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Dynamic monitoring and modeling of the growth-poverty-inequality trilemma in the Nile River Basin with consistent night-time data (2000–2020)

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A R T I C L E I N F O

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A B S T R A C T

Aligning with UN Sustainable Development Goals (SDGs) 1 and 10, the ‘growth-poverty-inequality’ (GPI) nexus has become widely discussed in economic development research. It remains an important discourse regarding sustainable development. To monitor spatiotemporal economic development and analyse the GPI trilemma, especially in developing and undeveloped regions, a novel framework based on long-term, consistent night-time light (NTL) remote sensing (RS) data (2000–2020) was proposed and applied to the Nile River Basin. An optimized, multitemporal estimation strategy was developed for gross domestic product (GDP) estimation and spatialization. Then, the poverty map and inequality indices for the entire basin and each country were prepared. Combining GDP growth, the poverty map, inequality index, and other relevant economic statistics, the GPI nexus for the Nile River Basin was modelled. Findings suggest that the proposed framework can not only effectively map GPI dynamics but also accurately model the GPI nexus. We found that the economic development of countries in the Nile River Basin is characterised by widespread poverty and inequality and restricted spatial distribution. The spatiotemporal evolution patterns of GPI vary with upstream and downstream geographic locations. Regarding their interaction, study findings revealed that economic growth relieves poverty, whereas high inequality levels aggravate poverty. Moreover, high inequality dampens the positive effect of economic growth on poverty reduction. This study offers new insight into GPI trilemma modeling and analyses using NTL data, an economically viable alternative to mass field surveys that is especially relevant for developing and underdeveloped regions.

1. Introduction

Sustainable Development Goals (SDGs) represent a broad consensus for global advancement from economic, environmental, and societal perspectives (Sachs, 2012). Among 17 interlinked global goals, Goal 1: ‘End poverty in all its forms everywhere’, and Goal 10: ‘Reduce inequality within and among countries’ signify that poverty and inequality are two crucial and chronic socioeconomic issues in sustainable development, impeding social progress and development, especially in developing regions (UN, 2015). Poverty and inequality are different aspects of economic distribution and have direct or indirect interactions with economic growth, whereas both economic growth and inequality contribute to poverty reduction (Ravallion, 1997; Adams, 2004; Škare and Družeta, 2016). Growth, poverty, and inequality (GPI) are all crucial indicators when measuring the economic development level. However, any one of these three indicators is insufficient for providing a comprehensive perspective of the economic development process due to the complex relationships between them. For example, economic growth is always considered having a great positive impact on poverty reduction, but the impact would become insignificant in some special circumstances (Fosu, 2011; Škare and Družeta, 2016). The income inequality will also have influence on economic growth and

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poverty threshold, which, however, would vary with different stages of economic development (Dhrifi, 2015; Hartmann et al., 2017; Soava et al., 2020). It is a complex mechanism by which economic growth and inequality act on poverty reduction, and economic performance measured only with a single indicator is one-sided. Therefore, by focusing on SDGs concerning poverty and inequality, special attention should be devoted to the GPI trilemma (Fosu, 2011). Further research and continued discourses on this subject are important in the sustainable development process, especially in developing regions (Akanbi, 2016). Bourguignon (2004) proposed a triangular framework to confirm the measurement approach, theoretical basis, and empirical issues related to GPI. In fact, many studies regarding the economic dilemma or trilemma nexus have emerged in recent years, covering various research areas, especially developing regions (Bourguignon 2005; Marrero and Serven, 2018; Adeleye et al., 2020; Wan et al., 2021).

Previous studies have explored the tripartite connection of GPI in a variety of ways. Two common deficiencies exist: over-reliance on extensive field investigation statistics and the spatial limitations of indicator measurements with only one rough scale perspective. It has been identified that the research connected with the GPI nexus is closely related to reliable data sources and accurate measurements (Atkinson and Brandolini, 2009). However, in practice, the statistical source suffers from large regional variations in coverage, data quality, and a lack of compatibility concerning collection methodologies, especially for undeveloped regions, such as Africa (Atkinson and Brandolini, 2009). Traditional data collection methods usually lead to discontinuities in time and space. These large gaps in time series and incomplete spatial distributions pose challenges to the accurate and comprehensive spatiotemporal monitoring of the GPI trilemma issue (Jean et al., 2016). Despite considerable progress in the data acquisition approach and the quantity of economic data in recent years, there is still a lack of fine measurements of the economic conditions of particular populations in many developing regions (UN, 2014). Spatial expressions of GPI have been quantified coarsely with a low spatial resolution. Insufficient data sources and weak statistical systems are threatening achievement of the SDGs' 'leave no one behind' imperative in impoverished populations, especially in certain African countries (SDG Africa, 2020). In particular, with economic inequality in developing countries existing both within and among countries, inequality condition research is limited by scarcity, poor quality, uncertainty, the incompatibility of data, and insufficient measurement approaches (Mirza et al., 2021). It is worth noting that only a few previous studies have attempted to address these issues. Thus, there is a demand for novel data collection technology in the socioeconomic analysis of undeveloped countries that has the potential to provide global coverage in real time and at a low cost with high spatial resolution.

With the rapid development of remote sensing (RS) technology, satellite-based earth observations have provided an efficient and explicit approach for surveys concerning sustainable development (Burke et al., 2021). Until 2020, RS provided earth observation data for 18% of the SDG indicators directly or indirectly, of which a significant proportion was related to economic statistics (Estoque, 2020). Owing to the comprehensive data obtained, it is easier and more productive for RS technology to gain an advantage in statistical data acquisition in developing regions (Keola et al., 2015; Zhu et al., 2020). Compared with traditional approaches in which data are usually obtained through ground surveys, the main advantages of RS data for economic research can be described in terms of unique accessibility, high spatial resolution, and wide geographic coverage (Donaldson and Storeygard, 2016). This is an effective complement to the lack of data sources and statistical approaches in developing regions. Recently, a series of RS data, especially night-time light (NTL) data, have been applied in socioeconomic studies, making it possible to observe human activities directly and globally from space (Levin et al., 2020). Further, NTL RS systems, such as Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) and Visible Infrared Imaging Radiometer Suite from the Suomi National Polar-orbiting Partnership (NPP/VIIRS), provide advanced observational approaches and reliable data sources for many economic analyses at sub- and supranational levels in three key aspects: socioeconomic index estimation and spatialization (Doll et al., 2006, Mirza et al., 2021; Shi et al., 2014; Jean et al., 2016), economic dynamics monitoring (Bennett and Smith, 2017; Henderson et al., 2012), and economic wealth projection (Weidmann and Schutte, 2017). However, most previous studies only utilised data from a single NTL sensor to avoid systematic errors caused by large differences in the spatial resolution and system design of different NTL sensors. Additional limitations result from the time span in existing studies, which is not long enough to obtain accurate economic development patterns in time series (e.g., DMSP-OLS:1992–2013, NPP/VIIRS: since 2012). To date, no NTL data—let alone a long-term series of multi-sourced NTL data—have been introduced in economic studies pertaining to the GPI nexus.

To monitor the dynamic spatiotemporal GPI pattern and explore the complex relationship between each component, we initially proposed a novel framework based on long-term, consistent NTL data from DMSP and VIIRS (2000–2020) for developing and undeveloped regions. The previously generated NPP-like annual NTL dataset product (Chen et al., 2021) could effectively solve the problems of time span limitations and deviations among different sensors. Another contribution of this study is an optimized multitemporal estimation strategy developed to monitor the spatiotemporal dynamics of the GDP from 2000 to 2020 in the Nile River Basin. The corresponding poverty map and regional inequality were quantified based on the GDP estimation and spatialisation. Finally, a relational model was developed to explore the GPI nexus for the interaction analysis. We identified the main purposes of this study as follows: (1) to provide a way to quantify and spatialize the economic GPI with the long-term NTL dataset, (2) to reveal the spatiotemporal evolution of the rules regarding economic GPI over time, (3) to model the GPI nexus, and (4) in terms of studying the GPI nexus, eliminate the limitations of mass field survey economic data, especially for developing and undeveloped regions.

2. Materials

2.1. Study area

The Nile River flows from the River Luvironzo to the Mediterranean Sea, running from south to north. It is the longest river in the world, measuring approximately 6,695 km in length (NBI, 2017). The upper Nile is formed by two major streams: the Blue Nile, which stems from Lake Tana in the highlands of Ethiopia and flows to Sudan, and the White Nile, with the headstream flowing from Lake Victoria in the East African Community (Van Griensven et al., 2012). The basin spans a latitude of 35°. The climate is widely different between the south and north, with tropical savannah and tropical desert climates affected by latitudinal zonality and terrain (Abdelmalik and Abdelmohsen, 2019).

As one of the most important transboundary rivers in Africa and the world, the Nile River flows through 10 countries (Tanzania, Democratic Republic of the Congo (DR Congo), Burundi, Rwanda, Uganda, Kenya, Ethiopia, South Sudan, Sudan, and Egypt) from south to north (Fig. 1)). The river system provides countries in the basin with excellent natural resources and hydrological conditions, making the region economically developed in Africa (Belay and Mengistu, 2019). Even though it occupies only one-tenth of the continent (approximately 3.4 million km^2) (Awange et al., 2014), the Nile River Basin is an indispensable lifeline for almost two-fifths of Africa's population (approximately 500 million people) (UN, 2017) and contributes more than a quarter to the GDP (27.5% in 2020) (The World Bank, 2021). Agriculture and animal husbandry are the primary economic sources for most countries within the Nile River Basin (NBI, 2017).

However, economic development of the Nile River Basin countries, although at the forefront relative to the rest of the African continent, is still lagging behind the rest of the world. Compared to other regions

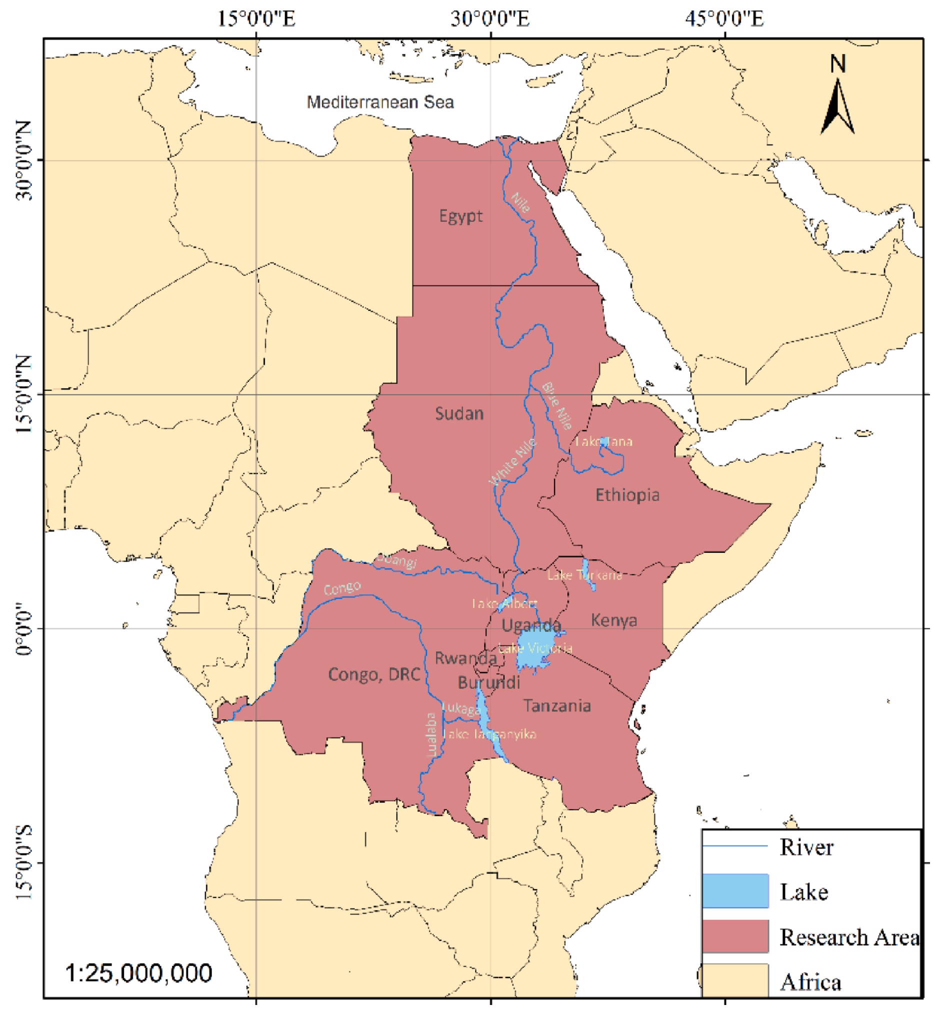


Fig. 1. Study area: the Nile River Basin.

worldwide, the Nile River Basin presents an important challenge to the economy as it relates to poverty reduction and the GPI trilemma. For the fiscal year 2021, The World Bank (2021) assigned the world's economies into several income groups. All countries in the basin were placed into low (Burundi, Ethiopia, Sudan, South Sudan, Rwanda, Uganda, DR Congo) and lower-middle (Egypt, Kenya, Tanzania) income country groups. Seven countries (Burundi, DR Congo, Ethiopia, Rwanda, Sudan (including South Sudan), Tanzania, Uganda) in the Nile River Basin are now categorised as the least developed countries with the lowest indicators of socioeconomic development and the lowest human development index ratings worldwide (UN, 2021). A low level of economic development and technology leads to a deficiency in economic statistics and regional data with low spatial resolution. This limits the feasibility of an accurate and systematic study of the economic development of the Nile River Basin.

It is worth mentioning that South Sudan gained independence from the Republic of the Sudan in 2011. However, to ensure consistency in the spatial scale of this research over the time span (2000–2020), we regarded South Sudan and Sudan as statistically significant components.

2.2. Data collection

2.2.1. NTL dataset

In this study, a quantitative analysis of socioeconomic growth in the Nile River Basin was conducted using a developed NPP-like annual dataset product, an annual extended time series NTL dataset (2000–2020) based on cross-sensor calibration from DMSP-OLS NTL data (2000–2012), and a composition of monthly NPP/VIIRS NTL data (2013–2020), conducted using an auto-encoder model with a convolutional neural network architecture (Chen et al., 2021). The NPP-like data was in the World Geodetic System 1984 coordinate system, with a spatial resolution of 15 arcseconds. It had a consistent temporal trend on both global and regional scales, with consistent population trends from 2000 to 2020 and a smooth temporal change boundary between the simulated and composited datasets. The NPP-like NTL dataset could meet the requirements for a large spatial scale and long time-series analysis in our study. The monthly NPP/VIIRS data in 2018, with a spatial resolution of 15 arcseconds, were adopted to validate the accuracy of the NPP-like NTL data for the Nile River Basin.

2.2.2. Regional statistical data

Annual socioeconomic statistics of countries in the Nile River Basin were collected from the official website of The World Bank, including the GDP (in 2010 constant US dollars), population count, per capita consumption expenditure growth (PCEGR), school enrolment rate (EDUC), and unemployment rate (UNEM) from 2000 to 2020. The annual WorldPop Population Count product with a resolution of 3 arcseconds was introduced in this study as supporting material for GDP per capita spatialization and a subsequent poverty and inequality analysis. Table 1 lists the data sources and descriptions.

3. Methodology and experiments

The study process is illustrated in Fig. 2. It consisted of four key steps:

Table 1
Data sources.

Dataset	Description	Time Horizon	Source
NPP/VIIRS	Monthly NTL data, spatial resolution 15 arcseconds for NPP-like validation	2018	EOG data
NPP-like product	Annual NTL dataset for GDP projection and spatialization	2000–2020	Chen et al., 2021
Socioeconomic statistics	Various statistics of countries in the research area (e.g. GDP, population count, PCEGR, EDUC, and UNEM)	2000–2020	worldbank.org
WorldPop	World Population counts product	2000–2020	worldpop.org

(1) accuracy verification of the NPP-like dataset, (2) a spatiotemporal analysis of economic growth, (3) quantification of poverty and inequality, and (4) an interaction analysis of the GPI trilemma. During steps 2 and 3, two growth variables (annual growth rate of GDP statistics (GR) and per capita GDP growth (PCGR)), two poverty variables (the proportion of the population under the poverty line (PV) and the natural logarithm of per capita GDP (lnPC)), two inequality variables (THEIL (Theil Index), and an interaction term (GrTheil = GR*THEIL)) were generated from the NTL dataset and GDP statistics. Except for the above variables, two more poverty variables, school enrollment rate (EDUC) and unemployment rate of the total labour force (UNEM), were provided by The World Bank dataset. Based on these results, the GPI nexus was modeled and estimated in step 4.

3.1. Accuracy verification of the NPP-like dataset

To verify the reliability of the newly proposed NPP-like annual dataset, the NPP/VIIRS annual data in 2018 for the Nile River Basin was generated using monthly calibrated NPP/VIIRS NTL data for the same year. In NPP/VIIRS data pre-processing, the data correction model proposed by Shi (2014) was adapted. Pixels with unstable NTL intensity and unusually high light intensity values were removed using a dark background mask and the NTL intensity threshold. In this study, the threshold was set based on the maximum digital number (DN) value of typical international metropolitan cities (Ma et al., 2014). Pixels exceeding the threshold were regarded as anomalous image elements and replaced by the maximum DN value in the adjacent eight pixels. After obtaining the pre-processed NPP/VIIRS monthly data, the corresponding NPP/VIIRS annual data were generated by selecting the median value of 12 months for each pixel. Resampling was consistent with the NPP-like product. Further, 10,000 pixels were randomly selected to calculate the correlation coefficient between the NPP-like dataset and the NPP/VIIRS data for accuracy verification.

3.2. Spatiotemporal analysis of economic growth

The spatiotemporal analysis of economic growth using NTL data was mainly based on a GDP estimation—that is, the process of building the mapping relationship between the NTL index and real GDP statistics. The total nighttime light (TNL) and the sum of the digital number (DN) of lighting within an administrative unit were calculated as the NTL indices for the estimation experiment in this study. The final GDP value of each pixel could be calculated by inputting its NTL value into the GDP estimation model. In terms of the study scale and spatial resolution of the statistics (such as country, city, or county level), the previous methods for estimating GDP with NTL data could be generally divided into temporal projection and spatial simulation models (Liang et al., 2020; Xiao et al., 2018).

3.2.1. Temporal projection model

In the construction of the temporal GDP projection model, only one regression model was applied to describe the relationship between the NTL index and real GDP statistics for the study area during the entire period (Liang et al., 2013; Chen and Li, 2019; Lan et al., 2019). The model is simple, with low computational requirements and the ability to project the temporal GDP trend based on the NTL time series data (Xiao et al., 2018). However, projection accuracy was closely related to the scale of the study area. The spatial difference in sub-regions' economic development could not be illustrated precisely given a large-scale study area.

3.2.2. Spatial simulation model

A spatial GDP simulation model is usually used when the spatial resolution of statistics is relatively high—that is, when statistics on smaller administrative units are available, such as at the city or county level. In this type of model, the NTL index and GDP statistics of the minimum administrative unit scale, which were obtained within the same time period, were adopted in the regression process to map their relationship (Yu et al., 2015). Contrary to the temporal projection model, the GDP distribution can be described more accurately by the spatial simulation model, especially for a large-scale study area. However, temporal changes in the economy cannot be estimated (Zhao et al., 2017).

3.2.3. Proposed multitemporal estimation strategy

To describe the temporal change and spatial distribution of GDP growth accurately and simultaneously, an optimized multitemporal estimation strategy is proposed from the findings of this study. The application of NPP-like data has made it possible to project a long time series of GDP growth (Chen et al., 2021). The main process is illustrated in Fig. 3. First, according to the minimum number of statistical administration units, the study area was divided into several subregions. Then, for each sub-region, an individual regression model was built. After constructing the relationship between the NTL index and real GDP statistics, spatialization was performed to allocate the real GDP value to each pixel with accuracy.

The Nile River Basin spans a vast geographical area, with nine sub-regions (countries) characterised by various national conditions and development patterns. Using the year-by-year TNL value as an independent variable and GDP statistical value as the dependent variable, four mathematical models (linear, logarithmic, quadratic, exponential) were separately introduced to build GDP regression models for nine countries. The model with the best fit (highest correlation coefficient (r^2)) was selected as the GDP projection model for each country. In the spatialization process, the widely utilised linear spatial distribution of GDP within the Nile River Basin, consistent with the NTL value, was considered. The GDP value for each pixel was calculated using the following formula (equation (1)):

$$\mathrm{GDP}_i = \frac{\mathrm{DN}_i}{\mathrm{TNL}_{country}} \times \mathrm{GDP}_{country} \tag{1}$$

where GDP_i represents the simulation value of each pixel, DN_i represents the digital number of each pixel, $\mathrm{TNL}_{country}$ represents the sum of the DN values of the country, and $\mathrm{GDP}_{country}$ represents the GDP statistical value of each country.

To verify the multitemporal estimation strategy, a comparative experiment with the temporal projection model, spatial simulation model, and our optimized strategy was conducted. The accuracy of GDP modeling was assessed using the relative error between the reference and estimated results. While building the temporal projection model, TNL and GDP data for one year were randomly selected as verification samples. The remaining TNL and GDP data of nine countries in the Nile River Basin were utilised as training samples in a single regression model. In the spatial simulation experiment, the TNL and GDP statistics

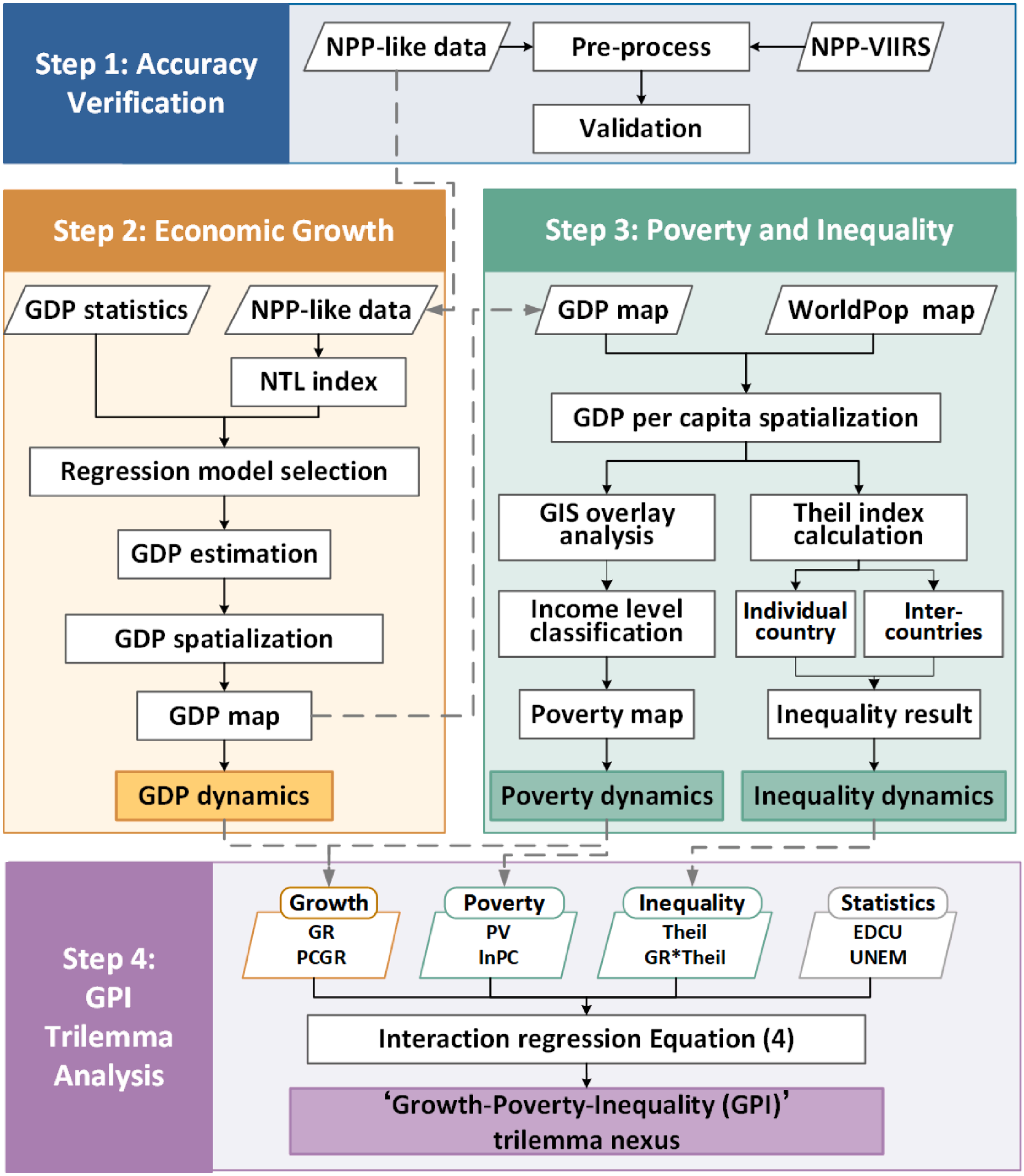


Fig. 2. Flowchart for our proposed framework.

of the eight countries in a single year were adopted in the regression model. In the proposed multitemporal estimation strategy, an individual regression model was built for each country, with year-by-year TNL and GDP statistical values as independent and dependent variables, respectively. For each model, data from one year were randomly selected as validation samples. Owing to the limitation of the sample number, only four candidate regression models were considered: linear, logarithmic, quadratic, and exponential.

3.3. *Quantification of poverty and inequality*

Poverty can be measured using the absolute poverty index of the proportion of a population below a particular poverty line. According to The World Bank (2021), poverty can be described by gross national income (GNI) per capita. The GNI is the nation's GDP plus overseas source income minus overseas expenses. In undeveloped countries, however, few people have overseas source income and overseas expenses. Therefore, the GNI per capita value can be approximated using GDP per capita data (The World Bank, 2021). In this study for the Nile

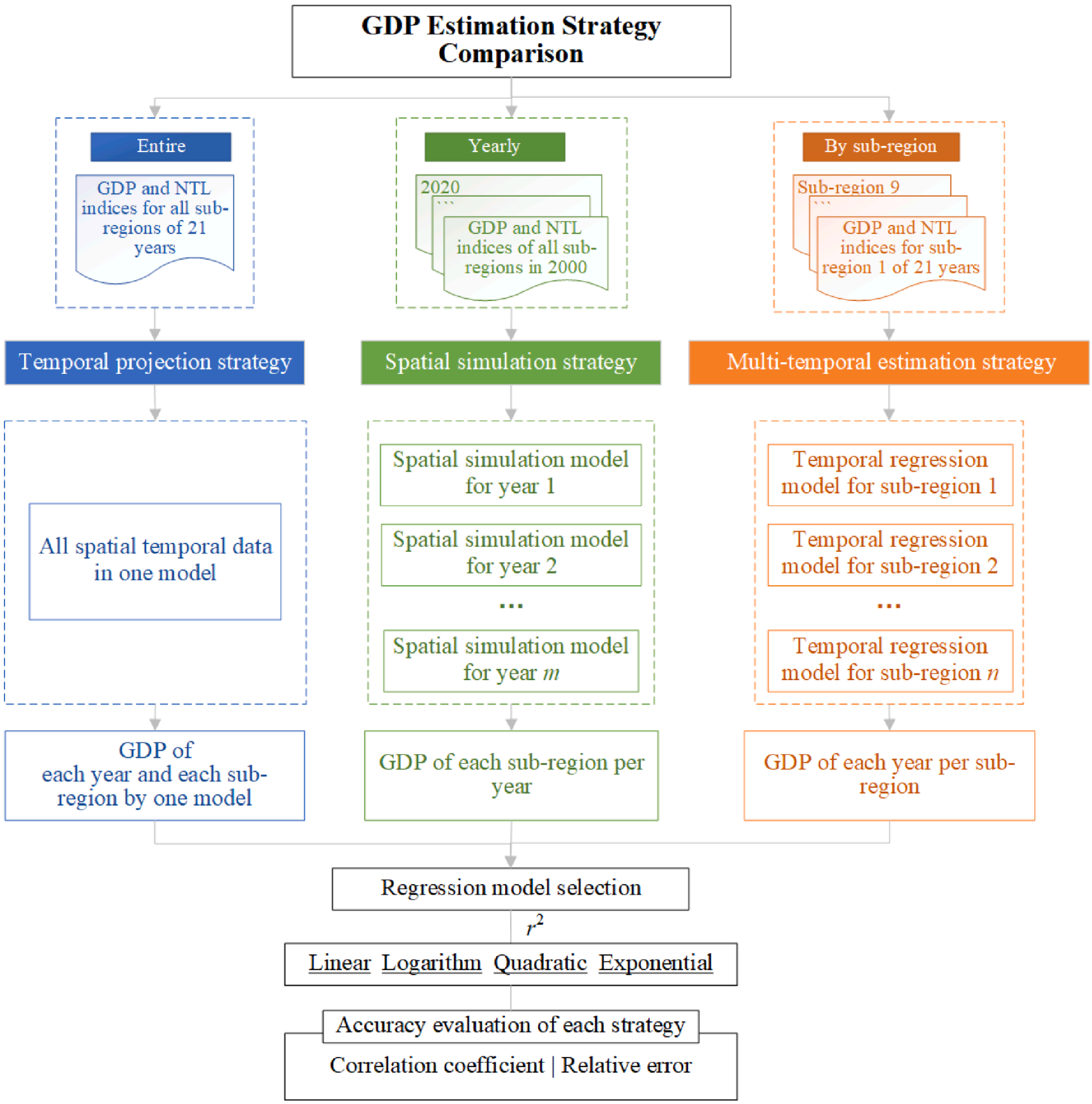


Fig. 3. Comparison of different methods for GDP estimation.

River Basin, poverty was spatialised using a GDP per capita map and calculated by dividing the population map into GDP estimation results. The population map was obtained from Population Count WorldPop and resampled to 15 arcseconds, in keeping with the NPP-like dataset in the pre-process.

To ensure consistency of the income level classifications over this study's timeframe, the income level threshold for poverty analysis was set as the mean value of the annual statistical GNI per capita (2010 consistent dollars) of each income level grouped by The World Bank (2021). Five income levels were generated for each year: low, mid-low, upper-mid, high, and extremely high. The proportion of the population per income level was calculated for all countries through WorldPop population data and poverty maps by an overlay analysis using Geographic Information System (GIS) tools. The proportion of the population in the low income level was used as a poverty variation in the interaction regression analysis described in Section 3.4.

Inequality refers to the disparity in the relative income distribution across countries in the Nile River Basin and within each country's population. In our study, inequality quantification was expressed by the Theil index, a statistic primarily used to measure economic inequality (Conceicao and Ferreira, 2005). The inter-country inequality index of the Nile River Basin (T_N) and the index within an individual country (T_C) were calculated separately using country-level statistics and pixel-level spatialization results (Eqs. (2) and (3)):

$$\begin{cases} w_i = \dfrac{\mathrm{GDP}_{country}}{\mathrm{GDP}} \\ \mu = \sum (w_i \times p_{country}) \\ T_N = \sum \left[w_i \times \log\left(\dfrac{\mu}{p_{country}}\right)\right] \end{cases} \tag{2}$$

$$\begin{cases} w_i = \dfrac{\mathrm{GDP}_{pixel}}{\mathrm{GDP}_{country}} \\ \mu = \sum(w_i \times p_{pixel}) \\ T_C = \sum\left[w_i \times \log\left(\dfrac{\mu}{p_{pixel}}\right)\right] \end{cases} \tag{3}$$

where p_{pixel} is the GDP per capita value of each pixel and $p_{country}$ is the statistical GDP per capita value.

The Theil index within an individual country (T_C) is the inequality variation and interaction variation in the GPI interaction regression analysis in Section 3.4.

3.4. Interaction analysis of the GPI trilemma

In this study, econometric modeling relied on a theoretical account of the GPI trilemma (Dhrifi, 2015), which was first described by Bourguignon (2004). Growth of the GDP and per capita GDP alleviates poverty, whereas inequality worsens poverty levels. To highlight the relationship between growth and inequality on poverty, inequality has a stronger positive effect on poverty than growth. In this study, the interaction between growth and inequality (Easterly, 2000) was considered as well. Additionally, the population under the poverty line was symbolic of the incidence of poverty. Based on the inequality and poverty indices obtained through spatialization results, two more pro-poor growth elements—education and unemployment—as independent poverty variables which could also reflect the varied poverty levels of countries effectively (Adeleye et al., 2020) were included. Therefore, the interaction analysis of the GPI nexus was established through a multiple linear regression model and expressed by equation (4), in which the per capita consumption expenditure growth rate (PCEGR) was taken as a dependent variable representing the poverty reduction index:

$$\begin{aligned} PCEGR = & a_0 + a_1 GR + a_2 THEIL + a_3(GrTheil) + a_4 \ln EDUC + a_5 \ln UNEM \\ & + a_6 PV + a_7 PCGR + a_8 \ln PC + e_{ij} \end{aligned} \tag{4}$$

Properties of the independent variates were categorised as follows: growth variables (*GR*, representing the annual growth rate of GDP statistics, per capita GDP growth (*PCGR*)); poverty variables (school enrollment rate (*EDUC*), unemployment rate of the total labour force (*UNEM*), proportion of the population under the poverty line calculated by the authors (P*V*), natural logarithm of per capita GDP (ln*PC*)), and inequality variables (*THEIL* (Theil Index)). The interaction term ($GrTheil$ = GR*THEIL). a_j (where $j = 1, 2, \ldots, 8$) is the parameter to be estimated, and e_{ij} is the error term. It is worth mentioning that in The World Bank database, there are no available statistics on consumption expenditures for Ethiopia; therefore, the regression model of the GPI nexus was built on variates of the other eight countries. Among the variations above, EDUC and UNEM were included in The World Bank dataset, whereas the others were produced by the NTL estimation results and GDP statistics.

4. Results

4.1. Accuracy evaluation results

4.1.1. Accuracy verification of the NPP-like product

As shown in Fig. 4, to verify the reliability of the NPP product, a scatter plot was fitted to the NPP-like product and NPP/VIIRS data for 2018. The r^2 value was 0.7858, indicating a significant correlation and reliable data quality of NPP-like products in the research area.

4.1.2. Accuracy evaluation of the GDP estimation

In the comparative experiment of GDP estimation models, data from 2019 were selected as validation data for accuracy evaluation. Table 2 shows the correlation coefficients for each model for different estimation strategies. Considering the correlation coefficient and actual simulated curves, the candidate regression expression with the best accuracy was selected as the estimation model. The corresponding estimation results, GDP statistics (regarded as the reference), and relative errors for each country are given in Table 3. The average relative errors of the temporal projection and spatial simulation models were 149.70% and 178.61%, respectively—more than 15 times larger than those of the optimized multitemporal model (9.12%). On the other hand, a dramatic fluctuation in the relative error occurred in the estimation results of the nine countries using the temporal projection and spatial simulation models. They both performed weakly for Burundi, which has the lowest GDP in the Nile River Basin, while their best performance was found in the estimation for Egypt, which is more developed than the others. Obviously, the smaller the national economic volume, the larger the relative error (e.g. Burundi and Rwanda).

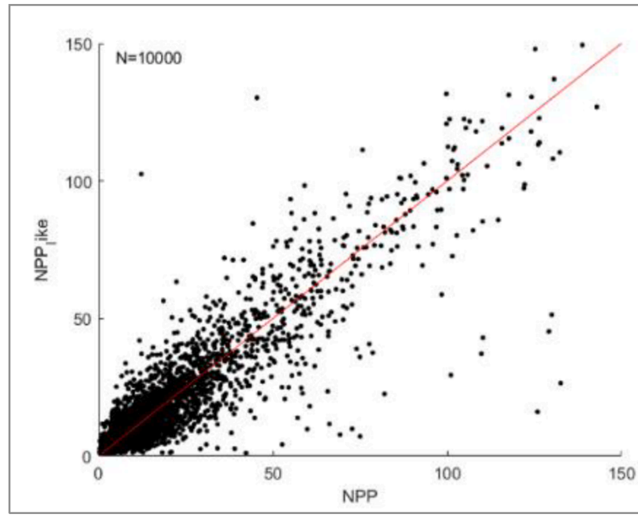


Fig. 4. Scatter diagram for NPP-like and NPP/VIIRS data. (Axis x and y represent DN for NPP/VIIRS and the NPP-like product, respectively; red line represents $y = x$.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In sharp contrast, the multitemporal estimation strategy had a much more stable performance, with a lower error per country and fewer differences between countries. The relative errors of Egypt, Ethiopia, and Sudan exceeded 10%, with Sudan having the highest error (18.4%). It is worth mentioning that the GDP statistics for South Sudan have not been updated in The World Bank database since 2015. In 2011, South Sudan gained independence from Sudan and endured the Civil War from 2013 to 2020, leading to economic instability. Thus, it is difficult to analyse economic evolution patterns through historical statistics. For Sudan and South Sudan, the NTL value may be a better indicator of GDP variation than the statistical value after 2015. The relative errors of the remaining six countries were all within 10%, with Uganda and Tanzania having less than a 3% error in 2019. Hence, the proposed GDP estimation strategy was more effective than the other two widely applied models in the Nile River Basin. It has impressive estimation ability, especially for regions with large differences in the administrative unit scale and national economic volume.

4.2. Spatiotemporal analysis of economic growth

4.2.1. GDP spatial distribution of the Nile River Basin in 2020

Based on the GDP estimation using our proposed strategy, the corresponding GDP spatial distribution for 2020 is shown in Fig. 5(a). The relatively economically developed regions in the Nile River Basin are mainly located in the downstream Mediterranean inlet delta (Egypt),

Table 2
Correlation coefficient for each model.

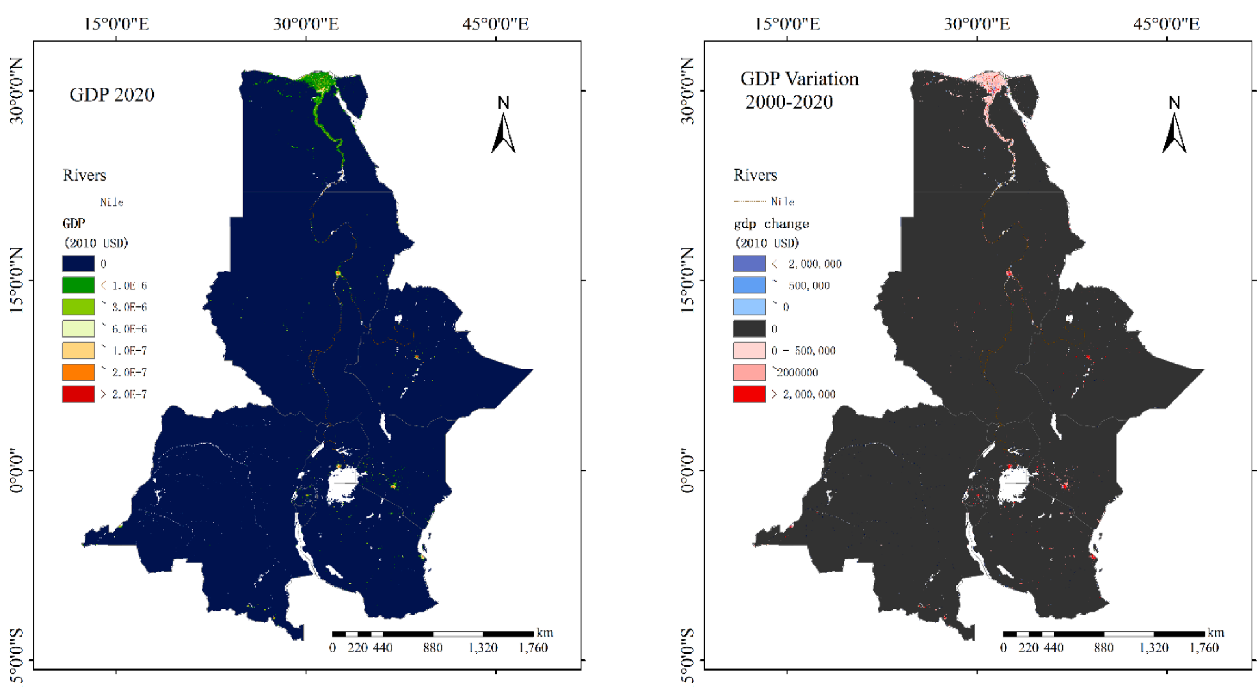
Regression model	Temporal projection model	Spatial simulation model (2019)	Multitemporal estimation model								
			EGY	ETH	KEN	SDN	BDI	UGA	RWA	TZA	COD
Linear	0.902	0.945	0.868	0.898	0.842	0.859	0.835	0.811	0.844	0.851	0.880
Logarithm	0.719	0.779	0.887	0.825	0.878	0.867	0.866	0.807	0.738	0.842	0.856
Quadratic	0.933	0.955	0.881	0.902	0.870	0.869	0.888	0.819	0.845	0.856	0.883
Exponential	0.347	0.391	0.855	0.829	0.756	0.841	0.827	0.708	0.724	0.737	0.813

Notes: EGY for Egypt, ETH for Ethiopia, KEN for Kenya, SDN for Sudan, BDI for Burundi, UGA for Uganda, RWA for Rwanda, TZA for Tanzania, COD for D.R.Congo, similarly hereinafter.

Table 3
Estimation results comparison (2019).

Country	Reference Data		Temporal Projection Model		Spatial Simulation Model		Multitemporal Estimation Strategy	
	TNL	GDP Statistics	Projection GDP	Relative error (%)	Projection GDP	Relative error (%)	Projection GDP	Relative error (%)
EGY	2,795,963	302,183	290,617	3.83	281,769	6.76	257,742	14.71
ETH	46,223	67,542	30,130	55.39	36,123	46.52	55,515	17.81
KEN	112,402	65,060	36,399	44.05	42,035	35.39	61,343	5.71
SDN	143,965	64,784	39,390	39.20	44,854	30.76	76,668	18.34
BDI	2145	2399.	25,955	981.80	32,185	1241.47	2544	6.03
UGA	26,933	42,611	28,303	33.58	34,399	19.27	43,487	2.06
RWA	11,519	11,381	26,843	135.86	33,022	190.16	10,407	8.56
TZA	63,263	55482.15	31744.52	42.78	37644.77	32.15	53903.10	2.85
COD	74,202	36767.98	32780.78	10.84	38621.97	5.04	34545.25	6.05
Average				149.70		178.61		9.12

Notes: GDP units are in 2010 constant dollars (millions).
TNL refers to the total nighttime light value.



(a) GDP distribution in 2020 (b) GDP variation between 2000 and 2020

Fig. 5. GDP spatial distribution in 2020 and spatiotemporal variation between 2000 and 2020 in the Nile River Basin.

surrounding coastal areas, and along the river. The GDP spatial distribution showed two different characteristics according to upstream and downstream geographic locations. For upstream countries, GDP is characterised by a decentralised distribution within the national territorial area. High-GDP areas are concentrated in capital cities or large urban agglomerations which were mostly built on the shores of lakes connected with the White Nile, especially for countries in the Great Lake Regions, such as Uganda, Rwanda, Burundi, and Tanzania. In this study, compared to upstream countries, the GDP distribution in downstream countries, such as Egypt, Sudan, and South Sudan, showed a more pronounced distribution characteristic along the Nile River and in the inlet delta. For instance, in Egypt, in the river valley and delta region downstream, Cairo and its northern region contributed the vast majority of lightning despite representing a minority in terms of land area.

4.2.2. Spatiotemporal evolution of GDP

To show the spatiotemporal evolution of GDP intuitively, we detected and visualised the spatiotemporal variation of the GDP distribution between 2000 and 2020 (Fig. 5(b), Table 4). It is obvious that economic growth in the study area reflected a significant spatial expansion, with a total increase of 211.4% and an expansion degree of more than 20% every five years (Table 4). All countries grew substantially in terms of the total GDP and GDP distribution area. Compared with countries in the White Nile Sub-basin (Uganda, Rwanda, Tanzania, and Kenya), the economic spatial distribution of downstream countries (Egypt and Sudan) was less expansive. With a relatively slow GDP growth rate, the economic volume of Egypt remained the largest compared to other countries, and the human activities and spatial economic expansion were limited by the surrounding desert landscape. As for Sudan and South Sudan, economic development and the urbanisation process were impeded by civil war and potential climate and water resource shortages in downstream countries (NBI, 2017).

More specifically, in the major cities of the Nile River Basin countries (Fig. 6), economic development was dominated by GDP spatial expansion and supplemented by an increase in GDP growth from 2000 to 2020. There was a more pronounced tendency for economic activities to spread and develop on the urban periphery. However, the spatiotemporal evolution of GDP in the urban centre of some major cities, such as Bujumbura (Burundi), Kinshasa (Congo), and Dar es Salaam (Tanzania), showed a slight decreasing trend. Combined with the results in Table 4, we found that this decreasing phenomenon always occurred in countries with higher spatial expansion degrees but lower GDP growth rates. It was expressed as an increase in the GDP contribution in the surrounding areas and a reduction in the GDP proportion from the former city centre. Growth in economic volume was diluted by rapid spatial expansion, and poverty group migration accounted for the vast majority of spatial economic expansion in these countries. The results showed a tendency towards the decentralisation of economic activities in the Nile River Basin.

4.3. Quantification of poverty and inequality

4.3.1. Spatiotemporal change in the poverty map

The results of the GDP per capita map were calculated based on the GDP spatialization results and the WorldPop population product (Fig. 7). On a national scale, for each country, the distribution of low per capita income regions was quite dispersed, with per capita income in most capital regions remaining at a relatively high level. The vast majority of the area can be regarded as low- or lower-middle income regions (expressed in green-yellow and green in Fig. 7). Areas with high per capita income in (blue) are very few in the Nile River Basin countries, with small fractions in large central cities and surrounding urban regions.

Table 4
GDP comparison: 2000 versus 2020.

Country	NTL area (km^2) 2000	NTL area (km^2) 2020	Spatial expansion degree (%)	GDP statistics 2000	GDP statistics 2020	GDP growth rate (%)
EGY	31,302	83,349	166.27	136,412	312,970	129.43
ETH	446	2688	501.58	13,074	71,633	447.87
KEN	685	6104	790.89	26,198	64,860	147.57
SDN (SSD)	1746	7521	330.57	30,179	92,897	181.86
BDI	42	219	411.05	1462	2406	64.59
UGA	256	1871	629.04	13,036	43,829	236.19
RWA	50	803	1483.82	27,856	10,997	294.72
TZA	639	4804	650.72	16,993	56,594	233.04
COD	652	2997	359.33	13,660	37,052	171.25
Nile	25,854	80,512	211.40			

Notes: GDP units are in 2010 constant dollars (millions).

To analyse poverty in the Nile River Basin quantitatively and systematically, the poverty rate—represented by the proportion of the population under the average GDP of low-income countries and territories—was calculated through a GIS overlay analysis. At the beginning of the 21st century, low-income rates in all countries, except Egypt, exceeded 90%. The countries experienced a decrease in the low-income population proportion during the past two decades, while Egypt had an opposite trend, from 26.52% in 2000 to 33.74% in 2020, which was still the lowest poverty proportion in the Nile River Basin. For Kenya and Tanzania, together with Egypt, poverty rates were less than 80% in 2020, and they were also the only countries not classified as low-income countries in the Nile River Basin by The World Bank. The poverty rates calculated for each country by year were used as the poverty variables in the interaction regression analysis.

The poverty map variations across the entire basin from 2000 to 2020 are shown in Table. 5. The proportion of groups classified as low income and above middle income decreased, whereas the proportion of the mid-low income group increased. Specifically, for groups with upper-high to extremely high-income levels, the proportion peaked around 2007 and 2008 and continued to decrease thereafter. For the group with mid-low-income levels, the trend was opposite that of the higher income groups, which reached its lowest point in 2008 and continued to rise until 2020. The proportion of the low-income group has been fluctuating. It reached its highest in 2008, declined steadily to a trough in 2019, and then rebounded in 2020. Relatively speaking, dramatic fluctuations for all groups occurred around 2008 and 2020, during which the financial crisis and COVID-19 emerged separately.

4.3.2. Economic inequality analysis

The Theil index—regarded as the expression of inequality—for the entire Nile River Basin and each country is shown in Fig. 8. The higher the Theil index, the larger the inequality. For the entire Nile River Basin, economic inequality has gone through a 'w-shaped' development course (Fig. 8(a)). Two sharp increases in the inequality index occurred in 2008 and 2020, during which there were global emergencies (the financial crisis and COVID-19). Subsequently, a steady downward trend was observed during other time periods. Within the past 21 years, the peak of economic inequality in the Nile River Basin occurred in 2009, with a Theil index of 0.2056. With the receding effects of the financial crisis, the inequality index decreased continuously over the next several years and reached its lowest point, 0.1835, in 2017. It sharply increased to more than 0.1917 in 2020 under the influence of COVID-19. Both the financial crisis and COVID-19 increased economic inequality among countries in the Nile River Basin.

Findings of this study revealed that within each country, inequality variation trends differed depending on the development patterns (Fig. 8(b)). Overall, the regional economic inequality reflected by the Theil index remained at a high and persistent level in all countries in the Nile River Basin. Inequality could also be inferred from the poverty map, in which there are still regions with high income levels (shown in blue and green-blue) in all countries, implying a huge income inequality gap between rich and poor rather than widespread poverty in the Nile River Basin. From a spatial perspective, inequality in upper and middle reach countries (Uganda, Rwanda, Tanzania, and Burundi) preceded that in the downstream countries (Egypt and Sudan). From a temporal perspective, global emergencies also had a significant impact on the level of economic inequality within individual countries. Most countries showed fluctuations in the inequality index in 2010 and 2020. It can be seen in Fig. 8(b) that Sudan experienced a steep increase in the inequality index after South Sudan's independence in 2011 and has maintained high levels of economic inequality throughout the subsequent civil war in South Sudan since 2013.

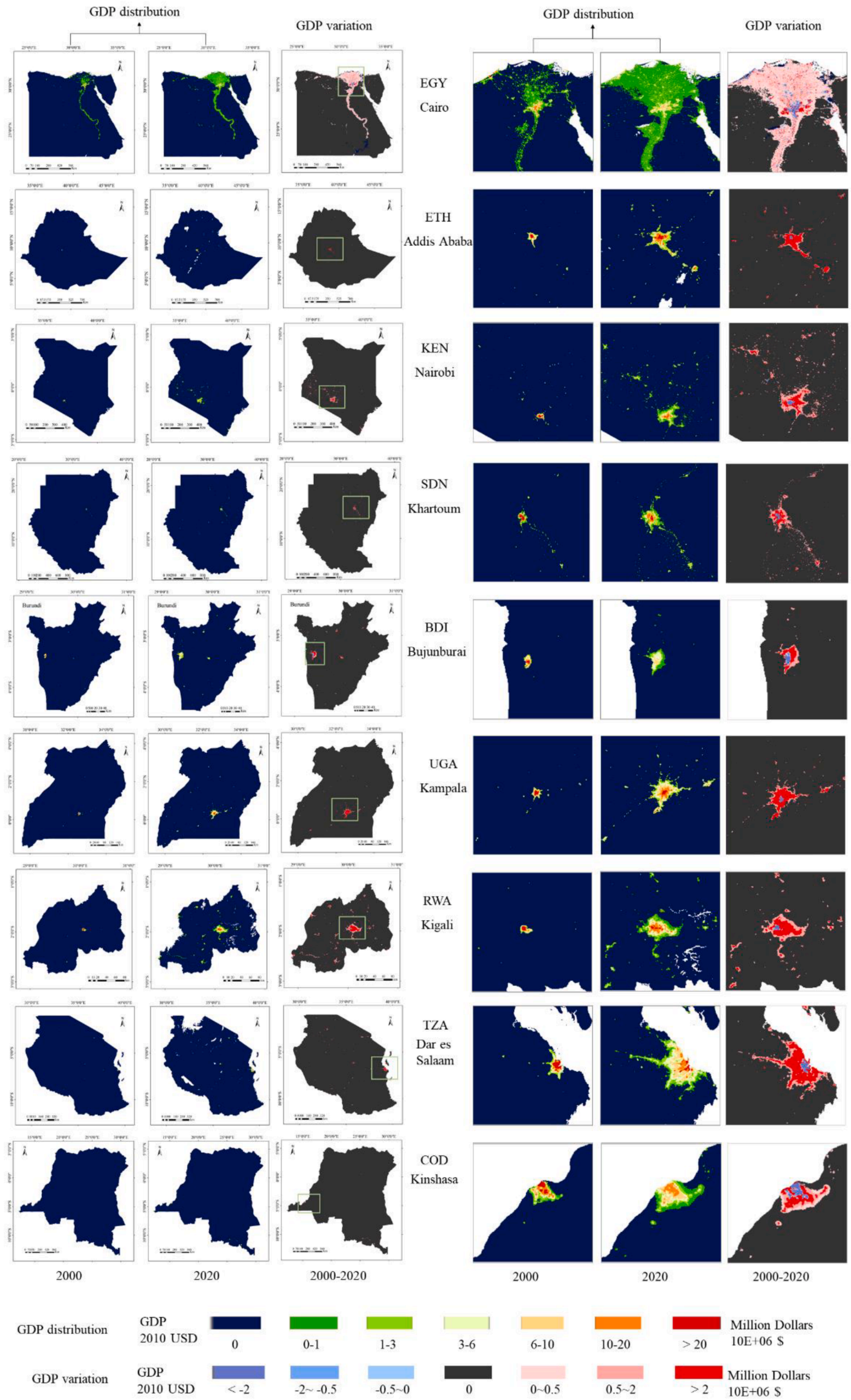


Fig. 6. Spatiotemporal changes of the GDP in the critical sub-regions.

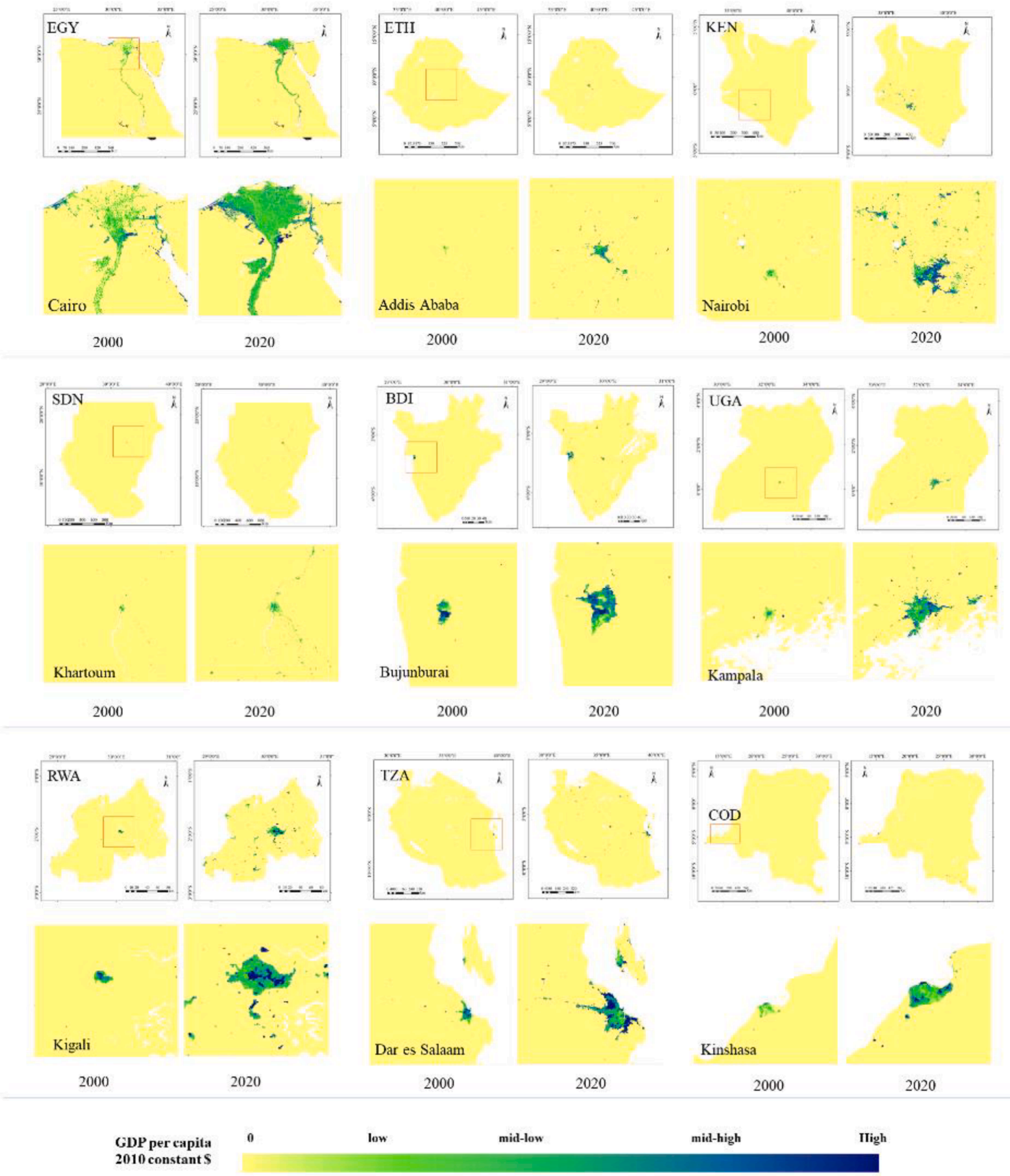
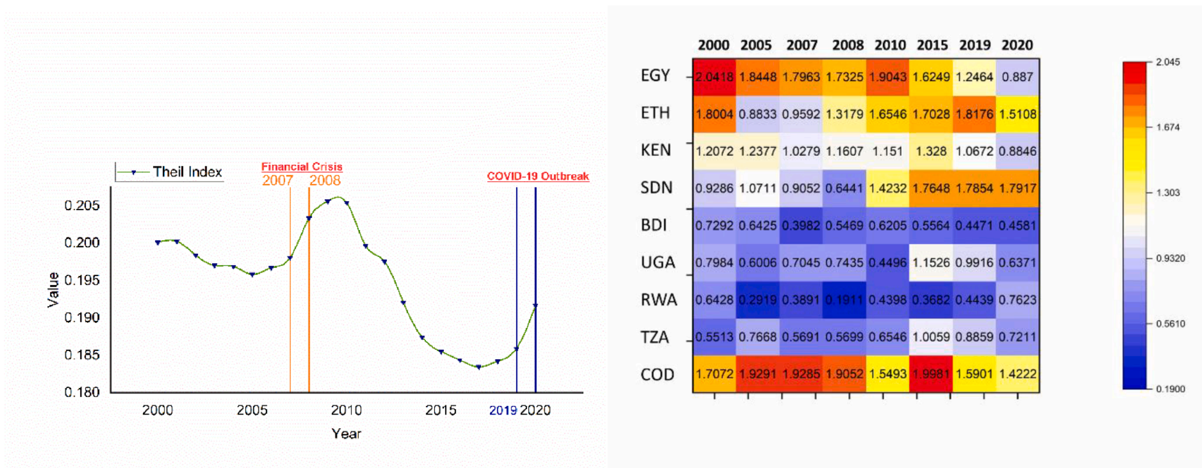


Fig. 7. GDP per capita spatialization map of individual countries and key regions in 2020.

Table 5
Income level proportion for the entire Nile River Basin (%).

Income level	2000	2005	2007	2008	2010	2015	2019	2020
Low	78.99	78.20	81.20	81.15	79.86	77.11	75.65	76.97
Mid-low	15.40	16.87	13.52	13.64	15.25	18.90	20.34	20.06
Upper-high	4.16	3.51	3.78	3.53	3.38	2.80	2.81	2.13
High	1.26	1.23	1.28	1.45	1.33	1.07	1.11	0.78
Extremely-high	0.18	0.19	0.21	0.23	0.19	0.11	0.10	0.07



(a) (b).

Fig. 8. Theil index of (a) the inter-country in the Nile River Basin for the period 2000–2020 (b) individual countries of key years.

4.4. Interaction regression analysis of the GPI trilemma in the Nile River Basin

The results in Table 6 reveal the bivariate correlation between the variables of the GPI. Since all correlation coefficients were below 0.7, variables could be treated as not having multicollinearity.

The interaction regression model represents the linkage of the GPI in the Nile River Basin based on a full-sample regression analysis (Table 7). The statistically significant F-statistic affirmed that the regressors were jointly significant in explaining per capita consumption expenditure growth in Nile River Basin countries. The analysis showed that GDP growth, the unemployment rate, and the poverty rate were statistically significant variables concerning the poverty index, all of which rose with statistical significance at the 5% level. Specifically, the coefficient of the GDP growth rate was 0.072, representing a positive effect on poverty reduction and suggesting that a percentage change in economic growth would lead to a 7.2% increase in per capita consumption expenditures. For the poverty rate, with a significant coefficient of −0.142, it can be inferred that a percentage change in the poverty rate would lead to a decrease in per capita consumption expenditures by 14.2%. This is a reasonable expectation, as civil-consuming intentions will decrease when the poverty-stricken population expands. Although it might not be statistically significant, four variables, including the constant, showed a positive correlation with per capita consumption expenditure growth, while the remaining five variables were negatively correlated.

5. Discussion

Aimed at the first SDG (‘End poverty in all its forms everywhere’) and 10th SDG (‘Reduce inequality within and among countries’), the GPI trilemma is a widely discussed topic in economic and sustainable development studies (Mohamd Shoukry et al., 2018).

First, continuous and stable economic growth can be observed spatially and temporally, and it is a crucial contributor to poverty reduction inferred from the significant positive coefficient of 0.072 for GDP growth (Table 7) in Nile River Basin countries. Although not significant statistically, increasing inequality promotes the consumption level and reduces absolute poverty to some extent, which is supported by the positive coefficient of the Theil index (Table 7). As the economy grows and international communication becomes unobstructed, more investments become available to owners of the production means. This, in turn, provides more jobs for those living in poverty, increases the income of the poor, and reduces absolute poverty (Adeleye et al., 2020). More people living in poverty have the opportunity to invest in and participate in economic production, generate economic value, promote GDP growth, and create a virtuous circle (Adeleye et al., 2020; Bourguignon, 2004). The significant negative correlation between consumption expenditure growth and the unemployment rate (Table 7) represents a common variation trend of the unemployment rate and degree of poverty. This also proves that the increase in job opportunities brought about by economic development is an important income source, as supported by previous studies (Ogundipe et al., 2019). However, poverty reduction is not as rapid and robust as economic growth, in which inequality plays an important role.

Table 6
Bivariate correlation coefficients.

	PCEGR	*THEIL*	*GR*	*PV*	*Theil*GR*	*UNEM*	*EDUC*	*PCGR*	*lnPC*
PCEGR	1								
THEIL	0.014	1							
GR	**0.521	−0.177	1						
PV	−0.141	**−0.465	0.030	1					
Theil*GR	**0.405	** 0.510	** 0.650	*−0.315	1				
UNEM	−0.163	** 0.492	−0.063	**−0.400	0.172	1			
EDUC	0.119	**−0.481	0.166	0.111	−0.178	**−0.630	1		
PCGR	−0.152	−0.186	−0.070	0.026	−0.147	0.140	−0.146	1	
lnPC	0.083	** 0.362	0.125	**−0.661	0.247	** 0.695	−0.316	0.164	1

Notes: **, * represent statistical significance at the 5% and 10% levels, respectively.
PCEGR: per capita consumption expenditure growth; *GR*: annual GDP growth rate; *THEIL*: Theil index; *EDUC*: school enrollment rate; *UNEM*: unemployment rate of total labour force; *PV*: population proportion under the poverty line; *PCGR*: per capita GDP growth; *lnPC*: natural logarithm of per capita GDP.

Table 7
Full sample analysis (dependent variable: *PCEGR*).

	GR	*THEIL*	*GR*THEIL*	*EDUC*	*UNEM*	*PV*	*PCGR*	*lnPC*	*Constant*
a	0.072	0.019	−0.002	−0.016	−0.323	−0.142	−0.096	0.007	0.085
t-statistics	3.171**	1.224	−1.022	−0.969	−2.429**	−1.983**	−0.400	0.634	0.883
R^2	0.378	**F-statistics**		5.716					

Notes:** represents statistical significance at the 5% level.

Next, the relationship between inequality and economic growth for countries in the Nile River Basin is indirect. Although tending to level off generally with economic growth over the past 20 years, the inequality index in the Nile River Basin has remained at a high level, though it is vulnerable to major emergencies (e.g. global financial crisis in 2008 and COVID-19 in 2020). In this study, there was no significant correlation between growth rate and inequality, with a bivariate correlation of only −0.177 (Table 6), or between the Theil index and per capita consumption expenditure growth (a coefficient of 0.019) (Table 7). This finding is similar to that of Marrero (2018), who proposed that the impact of inequality on economic growth was fragile and mostly dependent on the level of poverty in the Sub-Sahara region, which overlaps with Nile River Basin countries geographically.

Regarding the impact of inequality on poverty reduction, for most regions in Africa, a high inequality level was proved to be a principal factor in poverty exacerbation (Fosu, 2018). In this study, the growth-inequality interaction term GR*THEIL (the extent of inclusiveness) in the regression exerted a negative influence on per capita consumption expenditure growth, which is opposite to the influence of growth and inequality on poverty. This explains why inequality and growth had a joint effect on poverty within the research period to some extent, which is consistent with the finding that income inequality matters as much as growth for poverty reduction (Bourguignon, 2004). Although not statistically significant, the negative coefficient of GR*THEIL signals that a high inequality level has substantially reduced the contribution of economic growth to poverty reduction in the Nile River Basin (. Our findings based on NTL RS data also echo conclusions from GPI studies drawn from statistical data (Bourguignon, 2005; Fosu, 2017; Clementi et al., 2019) that the positive impact of economic growth on poverty reduction is limited by high inequality levels in some developing regions, especially Africa. This phenomenon has been continuing since 2000 in the Nile River Basin, where all countries are developing or undeveloped. For poverty reduction, besides enhancing economic growth, inequality reduction is also needed. Findings of this study indicate that the NTL RS approach with wide spatial and temporal coverage, simple accessibility, and efficient processing meet the requirements of regional poverty reduction studies.

6. Conclusion

This study uniquely contributes to the analysis of spatiotemporal economic development and the GPI trilemma by proposing a novel technical framework that combines economic statistics with the NTL dataset. In our framework, a GDP estimation and spatialization strategy was optimized to monitor the dynamic spatiotemporal evolution of GDP growth from 2000 to 2020 in the Nile River Basin. Additionally, an all-encompassing GPI nexus was modelled for typical undeveloped regions throughout the world. Findings revealed that (1) in terms of GDP estimation and spatialization and because of undeveloped countries and regions without elaborate statistics and fine administrative unit scales, it is advantageous to establish a multitemporal estimation strategy for individual sub-regions with RS data; (2) the economic development of countries in the Nile River Basin has been characterised by widespread poverty, high income inequality, and a restricted spatial distribution. However, economic development has improved slightly, with an increasing GDP and shrinking poverty. The spatiotemporal evolution patterns of GPI vary by geographic location; and (3) in the progressive economic growth trend of Nile River Basin countries, poverty reduction has been severely impeded by high income inequality levels.

Overall, the NTL imagery can be effectively applied to economic issues. It provides a poverty and inequality index that may be lacking in field statistics for the GPI trilemma analysis. This study provides new insights into the establishment of the GPI nexus in the economics of underdeveloped and developing countries of the Nile River Basin, combined with NTL RS approaches.

This study is the first effort towards monitoring the spatiotemporal evolution of the GPI trilemma using long-term NTL datasets. Further studies are needed, however. In this study, the spatial resolution of inequality was not gridded as growth and poverty, leading to a loss of spatial information. A more precise inequality map will be generated in the future so that a more accurate model of the GPI nexus can be constructed by adding geographic information, thus providing a comprehensive analysis of the regional GPI trilemma.

CRediT authorship contribution statement

Yi Lin: Project administration, Methodology, Writing – review & editing. **Tinghui Zhang:** Writing – original draft, Data curation, Methodology, Formal analysis. **Xuanqi Liu:** Data curation, Formal analysis. **Jie Yu:** Conceptualization, Writing – review & editing, Methodology, Investigation. **Jonathan Li:** Writing – review & editing. **Kyle Gao:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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