



Gridded GDP Projections Compatible With the Five SSPs (Shared Socioeconomic Pathways)

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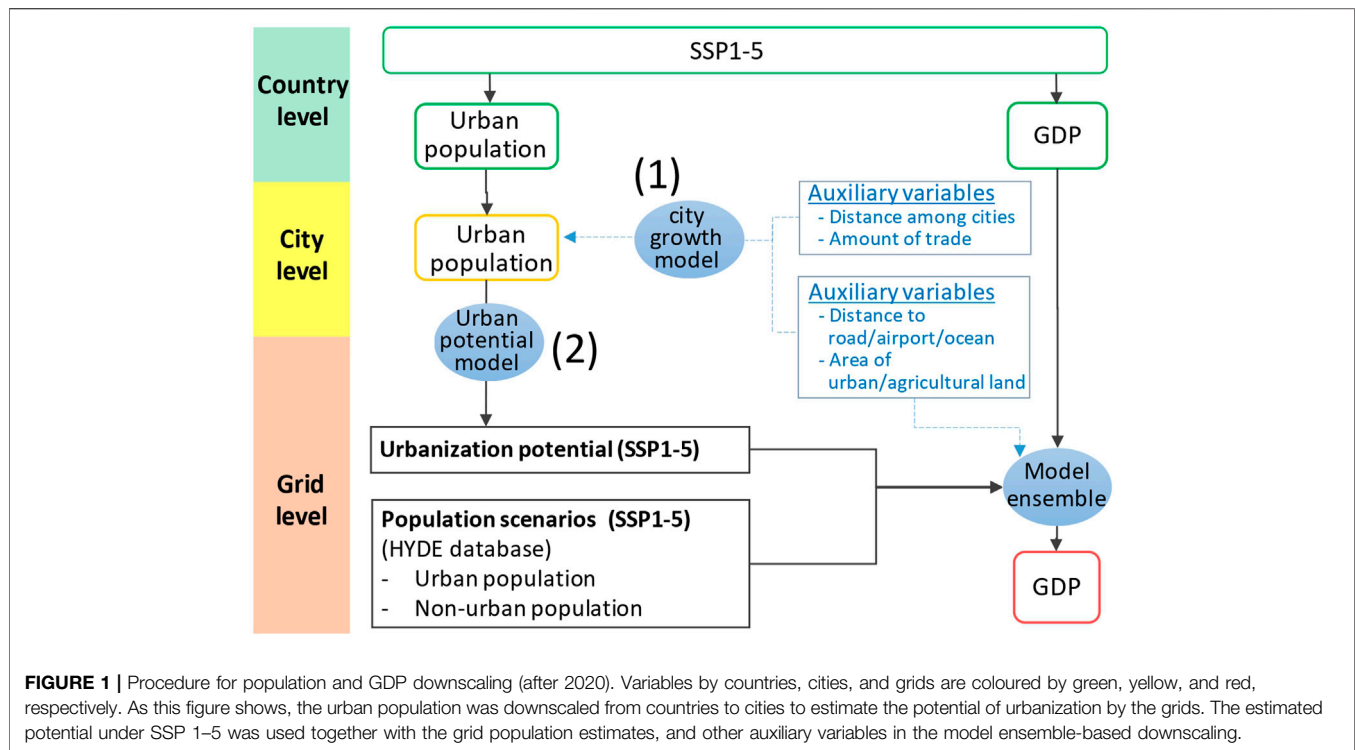
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Historical and future spatially explicit population and gross domestic product (GDP) data are essential for the analysis of future climate risks. Unlike population projections that are generally available, GDP projections—particularly for scenarios compatible with shared socioeconomic pathways (SSPs)—are limited. Our objective is to perform a high-resolution and long-term GDP estimation under SSPs utilizing a wide variety of geographic auxiliary information. We estimated the GDP in a 1/12-degree grid scale. The estimation is done through downscaling of historical GDP data for 1850–2010 and SSP future scenario data for 2010–2100. In the downscaling, we first modeled the spatial and economic interactions among cities and projected different future urban growth patterns according to the SSPs. Subsequently, the projected patterns and other auxiliary geographic data were used to estimate the gridded GDP distributions. Finally, the GDP projections were visualized via three-dimensional mapping to enhance the clarity for multiple stakeholders. Our results suggest that the spatial pattern of urban and peri-urban GDP depends considerably on the SSPs; the GDP of the existing major cities grew rapidly under SSP1, moderately grew under SSP 2 and SSP4, slowly grew under SSP3, and dispersed growth under SSP5.

Keywords: shared socioeconomic pathways, gross domestic product, downscale, 1/12-degree grid scale, spatial econometrics

INTRODUCTION

Building urban resilience against climate risks including flooding, storm, and heatwave, is an emergent task across the world. Future scenarios for population, economic productivity, and other socio-economic variables are required to estimate climate-related damage in the future and to consider countermeasures. IPCC (Inter-governmental Panel on Climate Change) published Shared Socioeconomic Pathways (SSP), which are future scenarios for socio-economic variables under possible future developmental paths that is, sustainability (SSP1), middle of the road (SSP2), regional rivalry (SSP3), inequality (SSP4), and fossil-fueled development (SSP5) (O'Neill et al., 2014; Jones and O'Neill 2016). Roughly speaking, SSP1 assumes rapid and compact urban growth, SSP2 assumes that the current state lasts in the future, SSP3 assumes failure of globalization that leads to a lower level of economic growth and low international priority for addressing environmental concerns, SSP4 assumes increasing inequality leading to higher growth in developed countries and lower growth in less developed countries, and SSP5 assumes a fossil-fueled or car-oriented development that results in large-scale urban sprawl. Additionally, the current COVID-19 pandemic may



accelerate and entrench longer-term reduction in product-trades and immigration flows. As the result, such a scenario would have parallels to the SSP3 scenario which projects slower economic growth than the other SSPs (Burgess et al., 2020).

While country-level SSPs data are available from the SSP Database (Riahi et al., 2017), climate risk considerably changes within countries. For example, flood risk of a city changes depending on whether the city is in a water-front area or not. Regional SSPs are needed to estimate climate risks in each country. With this background, country-level population scenarios have been downscaled into fine spatial grids under SSPs (Jones and O'Neill 2016; Murakami and Yamagata 2019; Wear and Prestemon 2019) and other future scenarios (Gaffin et al., 2004; Bengtsson et al., 2007; McKee et al., 2015; Yamagata et al., 2015).

By contrast, the SSP GDP scenario has rarely been downscaled, whereas GDP scenarios other than SSP have been done (Gaffin et al., 2004; Grubler et al., 2007; Fujimori et al., 2017; Kummu et al., 2018). One of the reasons for the lack of SSP GDP scenario downscaling is the difficulty compared to population downscaling. In the case of population downscaling, high-resolution population estimates from past to present are available; fine-grained population projection is readily obtained by extrapolating the past trend. Unfortunately, such extrapolation is not possible for GDP because of the lack of such past-to-present data. To the best of our knowledge, Murakami and Yamagata (2019) is the only one downscaling SSP GDP scenarios into fine grids. They estimated the explanatory power of each auxiliary geographic data (e.g., urban population, road network, distance to the ocean) on GDP distribution using an ensemble learning technique, and country GDPs were downscaled into grids based

on the results. Unfortunately, their database has the following limitations. First, their assumed spatial resolution of 0.5-degree grids is not fine enough to estimate the climate risk of individual cities. 0.5-degree nearly equals 55.83 (=111.66/2) km around the equator while 42.64 km in a 40-degree area. Multiple cities could be in one grid. Second, the authors did not consider SSP4 and SSP5. Third, their estimates are not available before 2010.

The objective of this study is to overcome these limitations. Specifically, we estimated GDPs by 1/12 grids for the period between 1850 and 2100 by 10 years by downscaling actual GDPs between 1850 and 2010 and projected GDPs under SSPs 1–5 between 2020 and 2100.

METHODS AND MATERIALS

We downscaled country GDPs into 1/12-degree grids. The downscaling was performed from 1850 to 2100 by 10 years. The procedure for each year after 2020 is summarized in **Figure 1**. **Table 1** summarizes the input data. In order to project the extent of urbanization in the future, we first estimated the growth of individual cities under each SSP ((1) of **Figure 1**). Then, based on the results, we projected the urbanization potential by the grids under each SSP ((2) of **Figure 1**). Note that we cannot consider COVID-19 because the SSPs, which we will downscale, ignore it. Consideration of COVID-19 will be an important next topic.

Projection of City Population

The following model was used for (1) the urban growth projection ((1) in **Figure 1**):

TABLE 1 | Auxiliary variables.

Description	Spatial unit	Source	Year
Urban population by SSP 1–5 Non-urban population by SSP 1–5	1/12-degree grids	History Database of the Global Environment (HYDE: Klein Goldewijk et al., 2010; Klein Goldewijk et al., 2010)	1980–2,100, by 10 years
Urban population	67,934 cities	Global Rural-Urban Mapping Project (GRUMP: Socioeconomic Data and Applications Center (2011))	1990, 1995, 2000
Urban area [km ²] Agricultural area [km ²]	1/12-degree grids	Schneider et al (2009)	2001–2002
Distance [km] from the grid left to the nearest major road		Natural Earth (2017)	2012
Distance [km] from the grid left to the nearest ocean			2010
Amount of bilateral trade [current US dollars]	Country	CoW: Barbieri and Omar (2016)	2009

$$y_t = (\rho_E \mathbf{W}_E + \rho_e \mathbf{W}_e + \rho_G \mathbf{W}_G + \rho_g \mathbf{W}_g) y_{t-5} + \alpha y_{t-5} + \sum_{k=1}^K \beta_k x_k + \varepsilon_t, \quad (1)$$

where y_t is a vector of urban population difference between year $t-5$ and t , x_k is the k -th explanatory variable in year t , and ε_t is a noise term. $\{\mathbf{W}_E, \mathbf{W}_e, \mathbf{W}_G, \mathbf{W}_g\}$ are matrices describing connectivity among cities, which are recoded in the GRUMP urban population database (see **Table 1**). \mathbf{W}_E and \mathbf{W}_e describe international and national trade intensity respectively. The (i, j) -th element of \mathbf{W}_E equals the amount of estimated international trade between cities i and j that is assumed zero if cities i and j are in the same country. The (i, j) -th element of \mathbf{W}_e is the estimated domestic trade amount between the cities i and j that is assumed zero if they are in different countries. These trade amounts between cities were estimated by a proportional distribution of bilateral trade data based on urban population (see **Table 1**). Concretely, the amount of trade between countries A and B was downscaled to the amounts between N_A cities in country A and N_B cities in country B . The distribution rates for each of the $N_A N_B$ city pairs equals the product of the two urban populations. \mathbf{W}_G describes the geographic proximity between cities in different countries while \mathbf{W}_g describes the same within the same country. For both, the spatial proximity was defined by an exponentially decaying function⁴.

In summary, **Eq. 1** estimates the 5-year population growth of individual cities based on international and domestic socio-economic interaction, geographic proximity, the population of the previous 5 years (y_{t-5}), and other explanatory variables (x_k).

The coefficients $\{\rho_E, \rho_e, \rho_G, \rho_g, \alpha, \beta_1, \dots, \beta_K\}$ were estimated from data. The GRUMP urban population data (1990, 1995, 2000; see **Table 1**) was used for the parameter estimation employing the 2-step least square estimation method. Because the city population data is available only between 1990 and 2000, it is difficult to accurately estimate the temporal variation of the parameters between 1850 and 2100. Therefore, in this study, the values of the parameters $\{\alpha, \beta_1, \dots, \beta_K\}$ were assumed constant over the years.

Based on SSP storylines, we assumed different values for the city-wise interaction parameters $\{\rho_E, \rho_e, \rho_G, \rho_g\}$. Specifically, the estimates from the current data were assumed unchanged in the

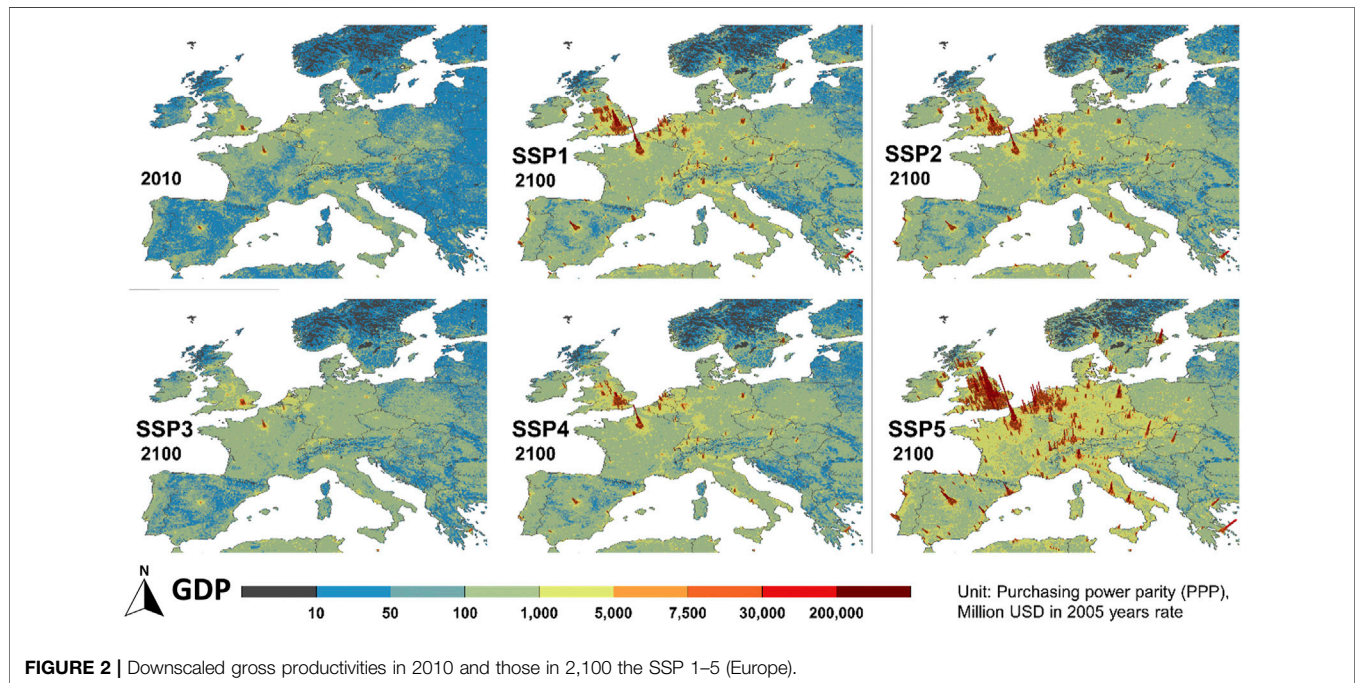
SSP2, which is a business-as-usual scenario. For the other scenarios, the values were changed by multiplying the multipliers, which equals 1.0 in 2010 and linearly increased/decreased to the values for 2100 (**Table 2**). For SSP1, the global socio-economic interaction was assumed to be double in 2100 while the domestic interaction was halved following the assumption of globalization. Following the assumption of regional division in SSP3 and 4, international socio-economic interactions were halved while national socio-economic interactions were doubled in these scenarios. For SSP 5, the international socio-economic interactions were doubled assuming the increase of international trading under the fossil-fueled development. Since SSPs have no quantitative assumption regarding the amount of the interactions among cities, we determined the amount of increase/decrease of the city interactions in each scenario to be consistent with the scenario assumptions and seem reasonable. In the future, we would like to examine validity of our assumption for the interactions among cities. Given these assumptions, the city-wise populations from 2020 to 2100 by 5 years were estimated by applying **Eq. 1** sequentially.

Projection of Urbanization Projection

The projected city-wise populations were used to estimate the urbanization potential by the grid ((2) in **Figure 1**). The potential $\hat{p}_{g,t}$ in the g -th grid in the t -th year was estimated by $\hat{p}_{g,t} = \hat{y}_{c,t} \exp(-\frac{d_{c,g}}{r})$, where $\hat{y}_{c,t}$ is the estimated population in the c -th city and $d_{c,g}$ is the great circle distance between the geometric center of the g -th grid and the c -th city. The r parameter determines the range of the spatial spill-over from each city. A large r yields large-scale urban sprawl, whereas a small r yields compact urban growth. The value was estimated by maximizing the correlation between the urban area by the grids in 2000 (see **Table 1**) and the $\hat{p}_{g,t}$ values in the same year. The estimated r value equaled 16.4 km. The value was assumed constant over the years in SSP2 and SSP4. To emulate compact urban development, the value was halved in SSP1, which is a sustainable development scenario. The r value was doubled in SSP3 and SSP5, both of which assume a low level of environmental awareness that will lead to a car-dependent development and urban sprawl as well.

TABLE 2 | Assumptions for the parameters in 2,100 in the urban growth model (SSP2: 1.0).

Model	Effect	SSP1	SSP2	SSP3	SSP4	SSP5
Urban growth model	International socio-economic interaction ρ_E	2.0	1.0	0.5	0.5	2.0
	National socio-economic interaction ρ_e	0.5	1.0	2.0	2.0	1.0
	International spatial interaction ρ_G	1.0	1.0	0.0	0.0	1.0
	National spatial interaction ρ_g	1.0	1.0	1.0	1.0	1.0
Urban potential model	Spread of urbanization potential: r	0.5	1.0	2.0	1.0	2.0



Downscale of Country GDPs

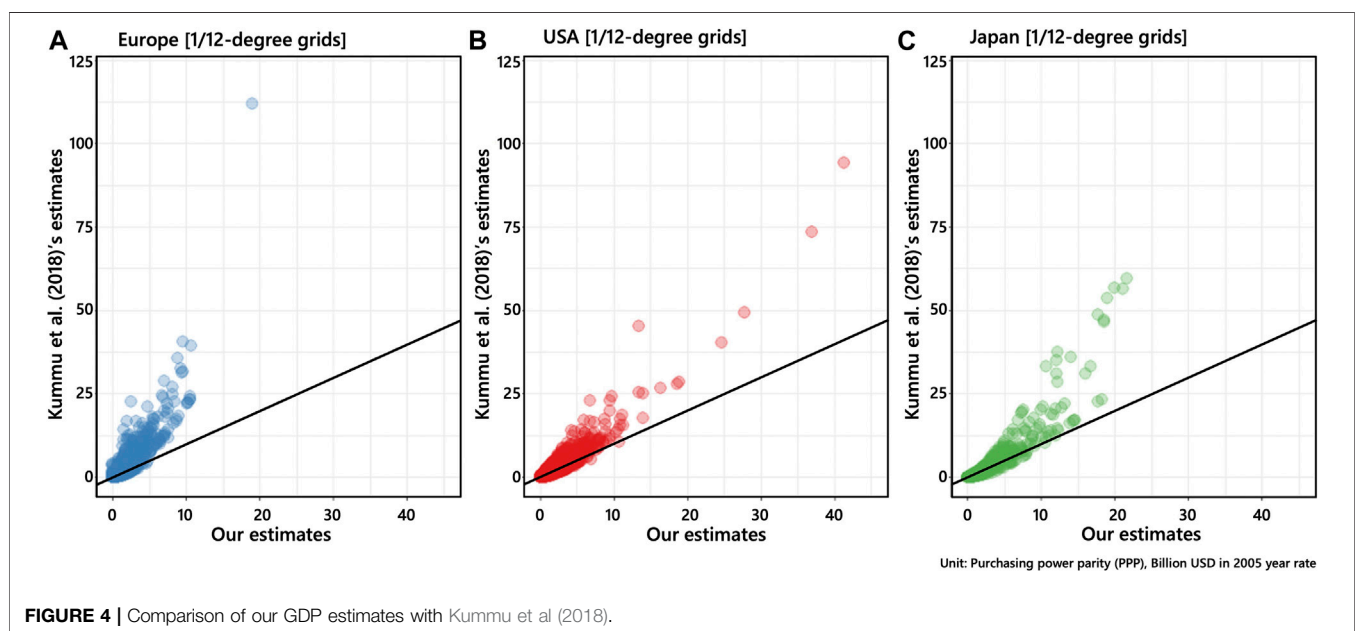
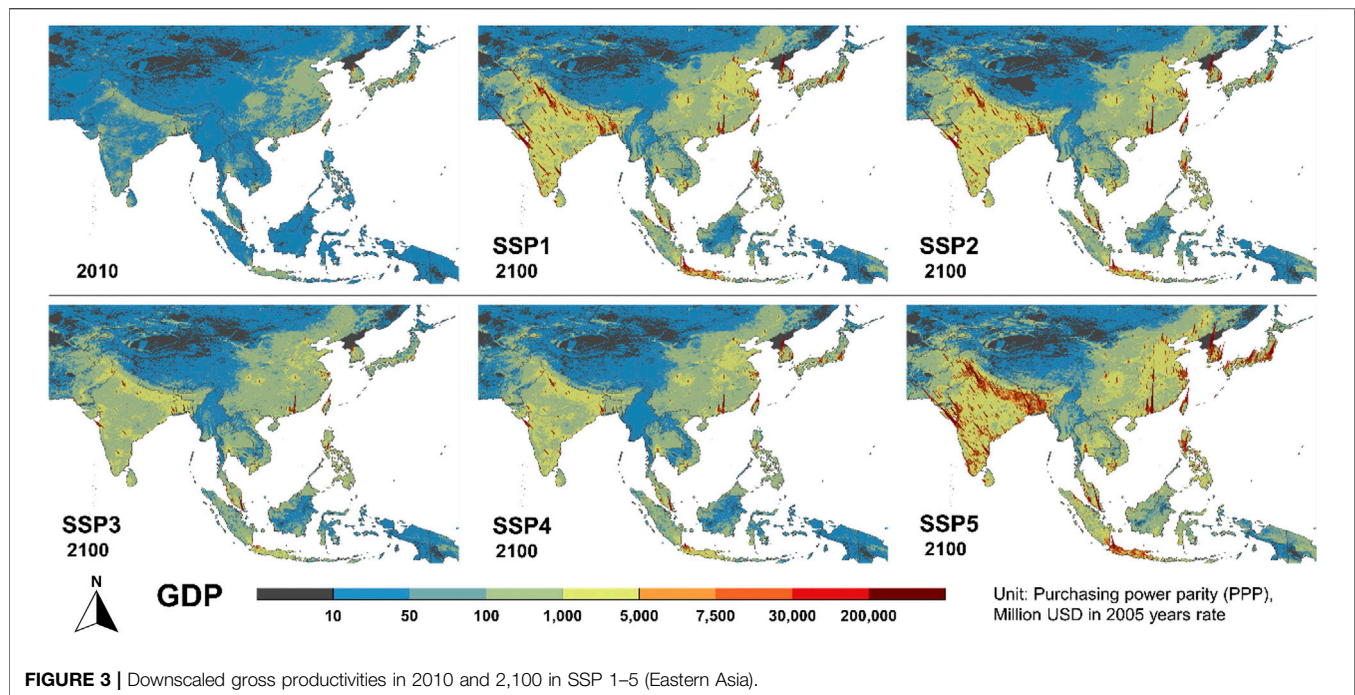
The gridded urbanization potential under SSPs, which was estimated in *Projection of urbanization projection*, was used as an auxiliary variable for the GDP downscaling ((2) in **Figure 1**). The other auxiliary variables are as follows: urban and non-urban populations by the 1/12 grids by SSPs, urban area, agricultural area, accessibility measures including distance to the nearest major road, airport, and ocean. See **Table 1** for further detail.

Generally, downscaling is performed by proportionally distributing the target variable according to an auxiliary weight variable such as population and area. For accurate downscaling, it is crucially important to appropriately specify the weight variable. We optimize the weight variable using a gradient boosting technique. The weight in the g -th grid is defined by $\hat{z}_g = \sum_{p=q}^P \omega_q z_{g,q}$ where $z_{g,q}$ is the value of the q -th auxiliary variable on the grid, and ω_q is a parameter estimating the importance of the q -th variable. The parameter is estimated by using a gradient boosting technique. This technique iteratively updates the ω_q value using the gradient of the loss function to minimize a loss function until the loss value converges. The mean squared error for the country GDP is used as the loss function. In a word, the importance/weight of each auxiliary variable was

estimated using the technique, and GDPs by the 1/12 grids were estimated using the estimated weights. The estimation is done by SSPs by year. Overall, population is estimated as the most significant factor explaining GDP distribution in the past while building area and urban potential from the present to the future.

RESULTS

Figures 2, 3 plot the gridded GDP estimates in 2010 and 2100 under SSP 1–5 in Europe and Eastern Asia, respectively. Our estimates produced considerably different map patterns across SSPs. SSPs 1 and 2 indicated a higher level of urban growth within the existing major cities. Still, growth in non-urban areas were as slow as SSP 3, which is a less urbanized scenario. This tendency was prominent in SSP1. These results are consistent with the assumption of rapid and compact urban growth in the SSP 1 scenario. Conversely, SSP 5 resulted in severe urban expansion. Because SSP 5 assumes a fossil-fueled development that yields widespread road networks, this result is reasonable. SSPs 3 and 4 had a lower level of urban growth, especially in Asian countries because of the assumption of the limited globalization. SSP 3 results in a notably small GDP growth nearby major cities (e.g.,



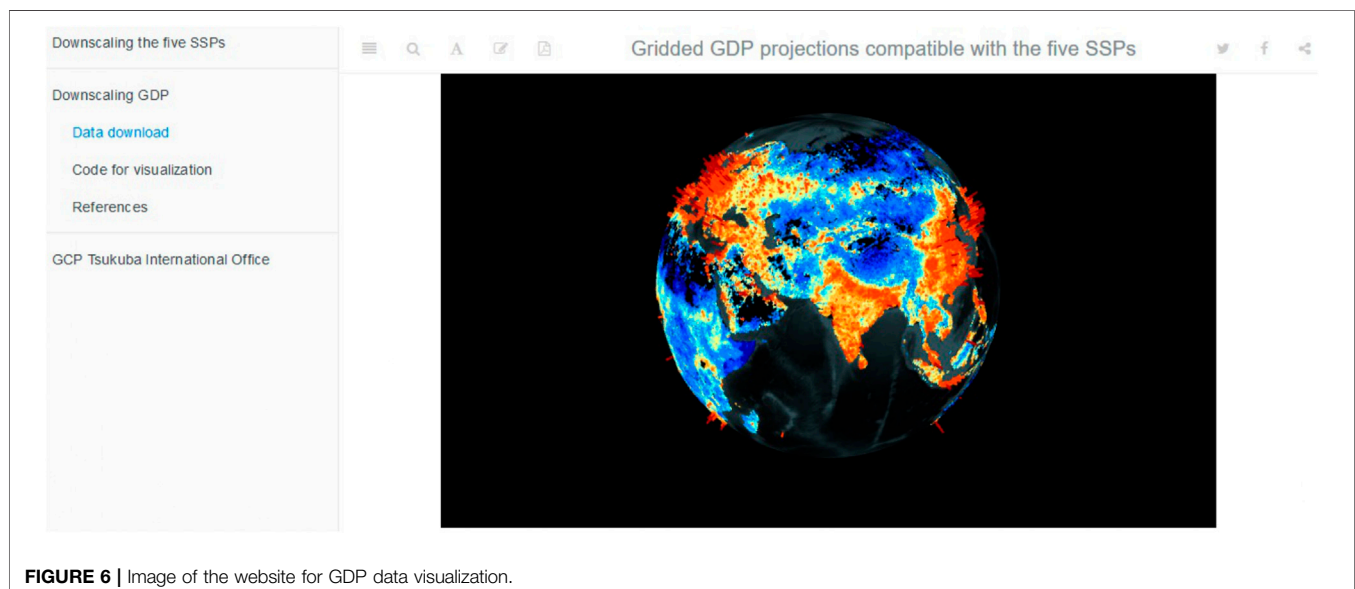
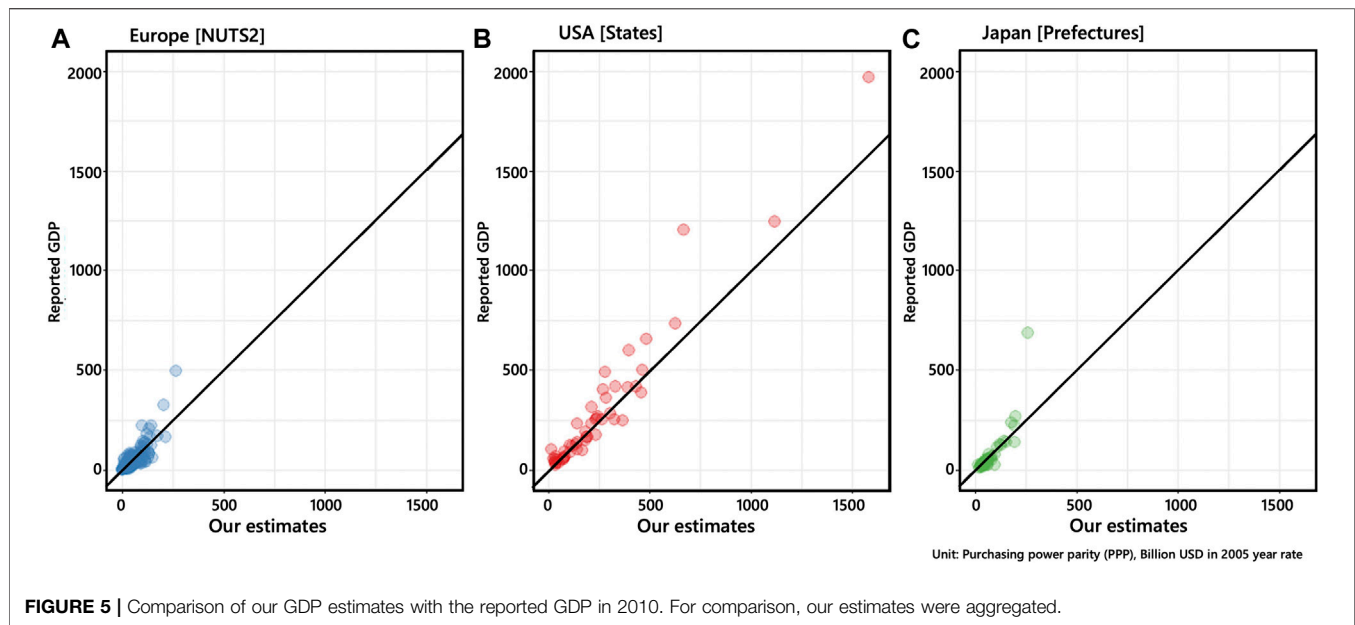
London, Paris, Shanghai). All these results are consistent with the assumptions underlying SSPs.

DISCUSSION

This section examines the accuracy of the downscaling. We first compared our GDP estimates with those of Kумму et al (2018), which were calculated based on a time-series modelling of sub-national GDPs and downscaling based on gridded population

estimates. Here, GDP estimates in 2010 by 1/12-degree grids, which are available in both our estimates and Kумму et al (2018)'s estimates are compared. The study areas for the comparison include the NUTS 2 regions, which usually have populations between 800,000 and 3 million people, in Europe (Eurostat 2020), United States excluding Hawaii and Alaska (United States Census Bureau 2020), and Japan (Statistics Bureau of Japan 2015).

Figure 4 compares our GDP estimates with the gridded GDP of Kумму et al (2018) in 2010. This plot suggests that these



estimates have similar patterns. The R-squares between the two GDP estimates are 0.720 (Europe), 0.885 (United States), and 0.834 (Japan), respectively, confirming the similarity of these estimates. On the other hand, our estimates have lower GDP values than Kummur et al (2018) in developed areas. This is because we distribute national GDP for not only developed areas but also the neighbouring areas based on the distribution weight depending on auxiliary attributes (urbanization potentials, road networks...), which is optimized by the gradient boosting technique. In other words, the lower GDP value in developed area is attributable to our optimized distribution weights allocating more GDP on the neighboring areas.

Then, to examine consistency of our estimates with actual GDP, we compared our estimates for 2010 with the regional GDPs in the NUTS 2 regions, the 49 states of the United States, and the prefectural GDP in Japan. In each region, our estimates were aggregated into the aggregate units which these databases assume. **Figure 5** summarizes the comparison results. The R-squares were 0.685 in the NUTS2 regions, 0.937 in the United States, and 0.735 in the prefectures in Japan. The results suggest that our estimates are fairly accurate despite the fact that our downscaling did not use any regional GDP statistics.

The downscaled GDP data is potentially useful for decision making toward sustainable development. For example, by spatially overlaying hazard map with our estimates, possible

economic loss due to flood, earthquake, and other natural disasters can be estimated. The result will be useful for disaster risk management. The estimated GDPs are also useful to estimate the map pattern of carbon emissions in the future and consider policies toward low carbon development.

CONCLUSION

SSP scenarios on population and GDP used by IPCC are central for the analysis of future climate risks and policy. Population projections are generally available; however, GDP projections—particularly for scenarios compatible with SSPs—are limited. In this study, we estimated the GDP in a 1/12-degree grid scale for the period of 1850–2100 in 10-year intervals by using spatial econometric based downscaling algorithm. Our results suggest that the spatial pattern of urban and peri-urban GDP depends considerably on the SSPs; e.g., the urban GDP under SSP1 grew rapidly within the existing major cities. These cities grew moderately under SSP2 and SSP4. In contrast, that under SSP3 exhibited a lower growth level, and that under SSP5 exhibited extreme dispersion.

The major improvements relative to Murakami and Yamagata (2019) are as follows: (i) GDPs by the 1/12 grids, which are considerably finer than their assumed grids, were estimated; (ii) GDPs were downscaled under SSP4 and SSP5; GDPs were downscaled not only in the future but also in the past. The high resolution and long-term GDP estimates will be useful to analyse the relationship between urban development and climate change in detail.

Some important issues remain in this study. First, spatially finer auxiliary data are needed to sophisticate our downscaling approach. For example, microscale urban data, such as industrial structure, detailed road network, and traffic volume, are required to consider urban phenomena including industrial agglomeration, growth of transportation networks. Consideration of the birth of new cities is also an important topic. Since consideration of these factors can increase the uncertainty of downscaling, it is crucial to employ a robust estimation approach like Bayesian estimation (see, e.g., Raftery et al., 2012 for population projection).

Second, assumptions for the parameters in the urban growth model should be enhanced. As discussed in

Hausfather and Peters (2020), and Pielke and Ritchie (2020), high emission scenarios should not be used as the reference baseline in climate research. Future scenario should be developed considering a wider range of assumptions due to the uncertainty in urban growth. Another important topic is to estimate the difference in urban metabolism pattern in each country/city. For instance, road density might have stronger impact on GDP in United States, which has developed heavily dependent on cars, while weaker impact in Europe. Unfortunately, our model, which assumes the relative importance of each auxiliary variable as constant across countries, ignores such spatial heterogeneity. Estimation of the heterogeneity for example by incorporating our model with country-level local models is an important next subject.

It is also important to consider the impact of COVID-19 pandemic that may change economic systems (Burgess et al., 2020). Spatially fine scale projection can be useful for policymaking for city-level economic development and climate risk mitigation. It is important to update scenario assumptions considering uncertainty relating COVID-19 and other factors.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: <https://doi.org/10.6084/m9.figshare.12016506>. The usage note of the data and the visualization is also available online. **Figure 6** shows a snapshot of the website. This website includes an interactive 3-dimensional visualizer. Users can zoom-in/zoom-out any region and change the colour scale. This function will help users to understand the map patterns of GDP even without downloading the data.

AUTHOR CONTRIBUTIONS

DM performed the downscaling and wrote the draft. TY wrote the draft and made the website to publish the data. YY directed and managed this downscaling project.

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