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Projecting Global Urban Area Growth Through 2100 Based on Historical Time Series Data and Future Shared Socioeconomic Pathways

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Key Points:
- We projected urban area growth until 2100 in each country by developing country-specific urban growth models
- Global urban area would increase by 40–67% under five SSPs until 2050 with large variations among countries
- The generated data set is the first country-level urban extents under five SSPs with potential use in studies of global environmental changes

Supporting Information:
- Supporting Information S1

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Abstract

Improved understanding of the potential growth of urban areas at the national and global levels is needed for sustainable urban development. Current panel data analysis and local scale modeling are limited in projecting global urban area growth with large spatial heterogeneities. In this study, we developed country-specific urban area growth models using the time series data set of global urban extents (1992–2013) and projected the future growth of urban areas under five Shared Socioeconomic Pathways (SSPs). Our results indicate the global urban area would increase roughly 40–67% under five SSPs until 2050 relative to the base year of 2013, and this trend would continue to a growth ratio of more than 200% by 2100. The growth of urban areas under relatively unsustainable development pathways (e.g., regional rivalry SSP3 and inequality SSP4) is smaller compared to other SSPs. Although developing countries would remain as leading contributors to the increase of global urban areas in the future, they may exhibit different temporal patterns, that is, plateaued or monotonically increasing trends. This variation is primarily attributed to the compounding effect of the growth in population and gross domestic product. Our urban area data set presents a first country-level urban area projection under the five SSPs, spanning from 2013 to 2100. This data set has a great potential to support various global change studies, for example, urban sprawl simulation, integrated assessment modeling for sustainable development goals, and investigation of the impact of urbanization on atmospheric emissions, air quality, and human health.

Plain Language Summary

Improved understanding of the potential growth of urban areas at the national and global levels is highly needed for sustainable urban development. In this study, we developed country-specific urban area growth models using the time series data set of global urban extents (1992–2013) and projected the future growth of urban areas under five Shared Socioeconomic Pathways (SSPs). We found the global urban area would increase by roughly 40–67% under five SSPs until 2050 relative to the base year of 2013, and this trend would continue to a growth ratio of more than 200% by 2100. Although developing countries would remain as leading contributors to the increase of global urban areas in the future, they may exhibit different temporal patterns, that is, plateaued or monotonically increasing trends. Our urban area data set presents a first country-level urban area projection under the five SSPs, spanning from 2013 to 2100. This data set has a great potential to support various global change studies, for example, urban sprawl simulation, integrated assessment modeling for sustainable development goals, and investigation of the impact of urbanization on atmospheric emissions, air quality, and human health.

1. Introduction

Our planet has been experiencing rapid urbanization over past decades, which changes the urban environment and affects human health, and further challenges the realization of sustainable development goals (SDGs). According to the latest World Urbanization Prospects (United Nations, 2018), more than 66% of the global population is projected to reside in urban areas by 2050. Moreover, the urbanization rate is higher in developing regions, such as countries in Africa and Asia, where many people are migrating from rural to urban, resulting in a notable expansion of urban extent and other concerns about energy and urban environment (Alberti et al., 2017; Güneralp et al., 2017; Li et al., 2016). As one of the key indicators of urbanization, the rapid global urban sprawl poses a wide range of challenges to the sustainable development at the local, national, and global scales. For example, it adversely affects forest and agricultural ecosystems and services they provide, such as food, fiber, and energy for humans (DeFries et al., 1999; Foley et al., 2005). Rapid urbanization and urban sprawl can also intensify urban heat island effect and increase building energy consumption (Imhoff et al., 2010; Zhang et al., 2013; Zhou, Clarke, et al., 2014). Also, it can negatively affect the urban environment by raising concerns about air pollution and public health (Gong et al., 2012; Li et al., 2019) and can result in drastic land use conversion and then significantly influence ecosystem services (Wang et al., 2019). Therefore, understanding the ongoing urbanization and quantifying its pace and magnitude going forward is crucial to sustainable development (Lu et al., 2015).

It is challenging to expand local-scale urban area growth modeling to other regions or use them for the projection of global urban area growth because of the differences such as methods and socioeconomic drivers used in these studies (Santé et al., 2010). For example, He et al. (2016) predicted the increase of urban areas in Beijing (China) through 2030 using population data. The urban area growth model was built on a simple linear regression model, in which the projected population primarily determined the growth of urban areas. However, the relationship between urban areas and socioeconomic indicators (e.g., population and gross domestic product - GDP) is treated differently in the literature (Santé et al., 2010). Approaches used for urban area projection range from directly coupling with the estimated population growth rate (Li & Yeh, 2000) or employing the urban area planned by the government (Chen et al., 2002) to adopting ancillary socioeconomic indicators such as per capita GDP or income (Li et al., 2014; Wu et al., 2010) or using more sophisticated system dynamics models (Han et al., 2009). Overall, the derived city (or local) scale relationships are not applicable to cities with different urbanization levels (Irwin & Geoghegan, 2001), and the required data sets in these city-scale models are not widely available at the regional or global scale.

Most studies on global urban area growth do not consider historical pathways of urban areas at the country (or regional) scales. Seto et al. (2012) estimated the increase of global urban areas using a Monte Carlo approach, which was implemented based on a global urban extent map (ca. 2000) and the estimated regional-scale population densities. However, historical pathways of urban area growth and spatially different urbanization levels were not considered. Klein Goldewijk et al. (2010) used the local urban density (i.e., per capita urban areas) to project the growth of urban areas at the global scale from 10,000 BCE to 2005. However, the resolution of resulting urban map is relatively coarse (around 8 km), and the model assumes an asymmetric bell-shaped curve to represent the temporal change of urban density only using a limited number of surveys from cities published in literature, which introduces high uncertainties in overall analysis (Dong et al., 2018; Hurtt et al., 2006; Li et al., 2016, 2017). Limited knowledge of the dynamics of urban areas over past decades has been the primary challenge in understanding the historical pathway of urban sprawl and projecting its future growth at the national and global scales (Li & Gong, 2016; Li et al., 2018).

This study aims to provide a global projection of urban area growth in the future for all countries. Unlike previous studies that were conducted at the local scale or ignored historical pathways of urban sprawl in each country, we developed country-specific urban area growth models using the time series (22 years) data of urban areas from satellite observations and projected global urban area growth in future, under different socioeconomic pathways. The remaining of this paper is organized as follows. Sections 2 and 3 provide descriptions of the data set and methodology, respectively. Section 4 analyzes projected growth of urban areas for individual countries and the global. Section 5 presents conclusions from this study and some directions for future studies.

2. Data

2.1. Historical Annual Urban Extents

One of the major data sets used in this study is the annual dynamics of global urban extent from 1992 to 2013, derived from the nighttime light data (Zhou et al., 2018). This data set differs from other existing nighttime light-based studies by mapping the urban extent at both regional and global scales (Small et al., 2005; Zhou, Smith, et al., 2014; Zhou et al., 2015). This data set is also unique because of its spatial and temporal consistency and a good agreement with other existing independent urban extent products (Li et al., 2015; Zhou et al., 2018). The derived urban extent data set has a 1-km spatial resolution and an annual temporal resolution, spanning from 1992 to 2013. The mean accuracies of this data set in the United States, China, and Europe are 96%, 86%, and 95%, respectively, at the urban cluster level according to the fine-resolution land cover data. This new data set depicts cities that have different urbanization rates in different regions. For

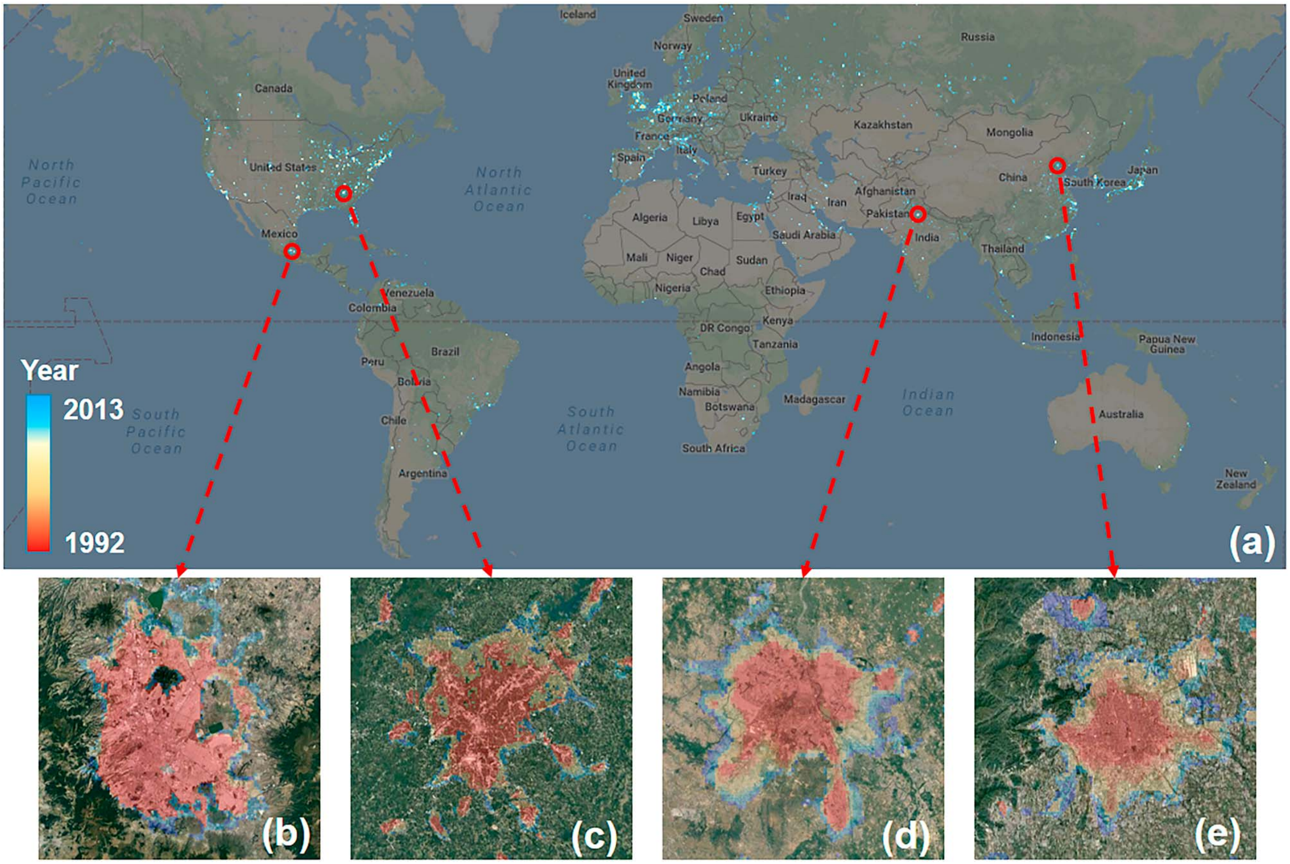

Figure 1. Overview of annual dynamics of global urban extent (a) and major metropolitans of Mexico City (Mexico; b), Atlanta (USA; c), New Delhi (India; d), and Beijing (China; e).

example, cities in developing areas such as in New Delhi (India) and Beijing (China) show a more notable expansion of urban extent compared to cities in developed regions, such as Atlanta (USA; Figure 1).

There is unprecedented and rapid urbanization worldwide over the past two decades, although the rate and extent of urbanization vary considerably across countries and years (Figure 2). Compared to the base year of 1992, most countries experienced more than a doubling of urban area growth by 2013. The majority of rapidly expanding urban areas are located in Asia, Africa, and South America, which appear to be the dominant driver of global urbanization in the future. At the same time, countries in these rapidly developing regions are likely to face more challenges for continuing the desired urbanization trends (Solecki et al., 2013), that is, achieving a balance between expanding the access to resources (such as fresh water, energy, and affordable and nutritious food) and minimizing adverse impacts on ecosystems and surrounding environment.

2.2. Socioeconomic Data

We used the historical records of socioeconomic data (i.e., population and GDP) to develop country-specific urban area growth models. Time series data of annual population and nominal GDP (1992–2013) were obtained from the World Bank database (http://databank.worldbank.org/). To make the GDP data comparable across countries and over time due to changes in living standards, we adjusted the nominal GDP to real GDP using the official rates of purchasing power parity and deflation. The resulting historical socioeconomic data (i.e., population and GDP; 1992–2013) were then used to develop urban area growth model for each of 171 countries used in this study, except for countries without records in the World Bank database.

We used future socioeconomic indicators derived from the Shared Socioeconomic Pathway (SSP) database to project the growth of urban area during 2013–2100. The SSP database is from the International Institute for

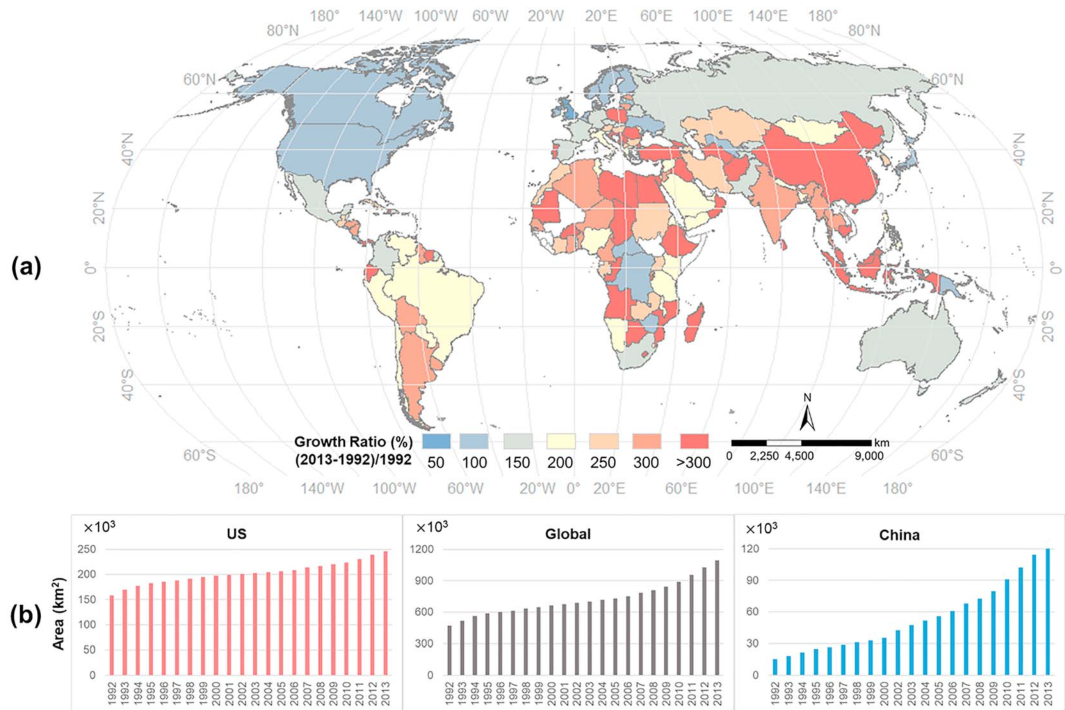

Figure 2. Growth ratios of urban areas at the global scale from 1992 to 2013 (a) and annual dynamics of urban areas for representative regions (b).

Applied System Analysis (https://tntcat.iiasa.ac.at/SspDb/), which quantifies possible pathways of socioeconomic development in the future (Riahi et al., 2017). There are five different socioeconomic narratives in the SSP database, which span a range of challenges to mitigation of and adaptation to climate change (Table 1). These narratives were translated into different pathways of socioeconomic development as they present various quantitative scenarios for national (regional) population and GDP change in the future (Figure 3). For example, SSP1 (sustainability) has the slowest pace of population growth and relatively rapid GDP growth, which is opposite to the SSP3 (region rivalry) scenario (Dellink et al., 2017; Kc & Lutz, 2017).

3. Methodology

We developed country-specific urban area growth models using the time series data of global urban extents (1992–2013) and then projected the future growth of urban area under five different SSPs (Figure 4). First, country-specific urban area growth models were developed based on the time series of per capita cumulative GDP and per capita urban areas, using a proposed sigmoid growth function. Second, future urban area growths under different socioeconomic pathways were projected using the population and GDP data from the SSP database, throughout the century (2013–2100). These two procedures are described in details in the following sections.

Table 1
Summary of SSP Narratives (Modified From O'Neill et al., 2017)

		Challenge	
Narratives	Name	Mitigation	Adaption
SSP1	Sustainability	Low	Low
SSP2	Middle of the road	Medium	Medium
SSP3	Regional rivalry	High	High
SSP4	Inequality	Low	High
SSP5	Fossil fueled development	High	Low

Note. SSP = Shared Socioeconomic Pathway.

3.1. Country-Specific Urban Area Growth Models

We developed country-specific urban area growth models using per capita urban areas (m^2) and per capita cumulative GDP (US $). Per capita urban areas were derived from the time series data of urban area and population. As for per capita cumulative GDP, we employed the cumulative real GDP of each country since 1992 rather than the annual GDP. This is first because the reported annual GDP that often fluctuated during the historical years; thus, the direct use of the annual GDP might yield temporary declines in urban areas, which would not be consistent with many

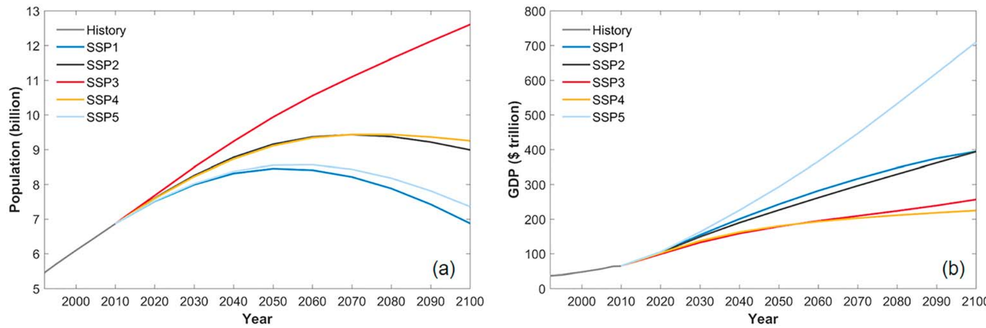

Figure 3. Projections of the global population (a) and GDP (b) under the five Shared Socioeconomic Pathways (SSPs).

previous urbanization studies that assume the irreversibility of urban extent expansion (Li et al., 2015; Mertes et al., 2015). Second, the cumulative GDP roughly follows the cumulative amount of economic outputs that the country consumes or invests over the historical period. Therefore, the scale of urban infrastructures and human settlements might be better correlated with the cumulative measure than with the annual measure. The proposed sigmoid growth model is described by equation (1).

$$pU_t = a + \frac{b}{1 + \exp^{-c^*(pCumGDP_t - d)}}, \tag{1}$$

where pU_t and $pCumGDP_t$ represent the logarithms of per capita urban areas (m^2) and per capita cumulative GDP (US $) of the year t; a and b are the parameters respectively denoting per capita urban areas at the beginning and ending phases of the urbanization process; and c and d are the coefficients that jointly determine the shape of sigmoid growth (Melaas et al., 2013; Seto et al., 2012; Yu et al., 2014).

The proposed sigmoid growth model can well capture different phases of urban development (i.e., initial, middle, and mature) in different countries (Figure 5). Trajectories of urban area growth at different urbanization phases were obtained from the annual time series data (Figure 5a). For countries at the initial phase of urbanization (e.g., countries in North Africa or middle Asia), the growth of per capita urban areas remains slow relative to the growth of per capita cumulative GDP. For countries experiencing a midphase of urbanization stage (e.g., emerging economies such as China or India), the per capita urban areas grow faster, possibly due to the industrialization that involves the development of urban lands. For countries at a mature phase of urbanization (e.g., countries in North America or Europe), the growth of per capita urban areas levels off at a high and stable level. The proposed sigmoid growth model can capture the relationship between the per capita urban areas and the per capita cumulative GDP at different phases of urbanization,

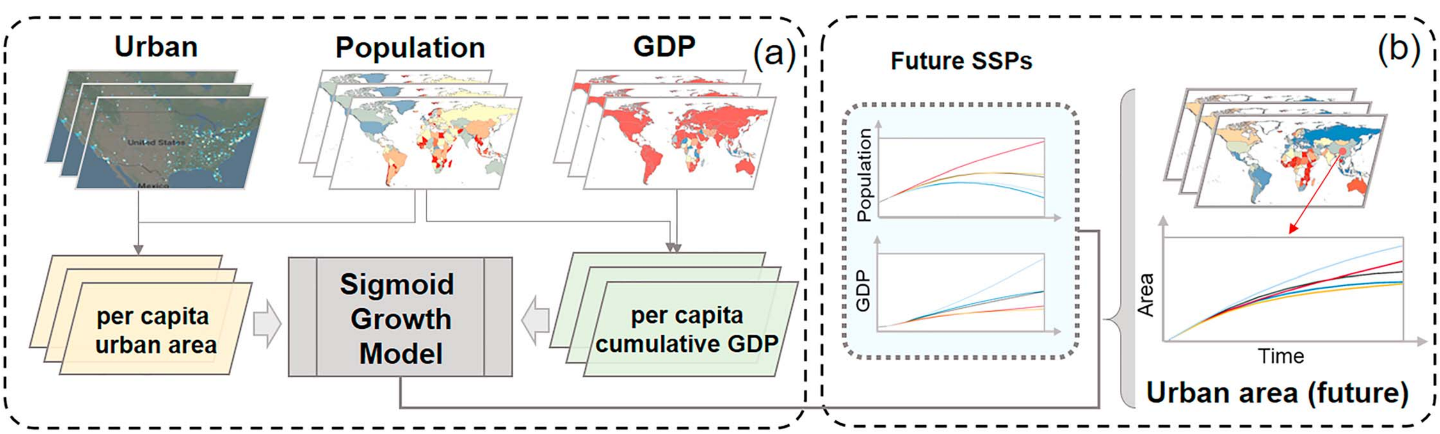

Figure 4. Schematic illustration of developing the urban area growth model (a) and projecting urban areas under Shared Socioeconomic Pathway narratives (b). GDP = gross domestic product.

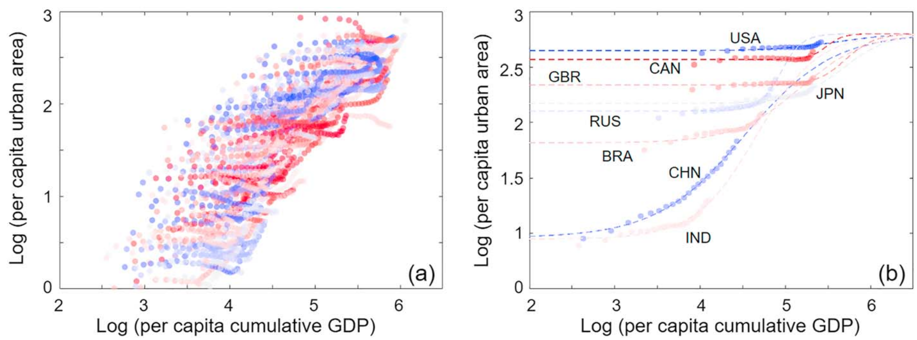

Figure 5. The relationship between per capita urban areas and per capita cumulative gross domestic product (GDP) for all countries in the world (a) and for representative countries that rank high regarding the urban area in 2013 (b).

using the long time series of urban areas. Compared to the multiregression model (Dong et al., 2018; He et al., 2013), which was generally performed in specific regions or countries, the sigmoid growth model only requires a constant set of parameters at different phases of urbanization. Although such stage-wise response of per capita urban areas to per capita cumulative GDP is observed in most countries, the fitted sigmoid curves vary by country as presented in Figure 5b. For example, curves of rapidly developing countries (e.g., China and India) are notably different from that of developed countries (e.g., United States and Canada). More cases can be found in Figure S1. These results are consistent with previous literature that report urbanization phases in different countries have different growth patterns, that is, a rapid expansion of urban areas in developing countries (i.e., midphase of urbanization) and a relatively stable (or steady) growth in developed countries (i.e., mature phase of urbanization; Eom et al., 2012; Liu & Phinn, 2003; Yu et al., 2014).

3.2. Urban Area Projection

We projected future growth of urban areas under five different SSPs through 2100, using the country-specific urban area growth models. First, the per capita urban area for each country was derived using equation (1), under the five SSPs. Then, future urban areas were projected through multiplying by population projections from the SSPs (equation (2)). Next, an adjustment is performed for countries exhibiting a declining population in future, for which the projected urban area would decrease according to equation (2). In this study, the shrinking of urban areas is used to maintain the temporal consistency of urban area increment, similar as other studies (Mertes et al., 2015; Santé et al., 2010). Thus, the projected urban areas were finally adjusted using equation (3).

$$U_t = pU_t{}^*P_t, \tag{2}$$

$$U_t^m = \begin{cases} U_t, t \leq t_{\text{peak}} \\ U_{\text{peak}}, t > t_{\text{peak}} \end{cases}, 2013 \leq t \leq 2100, \tag{3}$$

where U_t is the calculated urban area in the year t, from the projected per capita urban areas pU_t (m^2) and population P_t in the SSPs. U_t^m is the adjusted urban area, which stabilizes urban area from declining after it reaches the maximum of U_{peak} in the year t_{peak}.

4. Results and Discussion

4.1. Performance of Country-Specific Urban Area Growth Models

The proposed urban area growth model performs well for most countries in capturing historical urban area growth (Figure 6). The overall performance, as measured by the goodness-of-fit between the modeled and the observed data, is good with R-square values greater than 0.8 in most countries (Figure 6). This suggests that the proposed sigmoid growth model properly captures the historical pattern of urban sprawl. For several countries, however, the model performs relatively poor, and these countries are mainly located in middle Africa in which the urbanization level is relatively low. The lower quality of reported population and

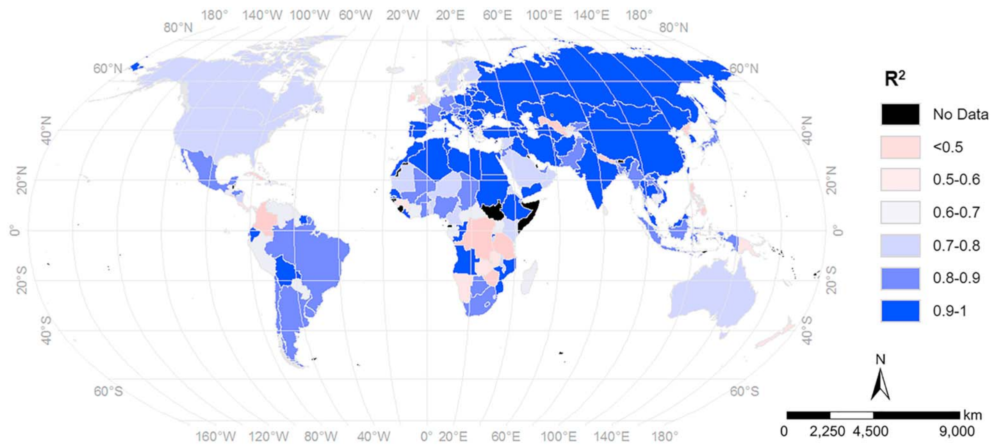

Figure 6. Performance of the proposed urban area growth model at the country level. The black areas indicate no available population and gross domestic product data according to the World Bank database.

GDP data for these countries is the likely reason for this poor performance of the proposed urban area growth model (United Nations, 2018).

4.2. Global Urban Area Growth

The projected urban area growth is different among the five SSPs used in this study, resulting in a notable difference of urban areas across SSPs in the second half of the century. All SSPs indicate a continued increase in urban areas under a range of development pathways (Figure 7), although the growth rate varies across scenarios. Projections under SSP3 and SSP4 are noticeably lower compared to SSP1, SSP2, and SSP5. This difference can be explained by different development narratives that influence population and GDP growth trajectories. For example, SSP3 represents the regional rivalry scenario, in which the income growth is not as fast as the population growth; SSP4 is the inequality scenario with highly unequal economic opportunities and political power across and within regions, resulting in the relatively slow growth of population and GDP (O'Neill et al., 2017). Thus, per capita urban areas under these two scenarios remain relatively low and so is the increase of total urban areas. Although SSP3 and SSP4 show similar GDP increments in the future, the population growth in SSP3 is notably higher than SSP4 (Figure 3), resulting in a lower per capita cumulative GDP in SSP3. Thus, the per capita urban area is also lower under SSP3 according to the sigmoid growth model, while, the lower per capita urban area and higher population under SSP3 together result in a similar total urban area as SSP4. Also, it should be noted that the global urban area growths under five SSPs were derived from aggregation of all countries, which have their own pathways. By contrast, under the other three scenarios (i.e., SSP1, SSP2, and SSP5) that exhibit a consistent rise in GDP and limited growth in population by the end of this century (Figure 2), a considerable growth of urban areas is observed, which is determined by the increment of both the per capita cumulative GDP and the total population. A medium level of growth in urban areas is found under the SSP2, consistent with its middle-of-the-road development projection (Figure 7). Also, the five SSPs all have a modest urban area growth until the midcentury before they take increasingly different growth pathways (Table 2). For example, urban growth rates for the five SSPs remain relatively low and similar until 2020 (around 6.8%), but they diverge as much as 27% by the midcentury (between SSP5 and SSP4), and almost 100% by the century end (between SSPs 1, 2, or 5 and SSPs 3 or 4).

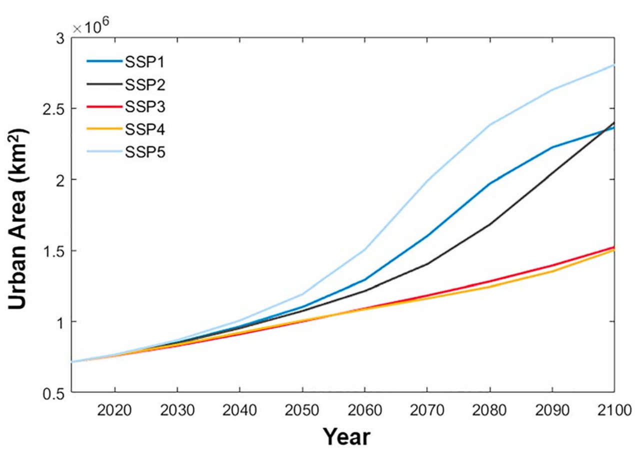

Figure 7. The projected global urban area by 2100 under the five Shared Socioeconomic Pathways (SSPs).

There is a distinctive spatial difference in urban area growth among the five SSPs. Regardless of the SSPs, the growth rate in developing areas, such as Africa and Asia, stays higher than that of developed regions, such as North America or Europe (Figures 8 and 9). This pattern is consistent with the trend over the past two decades (Figure 5). Besides, the

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Table 2
Growth Rate of the Global Urban Area Compared to 2013 (%)

Narrative	2020	2030	2040	2050	2060	2070	2080	2090	2100
SSP1	6.8	19.1	34.9	54.2	80.9	124.1	175.7	211.1	230.7
SSP2	6.8	18.7	33.4	50.3	70.0	96.3	135.3	185.7	235.8
SSP3	6.3	16.2	27.6	40.0	52.7	65.6	79.3	94.9	113.1
SSP4	6.6	17.0	28.8	40.8	52.0	62.7	74.0	89.0	110.3
SSP5	7.3	21.6	40.9	66.8	110.5	178.3	233.3	267.9	292.4

Note. SSP = Shared Socioeconomic Pathway.

expansion of urban areas in Asia and Africa is more pronounced than that of other continents. In particular, several countries, such as India or Nigeria, in which populations are projected to increase rapidly during the century (United Nations, 2018; Jiang & O'Neill, 2017), achieve almost doubled growth rate of the other regions in all SSPs, particularly in the second half of the century. Nevertheless, there is still a large gap to close before they reach the level of per capita urban areas of developed countries. By contrast, the developed regions, such as North America and Europe, exhibit a relatively modest increase in urban areas, with its growth rate being less than half of developing regions. Additionally, the developed regions exhibit rather significant growth in urban areas only under SSP5 due to its rapid economic development (Figures 8 and 9; Riahi et al., 2017).

4.3. Urban Area Growth in Major Countries

The growth of urban area shows noticeably different patterns across five SSPs in major countries, even though these countries currently are in similar urbanization phases. To better understand the influence of socioeconomic indicators on the growth of urban areas, we selected three major countries (i.e., the United States, China, and India) at different urbanization levels for further investigation (Figure 10). The United States is a highly urbanized country, and China and India are two rapidly developing countries each hosting more than 1.3 billion people. The total urban area of these three countries accounts for about 30% of the global urban area. Unlike the United States or China, which show a relatively slow growth or even a decrease in their population expected in the near future (ca. 2030), the population in India is likely to increase until 2050, totaling 1.7 billion people according to SSP2, the middle-of-the-road development pathway (O'Neill et al., 2017). Taking SSP2 as an example, although per capita cumulative GDP and per capita urban areas of these three countries would continue to rise, the increment of per capita urban areas in the United States is plateaued earlier compared to other two developing countries: China and India. Meanwhile, the growth of China's per capita urban areas would level off after 2050, which is distinctively different from India that would continue to increase (Figure 10). Considering the population dynamics in China and the United

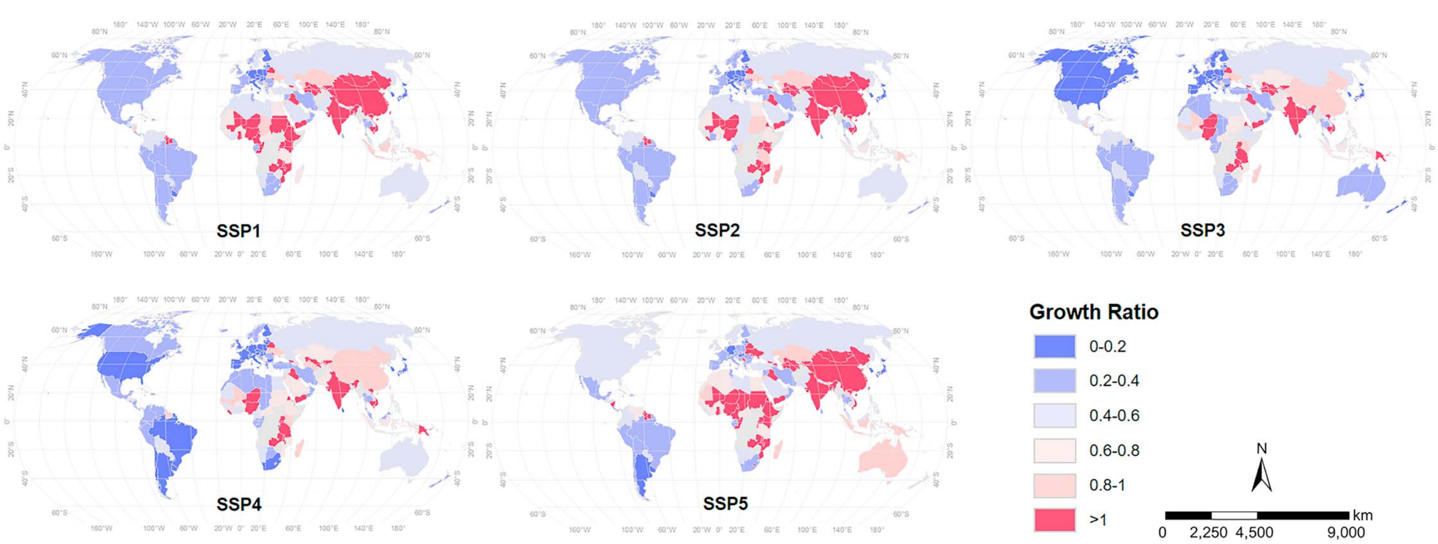

Figure 8. Urban area growth ratio (compare to 2013) at the country level by 2050 under five Shared Socioeconomic Pathways (SSPs).

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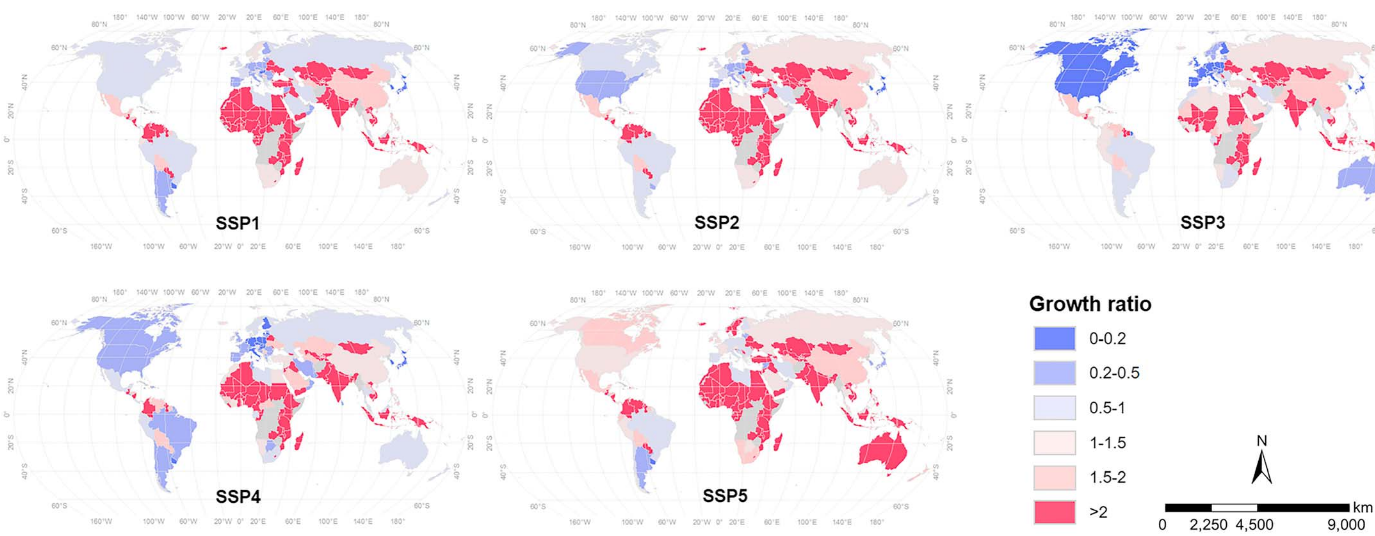

Figure 9. Urban area growth ratio (compare to 2013) at the country level by 2100 under five Shared Socioeconomic Pathways (SSPs).

States, to a lesser degree, they would exhibit a relatively modest urban area growth particularly in the second half of this century. Our results confirm that the United States shows a relatively slow increase in urban areas (a 48% growth compared to 2013) throughout the century, which is considerably lower than that of developing countries, such as China (175%) and India (800%; Figure 9). In SSP5, a fossil fuel-based development pathway, highly developed countries like the United States would likely to experience a continued increase in urban areas due to the rapid economic development combined with intensive consumption of resources (O'Neill et al., 2017). These different pathways of urban area growth under the five SSPs can provide a comprehensive and quantitative data set for spatially explicit modeling of urban sprawl and evaluating progress toward achieving the SDGs (Lu et al., 2015).

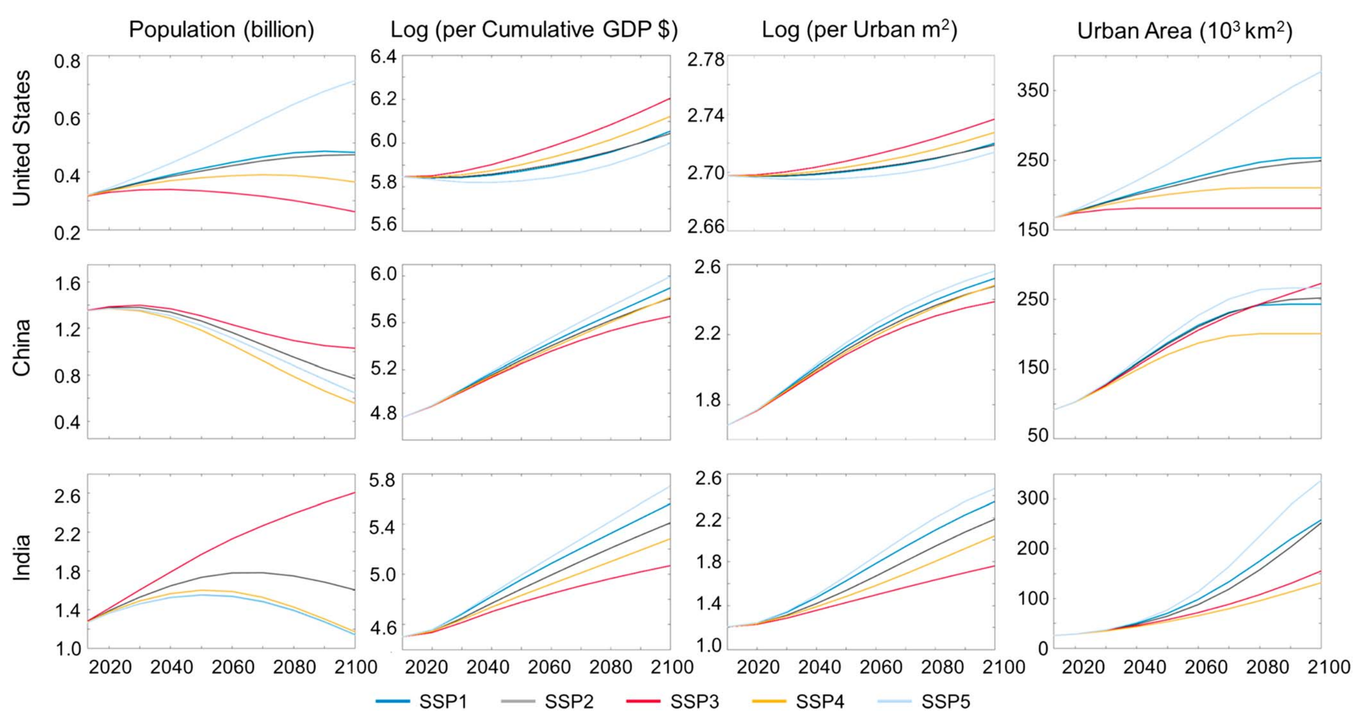

Figure 10. Projected population, per capita cumulative gross domestic product (GDP), per capita urban areas, and urban area growth in the United States, China, and India under the five Shared Socioeconomic Pathways (SSPs).

5. Conclusions

In this study, we developed country-specific urban area growth models using the time series of global urban extent and historical socioeconomic indicators (i.e., population and GDP) over the past two decades (1992–2013). The developed urban area growth models show a reasonably good performance for most countries worldwide. Our model is based on a long time series urban area data and can well capture different phases of urban development, which is notably different from the existing urban area analysis conducted using limited panel data observations. These models were used to project urban areas for different regions and countries for the rest of this century under five sets of population and GDP scenarios derived from SSPs. Our projections provide the first of its kind country-level data set of urban areas with due consideration to both historical urban growth pathways and future SSP scenarios, spanning from 1992 to 2100 (i.e., both retrospective and prospective) in a globally consistent manner.

Our projections reveal different pathways of urban area growth under the five SSPs across different countries, which is essential for investigating spatially explicit impacts of future urban sprawl on society and ecology and for achieving SDGs. There would be approximately 40–67% increase in urban areas globally under five SSPs by the midcentury, relative to the base year of 2013. The pace of urban area growth would be amplified from 2050 to 2100, possibly presenting doubling or tripling of urban areas depending on development pathways. Urban area growth under development pathways such as the regional rivalry scenario (SSP3) and the inequality scenario (SSP4) is constrained compared to other SSPs, such as the fossil fuel-based development scenario (SSP5) and the sustainable development scenario (SSP1). Also, the rapid growth of socioeconomic development in countries like China and India would continue to be the predominant driver of global urban area growth. Moreover, for some developing countries, such as China, urban area growth would level off around 2050, which is considerably different from the majority of developing countries such as India.

The projections of urban areas would be useful for global urban sprawl modeling and sustainable development studies. The top-down urban areas projected in this study can be coupled with a bottom-up spatial allocation model such as cellular automata (Li et al., 2014; Li & Gong, 2016), to simulate spatially explicit sprawl of urban extent. Besides, our SSP-variant urban area data set provides multiple urban development pathways that span a wide range of future challenges associated with climate change. Thus, human and ecosystem vulnerability and resilience to climate change and other environmental stressors can be assessed under various realizations of future socioeconomic development. This data set can also be used to explore potential risks (e.g., biodiversity hotspots) caused by urban sprawl (Myers et al., 2000), assess the challenges faced by individual countries in their efforts to achieve the SDGs and associated national targets (Güneralp et al., 2017; Seto et al., 2012), and develop robust responses and management of resources at the national and regional level. Additionally, this data set can be used with Earth system models to explore the anthropogenic impacts on water, energy and carbon cycles, and global environment (Bond-Lamberty et al., 2014; Collins et al., 2015). However, it should be noted that a more comprehensive assessment of global environmental changes would also consider a detailed representation of other quantitative inputs (e.g., natural resources, technologies, and investments) and qualitative narratives (e.g., policies, institutions, lifestyle, and settlement pattern) that are consistent with the major SSP indicators used in this study (i.e., population and GDP; van Vuuren et al., 2017). For example, although the total urban area under SSP1 (Sustainability) shows a twofold increase by 2100 relative to the base year of 2013, the new urban area mostly comes from developing countries in reducing inequality within and across countries for the sustainable development (Figure 10). Thus, future studies on urban area dynamics would benefit greatly in identifying plausible sustainable development pathways, especially for developing regions and nations worldwide.

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