Mapping Global GDP Distribution

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1 Introduction

Socioeconomic projections are crucial in climate change impact, mitigation, and adaptation research and risk assessments for future scenarios (O'Neill et al. 2014). The climate projections in the Scenario Model Intercomparison Project (ScenarioMIP) are formed based on different Shared Socioeconomic Pathways (SSPs) and specific Representative Concentration Pathways (RCPs) of Phase 6 of the Coupled Model Intercomparison Project (CMIP6) (O'Neill et al. 2016). The development of research on future socioeconomic impact and on reduction in exposure and vulnerability and increase in resilience to climate extremes (Wilbanks and Ebi 2014; Chen et al. 2020) can benefit from more spatially explicit socioeconomic data of higher spatial resolution and precision under five SSPs (O'Neill et al. 2016).

The GDP is a standard socioeconomic indicator in economic development assessment within and across countries

(Nordhaus 2011; Kummu et al. 2018; Tobias 2018), and is usually provided at the national scale from several global institutions such as the World Bank, the Organization for Economic Co-operation and Development (OECD), and so on. But regional GDP data at a finer spatial resolution (e.g., at the state, city, or county level) are often unavailable, especially in many developing countries (Nordhaus 2011; Kummu et al. 2018; Huang et al. 2018). The recent development of satellite-derived nighttime light (NTL) images and gridded population data helps disaggregate global and regional GDP into gridded datasets at various spatial scales (Doll et al. 2006; Ghosh et al. 2010; Nordhaus 2011; Zhao et al. 2017) to support current research on climate change and risk assessments. These disaggregated GDP data are, however, often biased due to saturation problem of NTL images or the assumption of even GDP per capita within a given administrative boundary when using population datasets. Besides, the global gridded GDP projections of future SSPs are rather limited (Jones and O'Neill, 2016; Jiang et al. 2017,2018; Kummu et al. 2018).

The objective of this research is to present a set of spatially explicit global gridded GDP data that are comparable and represent substantial long-term changes of GDP for both the historical period and for future projections under five SSPs (Wang and Sun 2020).

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2 Method

2.1 Global GDP Distribution

National GDP purchasing power parity (PPP) of 195 countries/regions for 2005 was obtained from Geiger (2018), which was mainly from the Penn World Tables, and data of missing countries were taken from another version and the World Bank after rescaling from 2011 to 2005 PPP in U.S. dollars.

2.2 Population-Based GDP Disaggregation

Broad literature has emphasized the role of human capital as a key driver of economic growth, and population can well capture the link between the human and economic systems in various models. Hence, gridded population dataset has been widely applied in spatial allocation of global and regional GDP based on several well-known population datasets, e.g., the LandScan Global Population database, the Gridded Population of the World dataset, Version 4 (GPWv4), the Worldpop, and so on. The GDP disaggregation based on population dataset (denoted as GDP_{Pop}) can be expressed as.

$$GDP_{pop} = Pop_{pixel} \times P_{cap} = Pop_{pixel} \times \frac{GDP_i}{Pop_i} \quad (1)$$

where GDP_{pop} and Pop_{pixel} are the GDP and population in each pixel in administrative unit i , and P_{cap} is the GDP per capita, which is the ratio of GDP total (GDP_i) to population total (Pop_i) in a given administrative area i .

2.3 NTL-Based GDP Disaggregation

Numeric modelings have shown that the satellite-derived NTL data are well correlated with GDP at all examined scales, and such data has been widely used in the spatial allocation of GDP across the globe. The Defense Meteorological Satellite Program's Operational Linescan System (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 were chosen as newer sensor would have less degradation of data quality) were used to disaggregate global GDP to a spatial resolution of 30 arc seconds. Based on the results of relevant studies (Ghosh et al. 2010; Nordhaus 2011; Zhao et al. 2017; Eberenz et al. 2020), the GDP totals were directly distributed to each pixel in

proportion to the DN values of pixels in a given administrative area, and the NTL-based GDP disaggregation (denoted as GDP_{Lit}) can be described as

$$GDP_{Lit} = GDP_{per_light} \times DN_{pixel} = \frac{GDP_i}{SL_i} \times DN_{pixel} \quad (2)$$

where GDP_i is the total GDP, SL_i is the sum of DN values, GDP_{per_light} is the constant in administrative unit i , and DN_{pixel} and GDP_{pixel} are the DN value and corresponding GDP in each pixel in administrative unit i .

The saturation problem in the DMSP-OLS NTL images, however, has resulted in biased GDP disaggregation (Zhao et al. 2017). Zhao et al. (2017) improved its accuracy by incorporating the gridded population data into NTL-based GDP disaggregation in each pixel, and Eberenz et al. (2020) further improved this method. By multiplying the NTL image with the LandScan population data, a LitPop image was produced based on Eq. (3), which was then used to spatialize GDP at the global scale (denoted as $GDP_{Lit-Pop}$) using Eq. (4):

$$LitPop_{pix} = \begin{cases} Pop & Lit = 0 \\ Lit \cdot pop & Lit > 0 \& Pop > 0 \\ Lit & Pop = 0 \end{cases} \quad (3)$$

$$GDP_{LitPop} = \frac{GDP_i}{SLP_i} \times LitPop_{pix} \quad (4)$$

where $LitPop_{pix}$ is the GDP value of each pixel of the *LitPop* data and SLP_i is the sum of values of the *LitPop* image in administrative unit i .

The technical flow of mapping global GDP is shown in Fig. 1.

3 Results

To examine the performance of the GDP_{Pop} , GDP_{Lit} , and GDP_{LitPop} , comparisons were made between GDP in 205 countries using the World Bank data (Fig. 2a); in 476 states (provinces) of 36 OECD countries, the United States, and China (Fig. 2b); and in 5231 counties in the United States and China (Fig. 2c) in 2005 that are spatially joined to the corresponding GIS-based administrative boundaries, respectively. The comparisons show that the accuracy of the three disaggregated GDP datasets decreases with the change

Fig. 1 Technical flowchart of mapping global GDP

Fig. 2 Comparison between official GDP and disaggregated results at the national **a**, state **b**, and county **c** scales in 2005, using population-based disaggregation method, NTL-based approach, and LitPop approach, respectively, and the value in each brackets is their corresponding R^2

Table 1 GDP statistics (trillion USD in 2005 PPP)

		High income	Upper middle income	Middle income	Low and middle income	Lower middle income	Low income
2005		37.01	10.73	0.27	1.14	0.55	0.09
2030	SSP1	70.28	83.63	0.95	5.93	2.67	0.58
	SSP2	62.28	66.36	0.84	5.06	2.29	0.47
	SSP3	70.28	83.63	0.95	5.93	2.67	0.58
2050	SSP1	95.07	136.08	1.95	14.90	8.69	2.72
	SSP2	85.06	101.78	1.64	11.27	6.33	1.71
	SSP3	68.63	76.92	1.46	7.96	4.51	1.11

(decrease) of their spatial scales, and GDP_{LitPop} is superior to GDP_{Pop} and GDP_{Lit} at the national, state (provincial), and county levels with clear advantages evaluated by their R^2 and RMSE (Fig. 2).

Gross National Income (GNI) includes the nation's GDP plus the income from overseas sources, and has been widely used to measure and track a nation's wealth from year to year. Based on GNI per capita (current international dollars in PPP) in 2019 level from the World Bank, the global and regional GDP growth depicts major differences under the three SSP scenarios in 2030 and 2050 by income level of countries (Table 1). For countries with lower middle income

(≤ 6761 GNI per capita) and low income (≤ 2458 GNI per capita), in 2030 the GDP is about 6 times that of 2005 for SSP1–3, and reaches as high as 30, 19, and 12 times in 2050, respectively. In developed countries with high income ($\geq 52,412$ GNI per capita), in 2030 the GDP will only be about 1.7–.9 times that of 2005, and increase to about 2.6, 2.3, and 1.8 times in 2050 for SSP1–3. Meanwhile, for countries with middle income ($\leq 11,934$ GNI per capita) and low and middle income ($\leq 10,937$ GNI per capita), in 2030 the GDP will be 3.5 and 6.2 times that of 2005, showing an unequal growth rate among regions.

4 Maps

Global gross domestic production (Baseline)

Projected global gross domestic production (2030, SSP1)

Projected global gross domestic production (2030, SSP2)

Projected global gross domestic production (2030, SSP3)

Projected global gross domestic production (2050, SSP1)

Projected global gross domestic production (2050, SSP2)

Projected global gross domestic production (2050, SSP3)

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