Spatiotemporal Evolution of Nighttime Light Data and Economic Development in the Yellow River Basin

Authors: Zhang Yansheng, Cao Zhiwei, Wei Wei, Hu Jie

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Abstract

A systematic understanding of the spatiotemporal evolution patterns of economic development in the Yellow River Basin can provide an important decision-making basis for high-quality development across the entire basin. Currently, GDP serves as the primary reference for measuring economic development patterns; however, GDP statistical data suffers from drawbacks such as non-uniform statistical standards and low spatial resolution, making it difficult to accurately characterize the spatiotemporal evolution features of economic development. Nighttime light data, with its relatively objective characteristics, can effectively reflect these patterns. This study obtains national and basin-scale nighttime light data imagery through correction and processing of national nighttime light data from 1992-2013, conducting economic spatial agglomeration analysis and comparative analysis with relevant factors. The research results indicate that: regions with high economic spatial agglomeration are distributed along the Yellow River channel, with intensity gradually increasing from upstream to downstream, and diffusing outward with provincial capital cities as core areas, showing a trend where agglomeration regions disperse toward surrounding areas while agglomeration intensity intensifies at existing agglomeration points; the changing trend of nighttime light data exhibits certain similarity with that of GDP, and demonstrates certain correlations with urbanization rate, population size, proportion of tertiary industry, per capita park green space area, and Basin Development Index (BDI); the overall changing trend of nighttime light data in the nine provinces of the basin is basically consistent with the national trend, showing a stable upward trajectory, but the overall values are lower than national nighttime light data, with the gap widening, making high-quality development of the Yellow River Basin imperative.

Full Text

Evolution Analysis of Nightlight Data and Economic Development Spatio-Temporal Patterns in the Yellow River Basin

ZHANG Yuansheng[1], CAO Zhiwei[2,*], WEI Wei[2], HU Jie[2], JIN Xin[2]
[1] Tianjin University, Tianjin 300072, China
[2] Yellow River Engineering Consulting Co., Ltd., Zhengzhou 450003, China

Abstract

Systematically understanding the spatio-temporal evolution patterns of economic development in the Yellow River Basin provides crucial decision-making support for high-quality development across the entire watershed. Currently, GDP serves as the primary reference for measuring economic development patterns; however, GDP statistics suffer from inconsistent statistical 口径 (caliber) and low spatial resolution, making it difficult to accurately characterize the spatio-temporal evolution features of economic development. Nightlight data, with their relatively objective characteristics, can effectively reflect these patterns. This study corrects and processes national nightlight data from 1992 to 2013 to obtain national and basin-scale nightlight imagery, conducts economic spatial aggregation analysis, and performs comparative analysis with relevant factors. The results indicate that regions with high economic spatial aggregation are distributed along the Yellow River channel, with thermal intensity gradually increasing from the upper to lower reaches. Provincial capitals serve as core areas that radiate outward, demonstrating a trend where aggregation regions disperse toward surrounding areas while the degree of aggregation at existing centers intensifies. The changing trend of nightlight data exhibits certain similarity with GDP trends and shows correlations with urbanization rate, population size, tertiary industry proportion, per capita park green space area, and the Basin Development Index (BDI). The overall trend of nightlight data in the nine provinces of the basin is basically consistent with the national trend, showing stable growth, but the overall values remain below the national average and the gap has widened, indicating that high-quality development of the Yellow River Basin is urgently needed.

Keywords: nightlight data; Yellow River Basin; spatio-temporal pattern; economic development

1 Introduction

The Yellow River Basin represents a complex giant system comprising river subsystems, ecological environment subsystems, and human economic subsystems, encompassing various elements of nature, economy, society, and ecology. These subsystems interact through synergy, competition, and game relationships, providing fundamental support for addressing major national issues. The human economic subsystem, as a vital component, primarily involves factors such as economy, tertiary industry, and population. Conventional evaluation models rely predominantly on the single indicator of GDP. New methods and objective indicators are needed to support research on economic development trends and enable objective assessment of spatial pattern evolution.

Early research on spatio-temporal evolution of economic development patterns includes: Wang et al. employed a comprehensive evaluation model to conduct quantitative spatio-temporal analysis of economic, environmental, and social development levels in cities along the Yangtze River Economic Belt [1]; Zhao et al. used the entropy-weighted TOPSIS method to determine indicator weights and ESDA to analyze spatial agglomeration and differentiation among 17 cities in Shandong Province [2]; He et al. studied spatio-temporal differences, pattern evolution, and driving mechanisms of county-level economies in Henan Province from 2005–2014 using Theil index, exploratory spatial analysis, and multiple linear regression; and Chung et al. [3] measured economic development disparities among districts in Hong Kong from 1976–2010 using SES (Social Economic Status) methods and government statistics. These studies primarily used GDP, per capita income, and other statistical data to represent economic development levels, which suffer from inconsistent statistical 口径 (caliber), complex constant-price conversions, and generally homogeneous panel data with low spatial resolution, making it difficult to represent intra-administrative spatial heterogeneity in economic development. Therefore, utilizing more objective and finer-scale data facilitates more comprehensive research on spatio-temporal pattern characteristics of economic development.

Nighttime light data can detect bright lights emitted from Earth' s surface and serve as an effective data source for studying human activities. The DMSP satellite sensor can obtain stable nighttime light imagery from cities, towns, and other persistent light sources while removing occasional noise from clouds, fires, and gas flaring [4]. Scholars have conducted extensive research in this area, focusing on urban spatial information extraction and expansion, construction of urban spatial characteristic light indices, population density and heat island effects, economic development status, power energy consumption, and impacts of urbanization on ecological environments [5]. Guo et al. [6] measured economic spatial pattern evolution and urban centrality in the Huaihai Economic Zone using weighted standard deviation ellipse, gravity model, and social network analysis based on four years of DMSP/OLS nighttime light data. Li et al. [7] quantitatively analyzed relationships between nighttime light data and socioeconomic data in southern Jiangxi and western Fujian using regression analysis and modified gravity models. However, few studies have reported on watershed-level analysis, particularly regarding correlation analysis with water-related elements.

This study takes the Yellow River Basin as the research object for the first time, combining it with the national strategy of ecological protection and high-quality development in the Yellow River Basin. It macroscopically analyzes the important role of nightlight data in retrieving economic spatio-temporal pattern evolution and reveals the close relationship between economic development and watershed elements, providing relatively objective reference basis for economic pattern research in the Yellow River Basin.

2.1 Data Sources

This study utilizes three types of data: vector data, raster data, and statistical data. Specific parameters are shown in Table 1 . The raster imagery data primarily uses data acquired by the Operational Linescan System (OLS) sensor onboard the Defense Meteorological Satellite Program (DMSP) satellites. Due to its unique photoelectric amplification capability, this sensor can detect weak near-infrared radiation from Earth' s surface at night, making nighttime light imagery increasingly useful for studying human activities.

However, the sensor data cannot be used directly because the acquisition process is affected by atmospheric absorption and scattering, solar elevation angles, terrain relief, and sensor calibration [8], resulting in differences between images from different sensors in the same year. Additionally, without on-board radiometric calibration during image acquisition [9], abnormal fluctuations occur in pixel values at the same location across consecutive years from the same sensor. These issues in long-term DMSP/OLS nighttime light image datasets cause discontinuity between images from different years and sensors, necessitating mutual correction for long-term scale applications. Furthermore, due to sensor spectral resolution limitations, pixel values in urban center areas exhibit saturation phenomena. The stable light imagery uses 6-bit quantization, limiting DN values to 0–63 and causing many areas, particularly urban centers, to reach the saturation value of 63 without further increase, making differences in urban core areas indistinguishable. Therefore, nightlight data correction is required, including mutual correction, saturation correction, and continuity correction between images.

In the early 1990s, Hall et al. [10] and Lenney et al. [11] proposed that relatively stable pixels exist in continuous multi-temporal remote sensing images and can be extracted as invariant target regions with specific transformation relationships between multi-temporal images. In 2009, Elvidge et al. [9] used Sicily as an invariant reference region with regression equations. This method is more suitable for global nighttime light data correction but less applicable at the national scale. In 2012, Liu et al. [12] and Lu et al. [13] proposed correction methods suitable for China' s nighttime light imagery, statistically analyzing GDP statistics and built-up area data for major Chinese cities from 1992–2008, identifying Jixi City in Heilongjiang Province as the invariant reference region for China, achieving mutual correction, intra-annual fusion, and inter-annual correction of long-term DMSP/OLS nighttime light data.

2.2 Data Correction

(1) Data Preprocessing

The collected stable light data covers the global extent with WGS84 coordinate system and 30" resolution. Data were clipped for China and the nine provinces in the basin.

(2) Mutual Correction and Saturation Correction

Mutual and saturation correction involves selecting invariant target regions and using appropriately radiometrically calibrated product data from suitable years and sensors as reference to perform quadratic regression model calculations for images to be corrected. Following Lu et al. [13], Jixi City in Heilongjiang Province was identified as the invariant region. The 2006 F16 sensor data from radiometrically calibrated products (already saturation-corrected) was selected as the reference dataset, with 34 periods of stable light imagery from 1992–2013 as the dataset to be corrected. The Jixi City area was used for clipping, DN values were statistically extracted, and quadratic regression model calculations were performed as shown in Equation (1):

$$DN_c = a \times DN^2 + b \times DN + c \quad (1)$$

where DN represents the pixel DN value of the stable light imagery to be corrected; DNc represents the corrected pixel DN value; and a, b, c represent different regression parameters. To ensure that lightless areas (DN = 0) remain consistent before and after correction, pixels with DN = 0 were masked and excluded from Equation (1) calculations. The model parameters for the quadratic regression model were calculated through Equation (1) to perform saturation and mutual correction on stable light imagery.

(3) Intra-annual Fusion Correction

Years with overlapping intra-annual data are 1994 and 1997–2007. For overlapping years, pixel value comparison calculations were performed: if both corresponding pixel values in the two datasets were 0, the resulting DN value was 0; otherwise, the average of the two pixel values was taken as the pixel value, as shown in Equation (2):

$$DN_{n,i} = \begin{cases} 0 & \text{if } DN^1_{n,i} = 0 \text{ and } DN^2_{n,i} = 0 \\ \frac{DN^1_{n,i} + DN^2_{n,i}}{2} & \text{otherwise} \end{cases} \quad (n = 1994, 1997, 1998, \ldots, 2007) \quad (2)$$

where $DN^1_{n,i}$ and $DN^2_{n,i}$ represent the DN values of pixel i from two different sensors after mutual correction for year n; $DN_{n,i}$ represents the DN value of pixel i in the corrected image for year n.

(4) Inter-annual Correction

Based on China' s continuously intensifying urbanization, it can be assumed that bright pixels detected as urban patches in the previous year' s imagery cannot disappear in the following year' s imagery [14]. Therefore, bright pixels in the previous year' s nighttime light imagery should remain bright in the same location in the following year' s imagery, with the DN value of bright pixels in the previous year not exceeding that of the same location in the following year [12]. When the DN value of a pixel in the following year' s imagery equals 0, the DN value of the same location in the previous year' s imagery should also equal 0; when the DN value in the following year is not 0, the DN value in the previous year should not exceed that of the following year. The correction equation is shown as Equation (3):

$$DN_{n,i} = \begin{cases} 0 & \text{if } DN_{n+1,i} = 0 \\ \min(DN_{n,i}, DN_{n+1,i}) & \text{if } DN_{n+1,i} \neq 0 \end{cases} \quad (n = 1992, 1993, 1994, \dots, 2013) \quad (3)$$

where $DN_{n,i}$ and $DN_{n+1,i}$ represent the DN values of pixel i in the nighttime light imagery after mutual correction, saturation correction, and intra-annual fusion for years n and n+1.

(5) Correction Results

After performing mutual correction, saturation correction, intra-annual fusion, and inter-annual correction on 34 periods of stable light imagery from 1992–2013, a 22-year time series of nighttime light imagery products was generated. These were clipped using China's national boundary (excluding the South China Sea islands) and the nine-province basin extent to obtain final nighttime light imagery products for the basin and its nine provinces. Due to space limitations, only pre- and post-correction images for 1992 and 2013 are shown (Figure 1 [Figure 1: see original paper], Figure 2 [Figure 2: see original paper]), with cumulative DN value statistics before and after correction presented in Figure 3 [Figure 3: see original paper]. The results demonstrate that pre-correction nighttime light data exhibited discreteness, while post-correction data through mutual correction, saturation correction, intra-annual fusion, and inter-annual correction show stable upward trends with significantly improved continuity.

3.1 Economic Spatial Aggregation Analysis

Heat maps visualize point density on maps through density functions, emphasizing spatial location and basic distribution characteristics, enabling density perception independent of scaling factors. Kernel density analysis for point features calculates the density around each output raster cell, with a smooth surface overlaying each point. Surface values peak at point locations and gradually decrease with distance. The density of each output raster cell equals the sum of all kernel surface values superimposed on the cell center, meaning high heat values indicate dense nighttime lights, while heat center shifts reveal transitions in nighttime light concentration areas. The kernel function is based on the quartic kernel function described in Silverman' s work (1986, p. 76, equation 4.5).

(1) Unweighted Distance Calculation
As shown in Equation (4):

$$d_i = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2 + (z_i - \bar{z})^2} \quad (4)$$

where x_i, y_i, z_i are the coordinates of feature i; $\{\bar{x}, \bar{y}, \bar{z}\}$ represents the mean center of features; and n equals the number of features.

(2) Bandwidth Calculation
As shown in Equation (5):

$$h = 0.9 \times \min(SD, \frac{D_m}{\sqrt{n}}) \times n^{-0.2} \quad (5)$$

where D_m is the (weighted) median distance from the (weighted) mean center; n is the number of points when no population field is used, or the sum of population field values when provided; and SD is the standard distance.

(3) Predicted Density at New (x,y) Location
Determined by Equation (6):

$$\text{Density}(x, y) = \sum_{i=1}^{n} \frac{\text{pop}_i}{h^2} \times K\left(\frac{\text{dist}_i}{h}\right) \quad (6)$$

where $i = 1, \ldots, n$ are input points included in the sum only if they lie within the radius distance of location (x,y); pop_i is the population field value for point i (optional parameter); and dist_i is the distance between point i and location (x,y).

Comparative analysis of kernel density maps reflecting economic spatial aggregation (Figure 4 [Figure 4: see original paper]) reveals that high kernel density values in the nine basin provinces concentrate along the Yellow River, with thermal intensity gradually increasing from upstream to downstream and radiating outward from provincial capitals as core areas. Over time, high-density distribution areas continuously expand, indicating increasingly dense economic spatial aggregation with population growth and economic development. Medium-density distribution areas continuously expand outward, demonstrating gradual decentralization of economic spatial aggregation regions.

3.2 Correlation Analysis

(1) Correlation with GDP
Comparison of GDP data and nighttime light data for the nine Yellow River Basin provinces (showing only 1992 and 2013 comparisons in Figure 5 [Figure

5: see original paper] due to space limitations) indicates that nighttime light data trends show certain similarity with GDP trends within the same year. Comparisons across different years demonstrate that nighttime light data have increased substantially with rapid economic development, urban expansion, and population growth, consistent with GDP growth magnitude.

(2) Correlation with Different Evaluation Indicators
Comparison of nighttime light data and total water consumption data for the nine basin provinces from 1992-2013 (Figure 6 [Figure 6: see original paper]) shows limited correlation: basin nighttime light data exhibit stable upward trends, while basin water consumption first slowly decreased, then dropped sharply in 2003, followed by gradual annual increases, likely related to water control policies in the Yellow River Basin. Trends are basically similar to urbanization rate, population size, tertiary industry proportion, and per capita park green space area, all showing gradual annual increases.

(3) Correlation Between Basin and National Nightlight Data
Comparative analysis of nighttime light data for the nine Yellow River Basin provinces with national light indices (Figure 7 [Figure 7: see original paper]) reveals that the overall trend in the nine basin provinces is basically consistent with the national trend, showing stable upward growth. However, overall values in the nine basin provinces remain below national nighttime light data levels, with the gap widening, indicating relatively lagging economic development in the nine Yellow River Basin provinces, possibly related to water resource shortages. With historically large populations and relative poverty in the Yellow River Basin, high-quality development is urgently needed.

(4) Correlation Between Basin Nightlight Data and BDI
The Basin Development Index (BDI) is a comprehensive indicator for analyzing basin development conditions, providing reference for development quality through multi-factor systems. Comparison of nighttime light data for the nine Yellow River Basin provinces with BDI (Figure 8 [Figure 8: see original paper]) shows strong correlation with basically similar trends, demonstrating stable upward growth and indicating that human economic activities significantly impact basin development quality.

4 Results and Analysis

The Yellow River Basin is a complex giant system encompassing natural, economic, social, and ecological elements. With intensifying human activities, system uncertainty increases. From the perspective of promoting high-quality economic development and enhancing people’ s well-being, social development indices for evaluating socioeconomic development quality are particularly important. The application of basin nighttime light data in the Yellow River Basin provides quantitative supplementation to social development indices from a new objective perspective at the macro scale. It can not only characterize the development status of the human economic subsystem but also, together with river health indices and environmental evolution indices, form a basin development index system to represent the development status of the basin' s giant system, providing decision-making support for comprehensive, systematic, and source governance in the new era.

5 Conclusions and Discussion

This study represents the first application of nighttime light data in the Yellow River Basin. Through mutual correction, saturation correction, intra-annual fusion, and inter-annual correction of national nighttime light data from 1992–2013, relatively accurate national nighttime light imagery was obtained. Comparative analysis between nighttime light data for the nine basin provinces and provincial social development indices, as well as between national and basin provincial nighttime light data, yields the following conclusions:

(1) Within the same year, nighttime light data trends show certain similarity with GDP trends; across different years, nighttime light data have increased substantially, basically consistent with GDP growth magnitude, and show correlations with urbanization rate, population size, tertiary industry proportion, per capita park green space area, and Basin Development Index (BDI).

(2) Regions with high economic spatial aggregation are distributed near the Yellow River channel, with thermal intensity gradually increasing from upstream to downstream and radiating outward from provincial capitals as core areas, demonstrating a trend of aggregation regions dispersing toward surrounding areas while aggregation intensity at existing centers intensifies.

(3) The overall trend of nighttime light data in the nine basin provinces is basically consistent with the national trend, showing stable upward growth, but overall values remain below national nighttime light data levels with widening gaps, indicating that high-quality development of the Yellow River Basin is urgently needed.

Nighttime light data, with their long time series, accessibility, and objectivity, represent important objective indicators for evaluating economic development quality within watershed giant systems, providing vital reference for objective analysis of basin development quality. Further research should focus on 挖掘 (excavating) the hidden value behind nighttime light data to better support rational allocation of basin water resources.

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Author Contributions Statement:

ZHANG Yuansheng: Conceived research ideas and designed the study framework
CAO Zhiwei: Drafted the manuscript
WEI Wei: Collected, cleaned, and analyzed data
HU Jie, JIN Xin: Revised the final manuscript version

Corresponding Author: CAO Zhiwei
E-mail: zhiwei.cao@outlook.com

Note: Figure translations are in progress. See original paper for figures.