorol. Soc.* <https://doi.org/10.1175/2009BAMS2769.1>.
- Majeed, M.T., Mazhar, M., 2020. Reexamination of environmental Kuznets curve for ecological footprint: The role of biocapacity, human capital, and trade. *Pak. J. Commer. Soc. Sci.* 14, 202–254. <https://doi.org/10.2139/ssrn.3580586>.
- Markandya, A., Golub, A., Pedrosa-Galinato, S., 2006. Empirical Analysis of National Income and SO₂ Emissions in Selected European Countries. *Environ. Resour. Econ.* 35, 221–257. <https://doi.org/10.1007/s10640-006-9014-2>.
- Marquart-Pyatt, S.T., 2010. Environmental Sustainability. *Int. J. Socio* 40, 65–84. <https://doi.org/10.2753/ijso020-7659400204>.
- Meine, P. van D., 2016. Is China grabbing land in Africa? A literature overview study, in: Conference: Landc Conference Utrecht. pp. 1–12.
- Meyfroidt, P., Lambin, E.F., Erb, K.H., Hertel, T.W., 2013. Globalization of land use: Distant drivers of land change and geographic displacement of land use. *Curr. Opin. Environ. Sustain.* <https://doi.org/10.1016/j.cosust.2013.04.003>.
- Moran, P.A.P., 1948. The Interpretation of Statistical Maps. *J. R. Stat. Soc. Ser. B* 10, 243–251. <https://doi.org/10.1111/j.2517-6161.1948.tb00012.x>.
- Msuya, I., Moshi, I., Levira, F., 2021. Land Pattern of Highly Urbanizing Cities: Change in Built-up Area, Population Density and Spatial Development of the Sprawling Dar es Salaam City. *Environ. Urban. Asia.* <https://doi.org/10.1177/0975425321998036>.
- Niccolucci, V., Coscieme, L., Marchettini, N., 2021. Benefit transfer and the economic value of Biocapacity: Introducing the ecosystem service Yield factor. *Ecosyst. Serv.* 48, 101256 <https://doi.org/10.1016/j.ecoser.2021.101256>.
- Pang, M., Yang, S., Zhang, L., Li, Y., Kong, F., Wang, C., 2019. Understanding the linkages between production activities and ecosystem degradation in China: An ecological input-output model of 2012. *J. Clean. Prod.* 218, 975–984. <https://doi.org/10.1016/j.jclepro.2019.01.299>.
- Payne, J.E., Apergis, N., 2021. Convergence of per capita carbon dioxide emissions among developing countries: evidence from stochastic and club convergence tests.

- Environmental Science and Pollution Research 28 (26), 33751–33763. <https://doi.org/10.1007/s11356-020-09506-5>.
- Pham, T.T.H., Tong, T.H.A., Pham, V.C., 2013. Becoming urban: How urbanization influences the loss of arable land in peri-urban Hanoi. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer Verlag, pp. 238–252. https://doi.org/10.1007/978-3-642-39649-6_17.
- Poumanyong, P., Kaneko, S., 2010. Does urbanization lead to less energy use and lower CO₂ emissions? A cross-country analysis. *Ecol. Econ.* 70, 434–444. <https://doi.org/10.1016/j.ecolecon.2010.09.029>.
- Rees, W., Wackernagel, M., 2008. Urban ecological footprints: Why cities cannot be sustainable and why they are a key to sustainability. In: *Urban Ecology: An International Perspective on the Interaction Between Humans and Nature*. Springer, US, pp. 537–555. https://doi.org/10.1007/978-0-387-73412-5_35.
- Rey, S.J., 2001. Spatial Empirics for Economic Growth and Convergence. *Geogr. Anal.* 33, 195–214. <https://doi.org/10.1111/J.1538-4632.2001.TB00444.X>.
- Rey, S.J., Dev, B., 2006. σ -convergence in the presence of spatial effects. *Pap. Reg. Sci.* 85, 217–234. <https://doi.org/10.1111/J.1435-5957.2006.00083.X>.
- Rey, S.J., Montouri, B.D., 2010. US Reg. Income Converg.: A Spat. Econom. *Perspect.* 33, 143–156. <https://doi.org/10.1080/00343409950122945> <https://doi.org/10.1080/00343409950122945>.
- Rounsevell, M.D.A., Reay, D.S., 2009. Land use and climate change in the UK. *Land Use Policy* 26, S160–S169. <https://doi.org/10.1016/j.landusepol.2009.09.007>.
- Rudolph, A., Figge, L., 2017. Determinants of ecological footprints: what is the role of globalization? *Ecol. Indic.* 81, 348–361.
- Sajjad, H., Iqbal, M., 2012. Impact of urbanization on land use/land cover of dudhganga watershed of Kashmir Valley, India. *Int. J. Urban Sci.* 16, 321–339. <https://doi.org/10.1080/12265934.2012.743749>.
- Salahuddin, M., Gow, J., Ali, M.L., Hossain, M.R., Al-Azami, K.S., Akbar, D., Gedikli, A., 2019. Urbanization-globalization-CO₂ emissions nexus revisited: empirical evidence from South Africa. *Heliyon* 5, e01974. <https://doi.org/10.1016/j.heliyon.2019.e01974>.
- Salvati, L., Zitti, M., 2008. Regional convergence of environmental variables: empirical evidences from land degradation. *Ecological economics* 68 (1–2), 162–168. <https://doi.org/10.1016/j.ecolecon.2008.02.018>.
- Sanchez, P.A., Leakey, R.R.B., 1997. Land use transformation in Africa: three determinants for balancing food security with natural resource utilization. In: *Developments in Crop Science*. Elsevier, pp. 19–27. [https://doi.org/10.1016/S0378-519X\(97\)80004-9](https://doi.org/10.1016/S0378-519X(97)80004-9).
- Shao, Z., Sumari, N.S., Portnov, A., Ujoh, F., Musakwa, W., Mandela, P.J., 2020. Urban sprawl and its impact on sustainable urban development: a combination of remote sensing and social media data. *Geo-Spat. Inf. Sci.* <https://doi.org/10.1080/10095020.2020.1787800>.
- Shujah-ur-Rahman, Chen, S., Saud, S., Saleem, N., Bari, M.W., 2019. Nexus between financial development, energy consumption, income level, and ecological footprint in CEE countries: do human capital and biocapacity matter. *Environ. Sci. Pollut. Res.* 26, 31856–31872. <https://doi.org/10.1007/s11356-019-06343-z>.
- Solarin, S.A., Bello, M.O., 2018. Persistence of policy shocks to an environmental degradation index: The case of ecological footprint in 128 developed and developing countries. *Ecol. Indic.* 89, 35–44. <https://doi.org/10.1016/j.ecolind.2018.01.064>.
- Solarin, S.A., Gil-Alana, L.A., Lafuente, C., 2021. Persistence and non-stationarity in the built-up land footprint across 89 countries. *Ecol. Indic.* 123, 107372 <https://doi.org/10.1016/j.ecolind.2021.107372>.
- Solarin, S.A., Tiwari, A., 2020. Convergence in sulphur dioxide (SO₂) emissions since 1850 in OECD countries: evidence from a new panel unit root test. *Environmental Modeling & Assessment* 25 (5), 665–675. <https://doi.org/10.1007/s10666-019-09687-5>.
- Steel, G., van Noorloos, F., Klaufus, C., 2017. The urban land debate in the global South: New avenues for research. *Geoforum* 83, 133–141. <https://doi.org/10.1016/j.geoforum.2017.03.006>.
- Sumaila, U.R., Hotte, N., Galli, A., Lam, V.W.Y., Cisneros-Montemayor, A.M., Wackernagel, M., 2015. Eco2: A simple index of economic-ecological deficits. *Mar. Ecol. Prog. Ser.* 530, 271–279. <https://doi.org/10.3354/meps11278>.
- Tan, Y., Xu, H., Zhang, X., 2016. Sustainable urbanization in China: A comprehensive literature review. *Cities* 55, 82–93. <https://doi.org/10.1016/j.cities.2016.04.002>.
- Tu, J., 2011. Spatially varying relationships between land use and water quality across an urbanization gradient explored by geographically weighted regression. *Appl. Geogr.* 31, 376–392. <https://doi.org/10.1016/j.apgeog.2010.08.001>.
- Turok, I., McGranahan, G., 2013. Urbanization and economic growth: The arguments and evidence for Africa and Asia. *Environ. Urban.* <https://doi.org/10.1177/0956247813490908>.
- Uisso, A.M., Tanrivermiş, H., 2021. Driving factors and assessment of changes in the use of arable land in Tanzania. *Land Use Policy* 104, 105359. <https://doi.org/10.1016/j.landusepol.2021.105359>.
- Ulucak, R., Apergis, N., 2018. Does convergence really matter for the environment? An application based on club convergence and on the ecological footprint concept for the EU countries. *Environ. Sci. Policy* 80, 21–27. <https://doi.org/10.1016/j.envsci.2017.11.002>.
- Ulucak, R., Kassouri, Y., Çağrı İlkay, S., Altıntaş, H., Garang, A.P.M., 2020. Does convergence contribute to reshaping sustainable development policies? Insights from Sub-Saharan Africa. *Ecol. Indic.* 112, 106140 <https://doi.org/10.1016/j.ecolind.2020.106140>.
- Wackernagel, M., 2014. Comment on “Ecological Footprint Policy? Land Use as an Environmental Indicator. *J. Ind. Ecol.* 18, 20–23. <https://doi.org/10.1111/jiec.12094>.
- Watson, V., 2014. African urban fantasies: Dreams or nightmares? *Environ. Urban.* 26, 215–231. <https://doi.org/10.1177/0956247813513705>.
- Weinzettel, J., Hertwich, E.G., Peters, G.P., Steen-Olsen, K., Galli, A., 2013. Affluence drives the global displacement of land use. *Glob. Environ. Chang.* 23, 433–438. <https://doi.org/10.1016/j.gloenvcha.2012.12.010>.
- World Bank, 2015. Republic of Côte d’Ivoire Côte d’Ivoire Urbanization Review. World Cities Report, 2020. Unpacking Value Sustain. *Urban.* 43–74. <https://doi.org/10.18356/c41ab67e-en>.
- Yilanci, V., Gorus, M.S., Aydın, M., 2019. Are shocks to ecological footprint in OECD countries permanent or temporary? *J. Clean. Prod.* 212, 270–301. <https://doi.org/10.1016/j.jclepro.2018.11.299>.
- Yilanci, V., Gorus, M.S., Solarin, S.A., 2021. Convergence in per capita carbon footprint and ecological footprint for G7 countries: Evidence from panel Fourier threshold unit root test: <https://doi.org/10.1177/0958305x211011461> <https://doi.org/10.1177/0958305x211011461>.
- York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecol. Econ.* 46, 351–365. [https://doi.org/10.1016/S0921-8009\(03\)00188-5](https://doi.org/10.1016/S0921-8009(03)00188-5).
- You, W., Lv, Z., 2018. Spillover effects of economic globalization on CO₂ emissions: a spatial panel approach. *Energy Econ.* 73, 248–257. <https://doi.org/10.1016/J.ENERECO.2018.05.016>.
- Yue, D., Xu, X., Hui, C., Xiong, Y., Han, X., Ma, J., 2011. Biocapacity supply and demand in Northwest China: a spatial appraisal of sustainability. *Ecol. Econ.* 70, 988–994. <https://doi.org/10.1016/j.ecolecon.2010.12.017>.
- Zhang, P., Hao, Y., 2020. Rethinking China’s environmental target responsibility system: Province-level convergence analysis of pollutant emission intensities in China. *Journal of Cleaner Production* 242, 118472. <https://doi.org/10.1016/j.jclepro.2019.118472>.
- Zhao, X., Pu, J., Wang, X., Chen, J., Yang, L.E., Gu, Z., 2018. Land-use spatio-temporal change and its driving factors in an artificial forest area in Southwest China. *Sustain* 10. <https://doi.org/10.3390/su10114066>.