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# Spatially explicit global gross domestic product (GDP) data set consistent with the Shared Socioeconomic Pathways

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## Abstract

The increasing demand of ScenarioMIP is calling for GDP projections of high resolution for the future Shared Socioeconomic Pathways (SSPs) in both socioeconomic development and in climate change of adaption and mitigation research. While to date the global GDP projections for five SSPs are mainly provided at national scales, and the gridded data set are very limited. Meanwhile, the historical GDP can be disaggregated using nighttime light (NTL) images but the results are not open accessed, making it cumbersome in climate change impact and socioeconomic risk assessments across research disciplines. To this end, we produce a set of spatially explicit global Gross Domestic Product (GDP) that presents substantial long-term changes of economic activities for both historical period (2005 as representative) and for future projections under all five SSPs with a spatial resolution of 30 arc-seconds. Chinese population in SSP database were first replaced by the projections under the two-children policy implemented since 2016 and then used to spatialize global GDP using NTL images and gridded population together as fixed base map, which outperformed at subnational scales. The GDP data are consistent with projections from the SSPs and are freely available at http://doi.org/10.5281/zenodo.4350027 (Wang and Sun, 2020). We also provide another set of spatially explicit GDP using the global LandScan population as fixed base map, which is recommended at county or even smaller scales where NTL images are limited. Our results highlight the necessity and availability of using gridded GDP projections with high resolution for scenario-based climate change research and socioeconomic development that are consistent with all five SSPs.

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## 1 Introduction

The development of socioeconomic projection scenarios plays a key role in the assessment of climate change impact and socioeconomic risks for the coming decades (O'Neill et al., 2014; Wilbanks and Ebi, 2014). The Shared Socioeconomic Pathways (SSPs), which qualitative and quantitative describe broad patterns of possible global socioeconomic development with assumptions about climate change and policy responses under different challenges to mitigation and adaptation (O'Neill et al., 2014), are one of the core contents in the Intergovernmental Panel on Climate Change (IPCC) scientific assessment reports (IPCC, 2014) and in the current literature (O'Neill et al., 2016; Wilbanks and Ebi, 2014). The climate projection scenarios in Scenario Model Intercomparison Project (ScenarioMIP) are formed based on different SSPs corresponding to specific representative concentration pathways (RCPs) within Phase 6 of the Coupled Model Intercomparison Project (CMIP6) (O'Neill et al., 2016). Scenarios of future socioeconomic impact on the global environment are built upon projections of economic output and strongly require socioeconomic data support of higher spatial resolution for the coming decades (B. Merz et al., 2010; O'Neill et al., 2016; Wilbanks and Ebi, 2014).

The Gross Domestic Product (GDP) is a standard indicator to assess and compare economic development within and across countries (Kummu et al., 2018; Nordhaus, 2011; Tobias, 2018), and is usually collected at national scale (Tobias, 2018). However, the collection of official GDP data at a finer resolution (e.g., at state, city or county levels) is problematic, especially in many developing countries (Kummu et al., 2018; Nordhaus, 2011). It is crucial to spatialize GDP data into a fine-scale so that it can be easily integrated with data from other disciplines (Chen et al., 2020; Kummu et al., 2018; O'Neill et al., 2016). A growing number of openly available historical GDP data sets are provided with the development of satellite-derived nighttime light (NTL) images and gridded population to support current research at various spatial scales in a more convenient way (Bennett and Smith, 2017; Doll et al., 2006; Ghosh et al., 2010; Nordhaus, 2011; Zhao et al., 2017). The Defense Meteorological Satellite Program's

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Operational Linescan System (DMSP-OLS) NTL imagery has been successfully used in GDP redistribution for 1992-2013. However, the disaggregated GDP depends highly on the DN values where a certain number of saturated pixels exist in DMSP-OLS NTL images, resulting in underestimations in urban centers and overestimations in rural regions (Zhu et al., 2017) but can be revised when incorporating with other ancillary data like gridded population (Zhao et al., 2017). The global Soumi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) NTL imagery made up this saturation problem and advanced its calibration, providing a more accurate approach in GDP downscaling since 2012 (Bennett and Smith, 2017). More research on reduction in exposure and vulnerability and increase in resilience to climate extremes can benefit from a spatially explicit GDP data set with increasing precision of NTL image products and population count at grid level (Chen et al., 2017; Chen et al., 2020; Wang et al., 2019; Wilbanks and Ebi, 2014).

However, the widely used GDP projections in the SSP database were provided only at national and super-national scales from several global institutes, which have depicted a wide range of uncertainty within different organizations (Riahi et al., 2017) and limited the usage of integration with data from other disciplines. Moreover, the spatially explicit global gridded GDP projections for all five SSPs are very limited, and Murakami and Yamagata (2019) have downscaled the global population and GDP for SSP1-3 only. Worse still, most socioeconomic development indicators for like the total factor productivity, capital stock, and labor input etc., are either short of data sources or provided mainly at national scale without proper conditions to make spatially explicit GDP predictions for future scenarios. The increasing vulnerability, exposure and resilience of socioeconomic activities to climate extremes are driving a need to move beyond administrative unit-based analyses to enable flexible integration with datasets of spatially explicit population and economic activities of long-term SSPs (Chen et al., 2017; Jones et al., 2015; Su et al., 2018; Winsemius et al., 2016).

Government policy change has a strong effect on GDP and should be taken into account for credible and quantitative information on demographic changes and socioeconomic development (Huang et al., 2019). The one-child for each couple policy implemented in China since the late 1970s has been replaced by the two-children policy since 2016, and would no doubt have a substantial effect on the demographic composition, the total population and GDP projections in China in the long run. However, this policy was implemented after the release of population and GDP projections in the SSP database. Jiang et al., (2017; 2018) have updated Chinese population and GDP projections at provincial level that qualitatively consistent with five SSP narratives, showing that the implementation of two-children policy can mitigate the labor shortages and aging problems in China to a certain extent, and are expected to a 38.1 – 43.9% increase in GDP in the late 21st century (Huang et al., 2019). It would be beneficial to update SSP database of long-term demographic and economic projections in China with consideration of this two-children policy for future GDP downscaling for spatial analyses.

To date, there is no global gridded GDP for all five SSPs provided, and historical dataset are mainly based on national GDP from the World Bank and then redistributed using NTL images with other auxiliary information but are not open accessed. There is a growing demand for spatially explicit GDP that can represent different patterns of development and are consistent with all five SSPs to match the ScenarioMIP research. The objective of this study is to present a set of spatially explicit global GDP that presents substantial long-term changes of GDP for both historical period (2005 as representative) and for future projections under all five SSPs by incorporating various data sources and methods. In the following were the inputs, assumptions, methodologies, and results that we use to spatialize GDP data into a fine-scale, providing an alternative choice for scenario-based climate change research and socioeconomic development pathways.

## 2 Data

### 2.1 Historical Population

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The distribution of population count (density) is a core indicator in measuring, mapping and assessing the exposure, vulnerability, and resilience of socioeconomic activities to climate extremes (Leyk et al., 2019). Several well-known global population data sets, namely the Gridded Population of the World (GPW), the Global Rural Urban Mapping Project (GRUMP), the WorldPop, and the LandScan Global Population database are summarized in this section.

### 2.1.1 the GPW Dataset

Using the areal interpolation techniques, the Gridded Population of the World dataset, Version 4 (GPWv4), Revision 11, was constructed from national or subnational administrative units in conjunction with the most detailed spatial resolution available from the Population and Housing Censuses occurring in 2005 and 2014. After extrapolated to produce population estimates for the years 2000 to 2020 at a 5-year interval with a resolution of 30 arc-seconds (approximately 1 km at the equator), these estimates were further adjusted to national totals to consist of the United Nation's World Population Prospects (UN-WPP) adjusted population estimates and densities for those years. The GPW dataset includes estimates for 2000, 2005, 2010, 2015 and 2020 respectively, and is freely accessible at http://sedac.ciesin.columbia.edu/data/collection/gpw-v4. The GPWv4 has provided globally consistent and spatially explicit disaggregated population data that is compatible with data set from other disciplines.

### 2.1.2 the GRUMP dataset

The Global Rural-Urban Mapping Project, Version 1 (GRUMPv1) dataset, which is based on GPWv3, has well identified urban area with observations of NOAA's NTL data collected over several decades. It differs from GPW by incorporating urban-rural reallocation of spatially distributed population in each census unit, and contains eight global data sets: population count, population density, urban settlement points, urban-extents, land/geographic unit area, national boundaries, national identifier, and

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coastlines. GRUMPv1 provides global population estimates for 1990, 1995, and 2000 at a resolution of 30 arc seconds (approximately 1 km at the equator) as well as at national, continental, and global scales at https://sedac.ciesin.columbia.edu/data/set/grump-v1-population-density. The GRUMP was the first global database that connects NTL images with population estimates, and helps better understand differences between urban and rural areas in terms of vulnerability, exposure, and resilience to environmental and climate change.

### 2.1.3 the WorldPop dataset

Growing from the AsiaPop, AfriPop, and AmeriPop population mapping projects, the WorldPop (www.worldpop.org) was initiated in Oct 2013 and provided full open access archive of spatial demographic information around the world (Stevens et al., 2015; Tatem, 2017). Based on the random forest model and contemporary census data from hundreds of national statistics offices and other organizations, survey, remote sensing outputs and geospatial data etc., the WorldPop produces consistent gridded population density at 3 and 30 arc-seconds (about 100 m at the equator for individual countries, and about 1 km for the global mosaics, respectively). Then it was adjusted to match the official United Nations population estimates for 2000 to 2020 annually. Comparing with previous gridded population results, the WorldPop shows clear advantage in its method advancement, contemporary and easily-updatable consistent population distribution, characteristics and changes over time, enabling flexible integration with datasets on other types of geospatial data.

### 2.1.4 the LandScan dataset

The LandScan Global Population database from the Urban Oak Ridge National Laboratory, USA is a widely used population data set that developed using best available census and geographic data, remote sensing imagery analysis techniques within a multivariate dasymetric modeling framework to disaggregate census counts within an administrative boundary (Bhaduri et al., 2007). Commercial data was utilized in LandScan for higher spatial accuracy in population allocation at 30 arc-seconds resolution for 1998, and 2000-2018 annually. The DN values represent population totals per grid cell. The global LandScan population data set is now available to the educational community free of charge at https://landscan.ornl.gov/, and has also been widely used in GDP disaggregation with fine reliability.

#### 2.1.5 census

National and subnational (at state level) population totals around the global can be easily obtained from the World Bank. Meanwhile, census at county level for the U.S. and China were adopted from the U.S. Census Bureau and the Statistical Yearbook from National Bureau of Statistics, China (NBS) respectively, offering the flexibility to perform analysis at state (or provincial) and county levels.

### 2.2 GDP

The official GDP is usually collected at national scale, but it is often problematic to obtain data at a finer resolution (e.g., at state, city and county levels), especially in many developing countries (Nordhaus, 2011). Using NTL images and some other auxiliary data can help improve the quality of spatial allocation of GDP and offer a reliable substitution to conduct cross-disciplinary research a large literature.

#### 2.2.1 national and subnational GDP

The World Development Indicators assembled by the World Bank (WB-WDI) provide a vast resource of relevant, high-quality, and internationally comparable socioeconomic statistics for 217 economies and more than 40 country groups which can be tracing back to more than 50 years. For most economies, GDP PPP (GDP converted using Purchasing Power Parity rates) values are extrapolated from the 2011 International Comparison Program (ICP) benchmark estimates or imputed using a

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statistical model based on the 2011 ICP. National GDP (in PPP) and GDP per capita (Pcap) figures in 2005: in current U.S. dollars and in current international dollars, were chosen and to be consistent with currency unit of GDP for SSP scenarios. For the meantime, national population totals are obtained from WB-WDI database as well.

Subnational GDP in 2005, 2010 and 2015 for the U.S. and China were obtained from departments of the U.S. Bureau of Economic Analysis and the Chinese National Bureau of Statistics, offering the flexibility to socioeconomic performance at state (or provincial), city and county levels. The Chinese GDP were obtained from the China Statistical Yearbooks, the China City Statistical Yearbooks, and the China County Statistical Yearbook with values recorded in RMB currency unit and then converted to USD using conversion factors provided from the World Bank.

### 2.2.2 the NTL-based GDP

The NTL images have shown well correlation with global and regional economic activities and been widely used to spatialize GDP data into a fine-scale (Ghosh et al., 2010; Nordhaus, 2011). The widely used version 4 DMSP-OLS stable NTL images for 1992 - 2013 can be obtained from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NGDC) at https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html, with a spatial resolution of 30 arc-seconds and latitudinal and longitudinal extent from 75˚N to 65˚S and 180˚W to180˚E. There are two separate annual stable NTL images derived from two sensors to avoid degradation problem, and each stable NTL image is a composition of all the available cloud-free data with background noises and ephemeral lights removed within this year. The DN values for DMSP-OLS stable NTL data range from 0 to 63 with saturation problem (DN values of 63) scattered mainly in city centers and other brightly lit zones (Bennett and Smith, 2017). To improve the DMSP-OLS data quality, the new generation of NTL products, namely the Suomi-NPP-VIIRS Day/Night Band (DNB) images, were lunched since 2012 with a higher resolution of 15 arc-seconds and a wider radiometric detection range. The Suomi-NPP-VIIRS DNB data

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can be obtained from https://eogdata.mines.edu/download_dnb_composites.html.

The NTL images have been widely used in spatial allocation of GDP at resolutions from 500 m × 500 m to 1° × 1° (Bennett and Smith, 2017; Nordhaus, 2011; Zhao et al., 2018). Based on the theory that national and sub-national GDP totals are directly distributed or regression related to each pixel in proportion to the DN values, global and regional NTL-based GDP can be spatialized into a fine-scale and integrated with data across disciplines (Chen et al., 2020; Ghosh et al., 2010; Zhao et al., 2017; Zhu et al., 2017).

## 2.3 SSP projection data

The long-term demographic and GDP projections have been promoted by different organizations to facilitate research on future impacts, adaptation, and vulnerability. The five SSPs (O'Neill et al., 2014), which are differentiated by different combinations of climate change mitigation and adaptation challenges, provide a wide range of information on possible global socioeconomic developments decennially up to 2100. SSP1 ("Sustainability") characterizes a world shifting gradually but pervasively in a sustainable path with low mitigation and adaptation challenges, emphasizing more on human well-being than economic growth. SSP2 ("Middle of the Road") follows a path of continuing historical trends associated with moderate income growth, facing medium challenges to mitigation and adaptation. SSP3 ("Regional Rivalry") is characterized by slow economic growth with restriction of high mitigation and adaptation challenges. SSP4 ("Inequality") represents a highly unequal world with high adaptation challenges, and economy growth rate inclines more to rich countries. Finally, SSP5 ("Fossil-fueled development") characterizes a world of rapid economic growth with high mitigation challenges.

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### 2.3.1 SSP Database

Based on harmonized assumptions for the interpretation of the SSP storylines in terms of the main drivers of economic growth, three sets of global GDP projections were provided in June 2013 in the SSP database. Recommended by the SSP database, the Organization for Economic Cooperation and Development (OECD) (Dellink et al., 2015) has developed a set of GDP projections based on different perspectives on future socioeconomic development, emphasizing on the key drivers of economic growth in the long run: population, total factor productivity, physical capital, employment and human capital, and energy and fossil fuel resources for 184 OECD countries up to the end of 21st century in 2005 USD in PPP for five SSP scenarios. The other two sets of GDP projections were developed by the International Institute for Applied Systems Analysis (IIASA) (Cuaresma, 2015) for 144 countries, and the Potsdam Institute for Climate Impact Research (PIK) (Leimbach et al., 2015) for 32 world regions. These three sets of GDP projections are openly available from the SSP database hosted by the IIASA Energy Program at https://tntcat.iiasa.ac.at/SspDb.

The three sets of GDP projections were developed using the demographic projections to maintain consistency in assumptions with education and ageing but differed with respect to the employed drivers, methodology and outcomes, spanning a wide range broadly representative of the current literature, and inevitably subjecting to large uncertainties especially for the later decades (Riahi et al., 2017). A wide range of possible factors, like policy actions, external shocks, governance barriers, and feedbacks of greenhouse gas emission and climate extremes, are failed to predict and disregarded in the SSP framework. Whatsoever, these GDP projections do illustrate a substantial variance in global socioeconomic development and provide a basis for quantitative analyzing the climate change impacts on economic for each SSP (O'Neill et al., 2014; Riahi et al., 2017).

Together with the GDP projections, the long-term demographic projections (KC and Lutz, 2017) in the SSP database for each SSP scenario were developed by the IIASA and the National Center for Atmospheric Research (NCAR). Using a multidimensional demographic model, national populations were projected based on alternative assumptions on future fertility, mortality, migration and educational transitions in each country for five SSPs (O'Neill et al., 2014; Riahi et al., 2017). The population projection can well capture the link between human capital and income growth in the econometric model as highlighted in the literature (KC and Lutz, 2017), and can also be accessed at https://tntcat.iiasa.ac.at/SspDb.

### 2.3.2 population projection of 1/8 degree from SEDAC

No doubt that the national projections in the SSP database failed to meet the increasing demand of spatially explicit demographic and GDP projections. Hence, Jones and O'Neill (Jones and O'Neill, 2016) have further extended the national totals and produced a scenario-based gridded population data set by downscaling the urban and rural population projections for each of the 232 countries to a spatial resolution of 1/8° (approximately 7.5 arc-minutes at the equator). The gridded population from the GRUMP dataset in 2000 at a resolution of 2.5′ was used as the base-year population for future projection downscaling. Using the parameterized gravity model-based approach, the demographic driving factors, namely the current fertility, income, urbanization, and international migration are explicitly included in the population projections corresponding to each SSP and thus can reflect its spatial pattern as prescribed. The gridded population projections data set are quantitatively consistent with total, urban, rural populations at a national level at ten-year intervals for 2010-2100, and with urbanization projections as well as with the assumptions of SSP narratives.

### 2.3.3 GDP projections from NIES, Japan

Based on Jones and O'Neill, Murakami and Yamagata (2019) from the Center for Global Environmental Research, National Institute for Environmental Studies (NIES), Japan, have developed a new set of data by spatializing the national population and GDP into 0.5-degree grids for SSP1, SSP2 and SSP3. As described in Murakami and

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Yamagata (2019), this gridded population projection data set trumps data from Jones and O'Neill by utilizing not only the urban and nonurban populations, but also taking the intensity of interactions among cities and auxiliary variables including road network, land cover, and location of airports into account. Among which, national urban populations are downscaled into cities based on a city growth model, and then used to project urban expansion/shrinkage with help of those auxiliary data. The GDP projections were then developed based on its populations at a spatial resolution of 0.5-degree for SSP1-3 only as well.

However, only two years data from settlement Points, v1 from GRUMP, SEDAC (http://sedac.ciesin.columbia.edu/data/set/grump-v1-settlement-points) were used in the city growth model parameterization and then in the future urban expansion/shrinkage projections (Murakami and Yamagata, 2019), which would raise some doubt on its credibility in these gridded population and GDP projections data sets.

### 2.3.4 Chinese Population Projections under two-children policy

The implementation of two-children policy in 2016 and clear differences among the drivers (e.g., age, education enrollment in the historical period) between the NBS, China and the U.N. (Huang et al., 2019) require updates in Chinese population and GDP projections for all five SSPs. Since the demographic changes play a decisive role on future labor force and therefore affecting socioeconomic development, Jiang et al. (2017; 2018) have adopted data from China Statistical Yearbook and the Sixth National Population Census and made projections of Chinese population and GDP for 2020-2100 based on assumptions of future fertility, mortality, and migration for each of five SSPs under two-children policy. Using the parameterized population-development-environment analysis model, Jiang et al. (2017) have implemented the population projections incorporating with national and provincial age, sex, and educational attainment that are quantitatively consistent with changes of birth rate under two-children policy in China. The provincial population projections were provided at a spatial resolution of 0.5-degree for five SSPs.

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Chinese GDP (Jiang et al., 2018) were also projected using the total factor productivity, capital stock, and labor force etc., as input for five SSPs but not been utilized in this research.

# 3 Method

## 3.1 the official data interpolation

National GDP PPP (in USD) for 2005 were obtained from the WB-WDI first for the 189 countries provided (data in China was for mainland only, and GDP in Hong Kong Special Administrative Region, Macao Special Administrative Region and Taiwan were divided but listed as individuals). For 36 island countries like British Virgin Islands, Cayman Islands, Cook Islands and etc., where GDP were unavailable from WB-WDI, data were obtained from the Central Intelligence Agency (CIA) World Factbook (released in 2015). GDP in Taiwan (China), Nauru, and Syrian Arab Republic were from the International Monetary Fund (IMF, released in Oct 2017). GDP for the rest 11 countries (namely Aland Islands, French Guiana, Holy See, Curacao, Bonaire Saint Eustatius and Saba, Norfolk Island, Pitcairn, Saint-Barthelemy, South Sudan, Svalbard and Jan Mayen Islands, and Tokelau) were set as zero where no data to be found. All GDP data were presented in PPP in 2005 USD using conversion factors provided from the World Bank.

Meanwhile, census data were also obtained to calculate GDP per capita in order to spatially allocate global GDP. National population totals in 2005 were obtained from the WB-WDI for 216 countries and regions. For the rest countries (regions) without available official census, data from other organizations were used instead. Population in Taiwan (China) was obtained from IMF. For Norfolk Island, Pitcairn, Saint-Barthelemy, Svalbard and Jan Mayen Islands, Guernsey, and Jersey, their population were obtained from CIA World Factbook. Mayotte, the Holy See, Cook Islands, Falkland Islands (Malvinas), French Guiana and others, 17 countries in total,

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populations were obtained from the Wire & Plastic Products Group. Population in Aland Islands was obtained in ASUB National accounts since it is not provided in those global organizations.

The official GDP for China and the U.S. in 2005 were obtained the China Statistical Yearbooks and the BEA at state (or provincial) and county levels. GDP for 51 states and 3193 counties in the U.S., and for 31 provinces and 2326 counties with valid values in China were obtained for validation and further updates. Meanwhile, global census at state level (1865 states with valid values) were obtained from World Bank as well.

## 3.2 population-based GDP disaggregation

### 3.2.1 baseline population selection

The historical gridded population varies substantially since they differ in the reliability and variety of input data sources, the interpolation and decomposition methods of disaggregating national and subnational totals, the modeling approach, and how they cooperate with each other to determine population distribution. To choose more suitable gridded population as base map in GDP disaggregation, comparisons were made between national and subnational census against the gridded data sets from the GPWv4, the GRUMP, the WorldPop and the LandScan, which were spatially joined to the corresponding GIS-based administrative boundaries.

At national and state scales, the biases were all relatively small in 2005. The $R^2$ are all approaching to 1.0 and averaged RMSE are 1.2, 4.1 and 5.1 million people for the GPWv4, World Pop and LandScan at national scale (Figure S1(a)). For 1565 states (provinces) around the globe, their $R^2$ are around 0.98 and averaged RMSE are 1.7, 1.8 and 1.8 million, respectively (Figure S1(b)). Further comparison of 3193 counties in the U.S. in four selected years: 2000, 2005, 2010 and 2015 showed that, $R^2$ are all around 0.95 and their slope are approximately 0.99 including about 200 specific counties with clear biases population totals. This is obvious since the openly available

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census are the primary input in constructing these gridded data sets.

<Figure 1>

Comparisons at county level in China for the years of 2000 (1870 out of 2345 counties with valid values), 2005 (1874 counties), 2010 (1923 counties) and 2015 (1801 counties) (Figure 1) show that the LandScan outperformed in its accuracy with $R^2$ slightly higher and RMSE relatively smaller, approximately two thirds of RMSE from the GPWv4 and the WorldPop (Figure 1). This shows that the Landscan can well estimate population redistribution at county level than GPWv4 and WorldPop, and therefore recommended as base map in spatial allocation of global GDP.

### 3.2.2 Population Based GDP disaggregation

Population can well capture the link between human capital and income growth in the econometric model, and broad literature has emphasized the role of human capital as a key driver of economic growth (Cuaresma, 2015; Dellink et al., 2015; KC and Lutz, 2017). Shiogama et al. (2011) have suggested the robustness of an ensemble learning-based downscaling approach, which are defined by (baseline variable) × (control variable) in accordance with distribution weights. This approach can be applied in spatial allocation of global GDP based on the LandScan population ($Pop_{pixel}$, as baseline variable) and GDP per capital (Pcap, ratio of GDP to population totals in a given administrative boundary i, as control variable) to 1 km × 1 km grids (denote $GDP_{Pop}$).

$$GDP_{Pop} = Pop_{pixel} \times Pcap = Pop_{pixel} \times \frac{GDP_i}{Pop_i} \quad (1)$$

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### 3.3 NTL involved GDP disaggregation

#### 3.3.1 NTL-based GDP disaggregation

The satellite-derived NTL data has been proven to correlate well with GDP at all examined scales and has been widely used in spatial allocation of GDP over large areas (Ghosh et al., 2010; Nordhaus, 2011). The DMSP-OLS NTL images in 2005 (average visible, stable lights, and cloud free coverages, satellites F14 and F15 simultaneously collected global NTL images and data from F15 was chosen as newer sensor would have less degradation of data quality) have been utilized to disaggregate global GDP to a spatial resolution of 30 arc seconds. Based on the theory that the GDP totals are directly distributed to each pixel in proportion to the DN values in a given administrative boundary, the NTL-Based GDP disaggregation (denoted $GDP_{NTL}$) can be described as,

$$GDP_{NTL} = GDP_{per\_light} \times DN_{pixel} = \frac{GDP_i}{SL_i} \times DN_{pixel} \quad (2)$$

where $GDP_i$ is the GDP totals, $SL_i$ is the sum of DN values and $GDP_{per\_light}$ is the constant in administrative unit i, $DN_{pixel}$ and $GDP_{pixel}$ are the DN value and corresponding GDP in each pixel in administrative unit i.

#### 3.3.2 NTL & population based GDP disaggregation

The saturation problem in the DMSP-OLS NTL images, however, has resulted in overestimation in urban centers and underestimation in rural and distanced areas. Zhao et al., (2017) have improved its accuracy by incorporating the gridded population data into NTL-based GDP disaggregation in each pixel since population data has an exponential relationship with DN values of NTL images. By multiplying the NTL image with the LandScan population data in 2005, Lit-Pop image was produced and then used in Equation 3 to spatialize GDP at global scale (denoted $GDP_{Lit\text{-}Pop}$):

$$GDP_{Lit-Pop} = \frac{GDP_i}{SLP_i} \times DN_{lp} \quad (3)$$

where $DN_{lp}$ is the DN value of each pixel of Lit-Pop data, and $SLP_i$ is the sum of the

DN values of Lit-Pop image in administrative unit i.

### 3.4 Historical GDP disaggregation

To examine the performance of three GDP disaggregation approaches above, namely the $GDP_{Pop}$, $GDP_{NTL}$ and $GDP_{Lit\text{-}Pop}$, national GDP in China and U.S. from WB-WDI instead of official state or county values were used to spatialize global interpolated official GDP into 1 km×1 km grid using the global LandScan population, DMSP-OLS NTL images in 2005. Meanwhile, GDP PPP (in 2005 USD) from 52 states in USA plus 31 provinces in China, 321 cities in China, and 3068 plus 2091 counties in USA and China in 2005 have been adopted and spatially joined to the corresponding GIS-based administrative boundaries respectively, and used to verify the disaggregated GDP results.

<Figure 2>

The comparisons showed that the accuracy of three disaggregated GDP decreases accompanied by the changes of their spatial scales, and $GDP_{NTL\text{-}Pop}$ is superior to $GDP_{Pop}$ and $GDP_{NTL}$ at national, state (provincial), and county levels with clear advantages evaluated by their $R^2$ and RMSE. In detail, $GDP_{Lit\text{-}Pop}$ can better identify the spatially allocated GDP at finer spatial scales with higher accuracy with $R^2$ reaching 0.78 and RMSE of 8.35 billion USD for 5221 counties in the U.S. and China. While the $R^2$ is only 0.47 and RMSE reaches as high as 14.34 billion between official GDP and $GDP_{NTL}$, indicating less advantageous due to the saturation problem.

Meanwhile, GDP using the global LandScan population only as base map ($GDP_{Pop}$) can well identify GDP redistribution at finer spatial scales as well. The $R^2$ between official GDP and $GDP_{Pop}$ at county level in the U.S. and China reaches as high as 0.73 and the averaged RMSE is 9.80 billion USD in 2005, which performs better than $GDP_{NTL}$ and is nearly comparable to $GDP_{Lit\text{-}Pop}$, indicating that $GDP_{Pop}$ can be used as

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an alternative when $GDP_{Lit\text{-}Pop}$ is limited.

Similar results can be obtained in 2015 as another validation case when using the NPP-VIIRS NTL images, the global LandScan population and official GDP (Figure S2). National GDP from WB-WDI were used in GDP disaggregation, and subnational GDP from the U.S. Census Bureau and the corresponding Statistical Yearbooks in China were used for validation purpose. $GDP_{Lit\text{-}Pop}$ outperformed with higher $R^2$ of 0.96 in 52 states in U.S. plus 31 provinces in China, and their RMSE (90.39 billion USD) is about one-half of that of $GDP_{Pop}$, and only one-third of $GDP_{NTL}$, showing clear advantage in spatial allocation of GDP at a medium spatial scale. Meanwhile, $GDP_{Pop}$ and $GDP_{Lit\text{-}Pop}$ both outperformed than $GDP_{NTL}$ at county level, and $GDP_{Pop}$ even performs a slightly superior with smaller RMSE of 14.11 billion USD than $GDP_{Lit\text{-}Pop}$ (RMSE of 15.36 billion USD) (Figure S2).

All above showed that population involved base map can be used in spatial allocation of GDP as well. The $GDP_{Lit\text{-}Pop}$ is recommended for global, state and county scales disaggregation, and $GDP_{Pop}$ can be used as an alternative and especially at county or even smaller scales where NTL images are limited in very rural regions.

Based on above, we updated official GDP and GDP per capita (in PPP) at county level in the U.S. and China, and then disaggregated the global GDP in 2005 into 1 km ×1 km grid based on the NTL images and the LandScan population together as base map to ensure spatial accuracy. This gridded GDP PPP in 2005 was used as historical gridded GDP in the following comparison. $GDP_{Pop}$ in 2005 was also provided.

### 3.5 Global GDP downscaling for SSPs

NTL image projections for future scenarios are off limits and therefore unavailable for spatial allocation of GDP for different SSP scenarios. Luckily, a set of global spatially explicit population projections that are consistent with SSPs was developed with a spatial resolution of 0.125 degree (Jones and O'Neill, 2016), which can be used in spatial allocation of GDP projections to a spatial resolution of 0.125 degree first using the above $GDP_{Pop}$ approach. Assuming that there will be no population mobility and such within countries and across the grids, the GDP projections can be further downscaled to 1 km × 1 km grids using NTL images and global LandScan population in 2015 as fixed base map.

First, we completed the GDP and population projections for all the countries (regions) in the SSP database. Population projections from IIASA were adopted since its historical data in 2005 were less biased with $R^2$ approaching 1.0 and averaged bias of 0.27% for 178 countries when compared against national population totals from WB-WDI data set. Population (GDP) projections for 182 (177) countries were obtained from IIASA (OECD, as recommended) in the SSP database. Meanwhile, the supranational projections for the rest countries where the associated world regions the countries belong to were obtained and filled to complete the future time series to ensure the consistency for all five SSP scenarios.

Next, we recalculated the GDP per capital. Instead of using the exact GDP (PPP in 2005 USD), population, and GDP per capital predictions directly since these values vary greatly among different originations, GDP per capita growth rate relative to that in 2005 (provided from SSP database) were obtained for each country. The new national GDP per capita for all five SSPs were recalculated by multiplying these growth rates with GDP per capita settled (based on the WB-WDI) for 2005. Meanwhile, extra arrangement was set for the following countries. To be more specific, in Pitcairn, Saint Helena, Svalbard and Jan Mayen Islands, and Tokelau, the national GDP per capital growth rate were set as 1.0 (constants for future scenarios due to missing predictions) for all five SSPs. The Somalia's GDP per capita growth rate was assumed to follow that of the African region since its GDP was missing in 2005. Furthermore, GDP per capital growth rate in Switzerland and Sudan were used to replace the values in Liechtenstein and South Sudan instead of the regional data due to geopolitical reason.

Then we disaggregate the global GDP projections using $GDP_{Lit\text{-}Pop}$ approach. We first updated Chinese population in the gridded population of 1/8 degree from SEDAC

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with population projections developed by Jiang et al., (2017) under two-children policy in China, which were downscaled to a spatial resolution of 0.125 degree for all five SSPs. After national and regional GDP per capita recalculated by utilizing the above GDP per capita, and spatially joined to the corresponding administrative boundaries, national GDP were preliminary redistributed by multiplying with scenario-based global population projections (Jiang et al., 2017; Jones and O'Neill, 2016) with a spatial resolution of 1/8° for 2030-2100 at 10-year intervals for all five SSPs using the $GDP_{Pop}$ approach. The DMSP-OLS stable NTL data in 2013 was adopted to replace the negative DN values from the Suomi-NPP-VIIRS DNB images in 2015. After resampled to a spatial resolution of 1 km, the global LandScan population in 2015 were introduced to calculate the base map. Following the $GDP_{Lit\text{-}Pop}$ approach, the preliminary redistributed GDP at 1/8° resolutions were further disaggregated to a spatial resolution of 30 arc seconds (~1 km) for all five SSPs, using Lit-Pop in 2015 as fixed spatially explicit pattern of GDP. Spatially explicit global GDP in 2005 and in 2030, 2050, and 2100 (as representative) are shown in Figures 3-5 to present substantial long-term changes of GDP under five SSP scenarios.

<Figure 3>

<Figure 4>

<Figure 5>

Last, we disaggregate the global GDP using LandScan population only as base map as an alternative choice. Following the same procedure, the LandScan global population in 2018 (latest obtained) was used as base map, and the above preliminary global GDP, which were downscaled to a spatial resolution of 1/8° for 2030-2100 at 10-year intervals for all five SSPs with Chinese GDP projections updated under the two-children policy, were disaggregated to 1 km×1 km grids (2030, 2050, and 2100 as representative and shown in Figure S6-S8). The GDP projections based on $GDP_{Pop}$ approach can be used as an alternative when NTL images are limited in very rural regions or at a finer spatial

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scale.

It is worth mentioning that the LandScan population data set was used as base map as an alternative in GDP disaggregation as 1) using population data set as base map performs no worse than that of $GDP_{Lit\text{-}Pop}$ (Figure 2), and 2) valid values only exists when the original NTL images and population were both not null in Lit-Pop, and that may result in some overestimation in city area.

## 4 Result

Consistent with the national totals in the SSP database and the SSP narratives, global and regional GDP depict different patterns among different SSP scenarios. The highest GDP projection will reach more than 21 times in SSP5 while the lowest projection only stays around 4.4 times in SSP3 that of 2005 by 2100 at global scale. Visible differentiations appear around 2060 with averaged about 4.9 times that of 2005 but expand to about 4.4 - 12.8 times by 2100 for SSP1-SSP4 globally. GDP in all five SSPs depict varying degrees of development with a slowing down in GDP growth rates over time, especially in the second half century in most developing countries. Meanwhile, GDP projections vary greatly across nations but are mainly consistent with the national GDP growth rate projections from the SSP database. For example, GDP in the U.S. expands only about 4.8 times in SSP5 and to about 2.2 times in SSP3 that of 2005 by 2100.

By replacing with two-children policy, the GDP projections in China, however, has led to different growing pattern among SSP scenarios. It exhibits a persistent increasing trend with highest of about 9.7 - 40.6 times that of 2005 by 2100 for all five SSP. While GDP projection from the SSP database shows a rapid development with a peak of around 2070-2080 for SSP1 and SSP3-5 with highest rates of about 7.1 - 18.7 times that of 2005 and then declined to about 6.9 - 18.1 times by 2100. These differences of Chinese GDP are result from the change of population due to the two-children policy,

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which are predicted to continue growing with a peak of approximately 1.39 - 1.45 billion around 2030, and then to decline under four SSPs with the exception of SSP3 (Jiang et al., 2017), against the continue growing with a peak of 1.36 - 1.40 billion around 2030 and then to decline under all five SSPs in the SSP database.

The regional GDP also depicts major differences inequality. Taking Northeast America (including Virginia, West Virginia, Pennsylvania, Connecticut, Delaware, Maryland, New Jersey, New York, and District of Columbia), five countries in Europe (including Netherlands, Germany, Belgium, France, and Luxembourg), and Circum-Bohai Sea Region in China (including Beijing, Tianjin, Hebei, Liaoning, and Shandong provinces) as case study since these three regions share similar latitude, highly developed, and are densely populated areas. Their GDP vary substantially among different SSP scenarios as well as among different regions over time (Figure 6), with highest growth rate reaching about 5.3, 5.2, and 39.2 times (in SSP5) but lowest of about 2.4, 2.5, and 9.4 times (in SSP3) that of 2005 by 2100 for five countries in Europe, Northeast America and the Circum-Bohai region in China, respectively. European region and Northeast America show similar GDP growth rate over time, and the city centers and places along traffic show much higher GDP (about 50 to 100 billion USD in per grid) than rural regions (less than 5 billion) in these three regions (Figure 6).

<Figure 6>

## 5 Data availability

There are two sets of global GDP (PPP in 2005 USD to enable comparison among years and across regions) disaggregation results for 2005 as historical period and for 2030-2100 as future projections for SSP1-5 at 10-year interval provided, one with Lit-Pop in 2015 as base map and the other using LandScan population in 2018 as base map. The two data sets are provided in “tif” format with a spatial resolution of 30 arc-seconds (approximately 1 km at the equator). The global GDP are disaggregated within its

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administrative boundaries, and therefore the Antarctica, oceans as well as some desert or wilderness areas are filled with value 0. The spatial extents are 65S-75N and 180E-180W (limited due to the Suomi-NPP-VIIRS NTL image extent), and 55.875S-83.65N and 180E~180W in standard WGS84 coordinate system for two data sets, respectively.

The detailed information regarding to these GDP disaggregation results is available from "Global dataset of gridded GDP scenarios", which is provided by the Global Change Risk of Population and Economic Systems (GCR-PES): Mechanisms and Assessments Project, Beijing Normal University, Beijing, China (http://gcr.bnu.edu.cn/). The two sets of gridded GDP projections are available at https://doi.org/10.5281/zenodo.4350027 (Wang and Sun, 2020).

## 6 Discussion and conclusion

In this study, we produced a set of spatially explicit global GDP, which to the best of our knowledge, the first data set that presents substantial long-term changes of GDP for both historical period (2005 as representative) and for future projections under all five SSP scenarios with a spatial resolution of 1 km. The combination of gridded population and NTL images outperformed in GDP disaggregation across the globe, and official census and GDP in U.S. and China at county level were incorporated within GDP disaggregation. Chinese population in SSP database were replaced by Jiang et al., (2017) which incorporates data from China Statistical Yearbook and the Sixth National Population Census at provincial scale and may offer a higher precision, and then used to spatialize GDP under two-children policy. The main objective is to provide a set of spatially explicit global GDP projections that is readily applicable across disciplines, and $GDP_{Lit\text{-}Pop}$ is recommended at national, state and county scales, while $GDP_{Pop}$ is recommended at county or even smaller scales where NTL images are limited in very rural regions.

However, this GDP dataset was bound to the national and subnational data of various data sources, and to the approaches including using uniformed national GDP

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per capita growth rate within a country, using fixed gridded population and NTL images in specific historical year as base map for future GDP disaggregation, and etc.

First, the national and super-national population and GDP in SSP database are highly depend on the methodology used in projection, including the model, the input drivers, and assumptions of future developments, leading to varying projections from different global organizations. Similar to the vast majority of literatures, the effect of financial crisis and climate change policies, scientific and technological progress, and many political and societal factors are, however, in absence beyond those in place when data was developed for GDP disaggregation. The climate system feedbacks are not considered on GDP disaggregation for five SSPs as well. The uncertainties for original SSP projections, especially where data coverage is limited, also exist in this disaggregated GDP and should be treated with caution.

Second, using fixed spatial distribution of gridded population and NTL images at historical level as base map is based on the assumption that population mobility within countries and across the grids will not occur, thus the gridded GDP projections fail to capture the future spatial differences caused by population migration. Meanwhile, the DN value of zero in either gridded population or NTL images (e.g., regions like farther north of 65N or very rural places) can directly cause zero proportion of GDP, resulting in some bias in such regions (GDP downscaling using the LandScan population as only base map is recommended as an alternative).

Last, simple approach of using uniform national GDP per capita growth rate within a country to downscale the national GDP to match the future population totals at 0.125 degree, can cause an even distribution of GDP in space, and is highly correlated with projected population distribution. Other inevitable shortages in this approach, like using the existing data that are combined with various techniques to replace missing values for future scenarios, the currency conversion factors used at national scale and etc., are no doubt adding more uncertainly in both historical and future GDP disaggregation.

Despite various known shortcomings and uncertainties that discussed above, this gridded GDP data set can provide a chance to allow for comparability of global and regional socioeconomic changes between historical period and future projections under different socioeconomic development pathways as described by the SSPs. It can also broaden the applicability of regional economic activities and potentially feed back to climate impact research. Our results highlight the necessity and availability of using gridded GDP projections with high resolution, especially in hazard exposure, vulnerability, and resilience analysis for the ScenarioMIP research.

**Author contributions.**

TW and FS designed the research, and TW performed the analysis and drafted the manuscript; FS provided insights on data product characteristics and underlying procedures.

**Competing interests.**

The authors declare that they have no conflict of interest.

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## Figure Captions:

Figure 1 Comparisons between official census and the gridded extractions from global population data sets for the years 2000 (a), 2005 (b), 2010 (c) and 2015 (d) at county level in China.

Figure 2 Comparison between official and disaggregated GDP at national level (a), and at state (b) and county (c) levels in U.S. and China in 2005, values in brackets are the RMSE.

Figure 3 The spatial allocation of global GDP using $GDP_{Lit\text{-}Pop}$ approach for 2005 (a) and 2030 under SSP1-5 scenarios (b-f) at a spatial resolution of 1 km.

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Figure 4 The spatial allocation of global GDP using $GDP_{Lit\text{-}Pop}$ approach for 2005 (a) and 2050 under SSP1-5 scenarios (b-f) at a spatial resolution of 1 km.

Figure 5 The spatial allocation of global GDP using $GDP_{Lit\text{-}Pop}$ approach for 2005 (a) and 2100 under SSP1-5 scenarios (b-f) at a spatial resolution of 1 km.

Figure 6 The spatial allocation of GDP in selected regions (Northeast America (a series), five countries in Europe (b series), and Circum-Bohai Sea Region in China (c series)) for 2005 as historical period and for 2030, 2050, and 2100 using $GDP_{Lit\text{-}Pop}$ approach under SSP1 scenario as study case (1 km resolution). Their spatial distribution and corresponding regional GDP growth (times that of 2005) are in the bottom.

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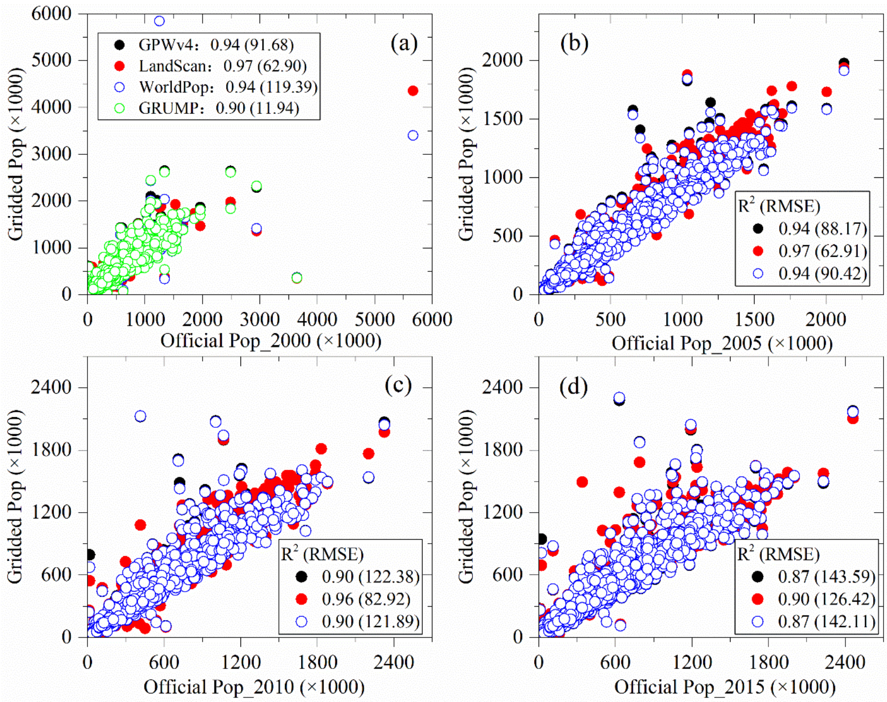
# Figure

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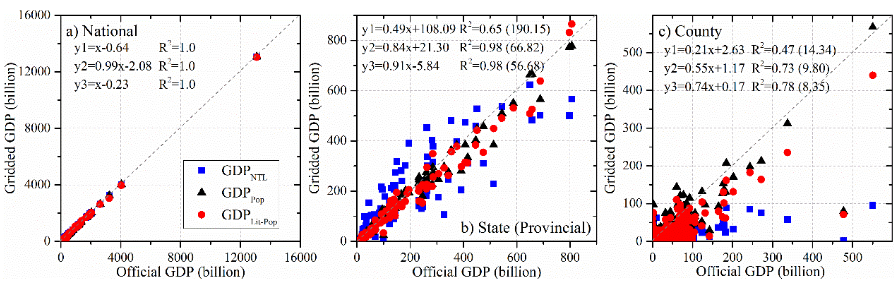


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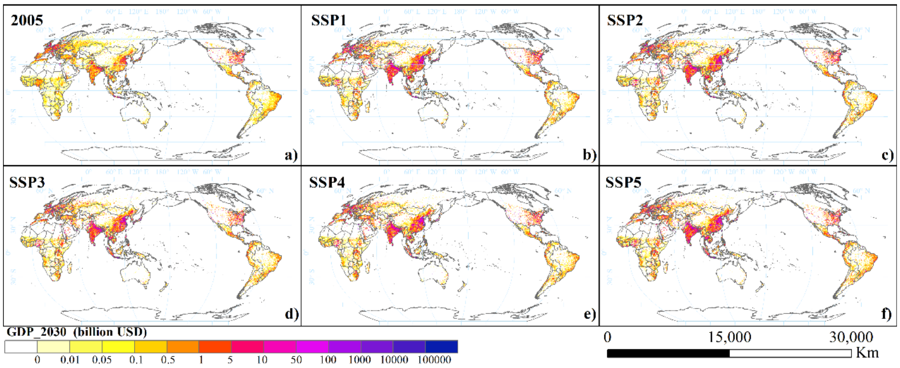


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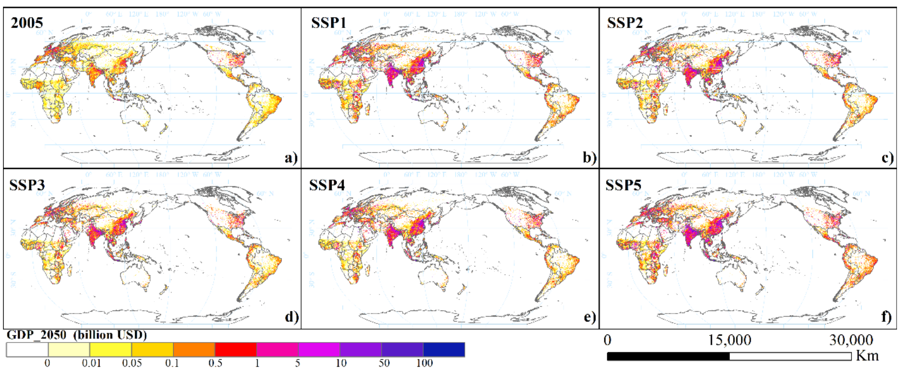


Figure 4 The spatial allocation of global GDP using $GDP_{Lit-Pop}$ approach for 2005 (a) and 2050 under SSP1-5 scenarios (b-f) at a spatial resolution of 1 km.

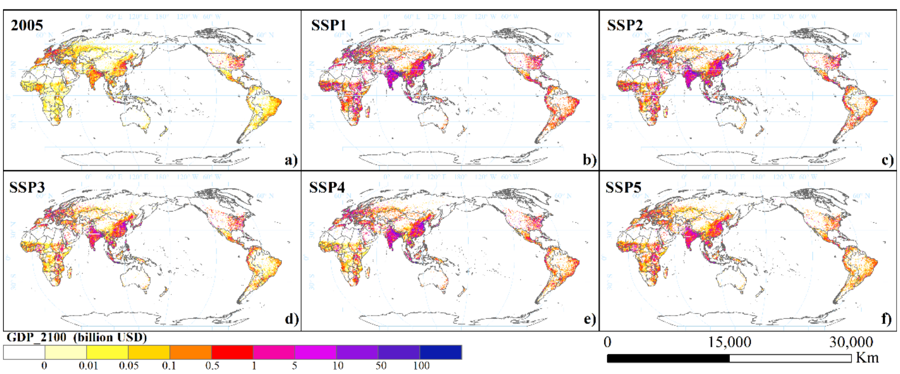


Figure 5 The spatial allocation of global GDP using $GDP_{Lit-Pop}$ approach for 2005 (a) and 2100 under SSP1-5 scenarios (b-f) at a spatial resolution of 1 km.

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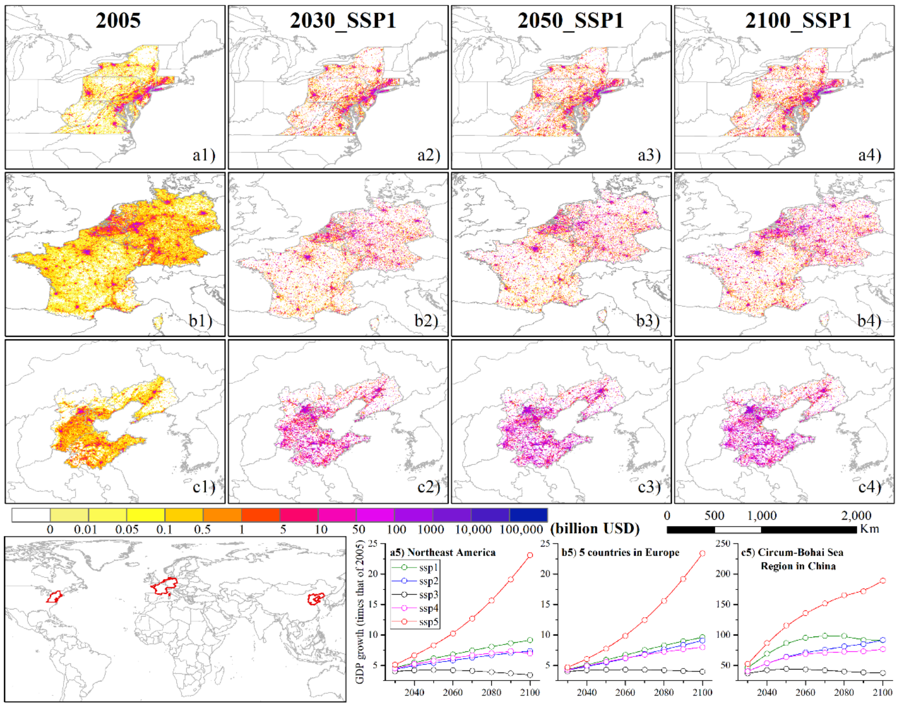


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