

Article

GDP Estimation by Integrating Qimingxing-1 Nighttime Light, Street-View Imagery, and Points of Interest: An Empirical Study in Dongguan City

Zejia Chen ¹, Chengzhi Zhang ¹, Suixuan Qiu ¹ and Jinyao Lin ^{1,2,*} 

¹ School of Geography and Remote Sensing, Guangzhou University, Guangzhou 510006, China; 32201400045@e.gzhu.edu.cn (Z.C.); 32109500005@e.gzhu.edu.cn (C.Z.); 32101400007@e.gzhu.edu.cn (S.Q.)

² Huangpu Research School, Guangzhou University, Guangzhou 510006, China

* Correspondence: ljy2012@gzhu.edu.cn

Abstract: In the context of economic globalization, the issue of imbalanced regional development has become increasingly prominent. Misreporting in traditional economic censuses has made it difficult to accurately reflect economic conditions, increasing the demand for precise GDP estimation. While nighttime light data, point of interest (POI) data, and street-view imagery (SVI) have been utilized in economic research, each data source has limitations when used independently. Furthermore, previous studies have rarely used high-resolution (over 30 m) nighttime light data. To address these limitations, we constructed both random forest and decision tree models and compared different indicator combinations for estimating GDP at the town scale in Dongguan: (1) Qimingxing-1 nighttime light data only; (2) Qimingxing-1 nighttime light and SVI data; and (3) Qimingxing-1 nighttime light, SVI, and POI data. The random forest model performed better than the decision tree, with its correlation coefficient improving from 0.9604 (nighttime light only) to 0.9710 (nighttime light and SVI) and reaching 0.9796 with full integration. Moreover, the Friedman test and SHAP values further demonstrated the reliability of our model. These findings indicate that the integrated model provides a more accurate reflection of economic development levels and offers a more effective tool for regional economic estimation.

Keywords: street-view imagery; nighttime light; Qimingxing-1; GDP; random forest; decision tree; points of interest



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1. Introduction

Gross domestic product (GDP) is a key indicator of the economic activity and development level of a country or region. It plays a crucial role in economic analysis, policymaking, international comparisons, and regional development assessment [1–4]. In recent years, with the increasing integration of the global economy, regional development disparities have become more pronounced. Moreover, conventional economic surveys frequently encounter challenges such as misreporting, which can compromise data accuracy and make it difficult to accurately reflect the actual economic situation [5–7]. As a result, the demand for reliable and precise GDP estimation has become increasingly urgent. With improvements in big data and artificial intelligence, new tools such as multi-source data (e.g., nighttime light and POIs) and machine learning models are now available to estimate GDP. These technologies can enhance the accuracy and efficiency of GDP estimation while providing deeper insights into the complex relationships between economic activities, the natural world, and society.

The remote sensing of nighttime lights has been widely utilized to analyze the spatial distribution of regional socioeconomic activities, primarily due to the cost effectiveness and extensive coverage of this technique. Studies have shown a strong correlation between socioeconomic activities and nighttime light data [8–13]. Elvidge et al., pioneered systematic research into the relationship between nighttime light data and economic activity. They found a significant positive correlation with indicators such as GDP [14]. Subsequently, Ghosh et al. used nighttime light data to estimate the informal economy and remittance flows in Mexico, further demonstrating their efficacy in revealing spatial variations in economic activity [15]. Recently, the utilization of nighttime light data to assess human socioeconomic activities has emerged as a prominent research focus in the academic community. For instance, Li et al. utilized NPP-VIIRS data to estimate total nighttime light and gross regional product [16]. Shi et al. used NPP-VIIRS data to estimate GDP and electricity consumption in different provinces in China [17]. Propastin and Kappas found that DMSP-OLS data can effectively track spatial and temporal changes in socioeconomic activity [18]. However, traditional nighttime light data have some limitations. First, issues such as oversaturation and the halo effect can lower data accuracy [19–25]. Second, the resolutions of DMSP-OLS and NPP-VIIRS data are only 1000 m and 500 m, respectively, making them less suitable for detailed economic estimation [26]. Therefore, using higher-resolution nighttime light data is necessary to overcome these limitations and improve the accuracy of economic analysis [27].

In 2022, China launched the multispectral satellite “Qimingxing-1” and made its data available to research institutions at no cost. With a spatial resolution of 21 m and a revisit period of approximately 11 days [28,29], the satellite’s nighttime light data are expected to offer more detailed information for socioeconomic research and address the limitations of traditional nighttime light data. Nevertheless, nighttime light data alone cannot capture the finer details of urban areas or the specific locations of human activities [30]. Consequently, it is imperative to integrate additional data sources to enhance the comprehensiveness of the information obtained.

In recent years, street-view data have become a valuable source for urban research, particularly in urban function identification and spatial analysis [31,32]. Street-view data have also shown potential in economic prediction. Some researchers used street-view data and deep learning to study the relationship between the built environment and poverty at the subdistrict level in Guangzhou [33]. Their findings indicated that the factors obtained from street-view data were important indicators of poverty levels. Other studies used Google street-view imagery with deep learning to estimate the socioeconomic characteristics of communities in the United States. They found a strong link between the distribution of vehicles in street-view imagery and socioeconomic factors [34]. Street-view data have also been employed to assess urban growth and decline [35] and to predict income levels [36]. These studies provide important evidence and practical guidance for using street-view data in urban economic assessment. Moreover, previous research has demonstrated that street-view features (SVFs) exhibit superior performance to point-of-interest (POI) and dynamic demographic data when estimating socioeconomic profiles. The integration of SVFs has been shown to greatly improve the accuracy of prediction models [37].

Street-view data, as a visually rich geospatial data source, have demonstrated significant application potential in urban studies, transportation planning, and environmental monitoring. Their advantage lies in providing high-resolution, multi-perspective urban real-scene images, effectively compensating for the lack of detail in traditional geographic data. Although many researchers recognize the potential of street-view imagery in socioeconomic research, several methodological limitations warrant careful consideration.

First, while street-view data offer excellent visual detail at the street level, their spatial coverage and temporal resolution remain constrained [38,39]. The imagery may exhibit geographic gaps in certain neighborhoods and temporal lags in capturing rapid urban transformations [35,40]. Second, empirical studies have demonstrated that including street-view features in regression models adds useful variables. However, using street-view data on their own leads to only small improvements in prediction accuracy [36]. Furthermore, both street-view and POI data in low-density areas suffer from infrequent updates and persistent quality issues, particularly regarding completeness, which may affect analytical accuracy [37]. Therefore, integrating street-view data with POI and nighttime light data can provide a more comprehensive understanding of urban functions, socioeconomic activities, and the human living environment [39,41,42].

Many studies that describe the spatial patterns of economic activities suffer from using only one type of data and a low spatiotemporal resolution. Most studies use a single data source, such as nighttime light or POI data, leading to a biased understanding of economic activities. For instance, while traditional nighttime light data can reflect nighttime economic activities, they overlook daytime economic dynamics; additionally, although POI data provide information on socioeconomic characteristics (e.g., location, name, and category of points of interest), they fail to provide an intuitive depiction of the surrounding environment, including details such as building facades and street layouts. Furthermore, many studies employ low-spatial-resolution remote sensing data, which struggle to capture the subtle variations in economic activities within cities and lack an analysis of the dynamic changes in economic activities. In light of these limitations, the aim of this study is to integrate multi-source data, including street-view data and high-resolution satellite data, to comprehensively and precisely characterize the spatial economic features of Dongguan City.

Nighttime light data reflect the overall distribution of economic activity in a city. In contrast, street-view data capture the micro-level features of individual streets. Nighttime light data can show a city's economic activity at night, while street-view data offer detailed environmental information during the day. The integration of these two data sources enables a comprehensive understanding of the relationship between economic activity and the urban environment over time and space. Additionally, POI data can help address the gaps left by street-view data. However, previous studies have rarely combined high-resolution nighttime light, street-view, and POI data to estimate socioeconomic indicators. Therefore, in this study, we aimed to build a multi-source data model using high-resolution nighttime light, street-view, and POI data. We compared the accuracy of different models in estimating GDP at the town scale in Dongguan and demonstrated the benefits of the integrated model, ultimately resulting in a more accurate and comprehensive approach to regional economic assessment.

2. Study Area and Data

2.1. Study Area

Dongguan, located in the central-southern part of Guangdong Province, is a leading proponent of China's reform and opening-up policies. Primarily driven by the manufacturing industry, the city has gained international recognition as the "world's factory". In recent years, Dongguan's economy has grown rapidly, with its GDP consistently ranking among the highest in Guangdong Province. It is a vital city in the Pearl River Delta region, known for its vibrant economy (Figure 1). We selected Dongguan for two main reasons: First, its economic development model is representative of Guangdong Province and even China as a whole. Second, the city's diverse geography and socioeconomic conditions provide valuable data for estimating GDP using nighttime light, street-view imagery, and

POI data. A comprehensive understanding of the economic conditions in each town of Dongguan is imperative for the government to formulate informed decisions regarding land-use planning and urban development policies.

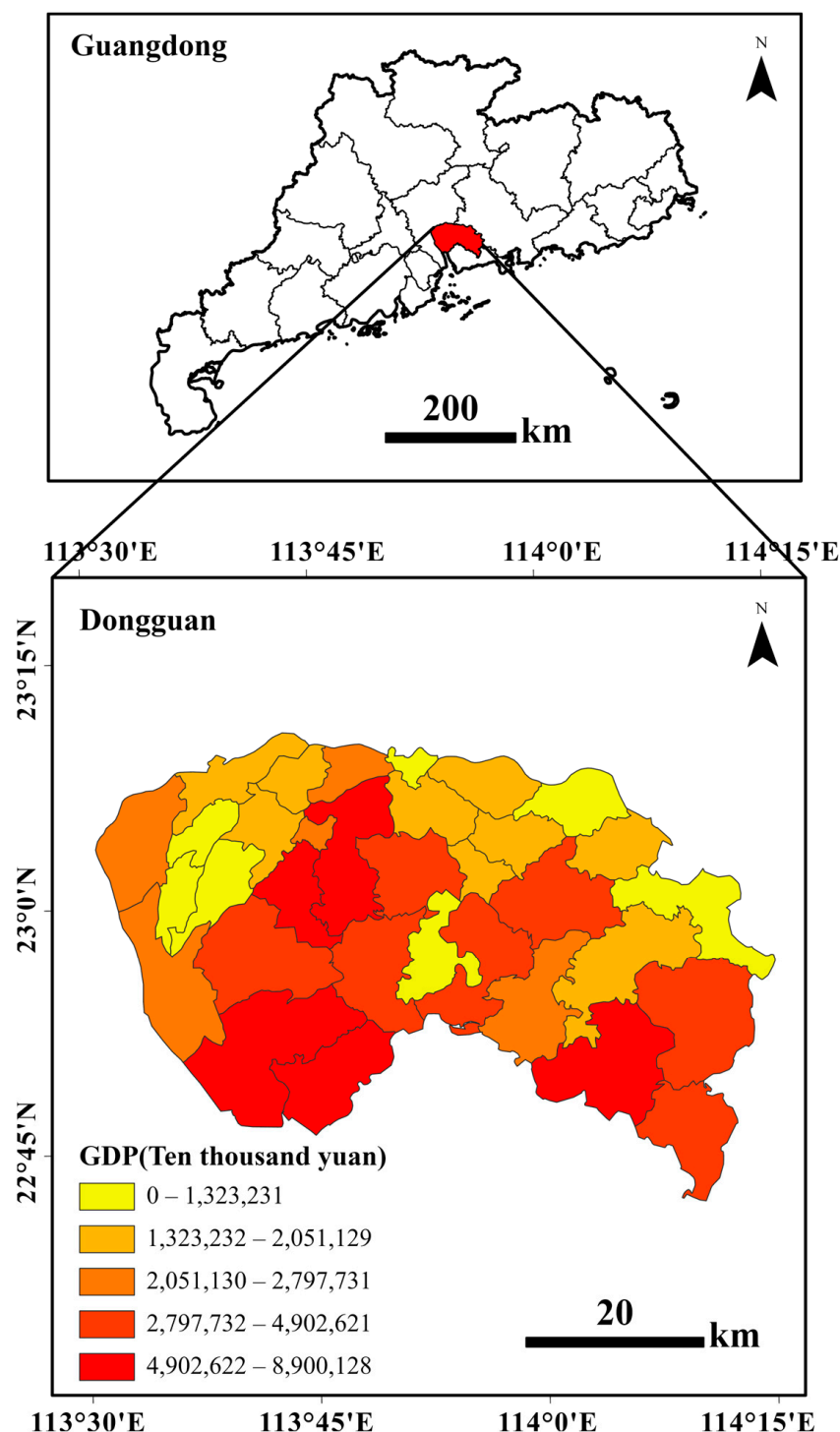


Figure 1. Overview of Dongguan.

2.2. Data

2.2.1. GDP

The GDP data utilized in this study were derived from the Dongguan Statistical Yearbook 2023, which was compiled by the Dongguan Bureau of Statistics. This yearbook offers a comprehensive and systematic reflection of the economic and social development

of Dongguan. It serves as an essential data source for the study of Dongguan's economy (Figure 1).

To validate spatial trends, we compared our model results with existing GDP spatial products. Due to the limited availability of publicly accessible high-resolution GDP spatial data for 2022, we employed the 1 km gridded GDP dataset of China (2020) from the National Earth System Science Data Center (<http://www.geodata.cn>, accessed on 30 May 2023) [43] and aggregated it to the town scale for validation. Despite the temporal discrepancy, Dongguan's economic spatial pattern remained structurally stable between 2020 and 2022, with no large-scale industrial relocation or new district development.

2.2.2. Qimingxing-1 Nighttime Light Data

The Qimingxing-1 nighttime light data provide important remote sensing information for analyzing economic activities and urban development dynamics. The data processing aimed to ensure high precision and reliability, with key steps including noise reduction, threshold setting, and geometric correction.

Firstly, we obtained the Qimingxing-1 data released in 2022. Noise reduction was performed to minimize the interference of background noise on brightness information, ensuring that the extracted nighttime light signals accurately reflected the economic activities and urban development characteristics on the ground (Figure 2a). Subsequently, we used statistical data from reference areas to establish a reasonable brightness threshold range. In this study, we selected the data from economically developed areas in the Dongguan Statistical Yearbook and integrated the population density, commercial activity density, and nighttime light brightness levels of these areas to determine the maximum brightness threshold. Specifically, the highest light brightness value within the economically developed area was set as the maximum threshold, and, for pixels exceeding this threshold, the maximum value of the eight neighboring pixels was applied to replace the abnormally high brightness values, thereby eliminating the impact of these values on the data analysis [44–46].

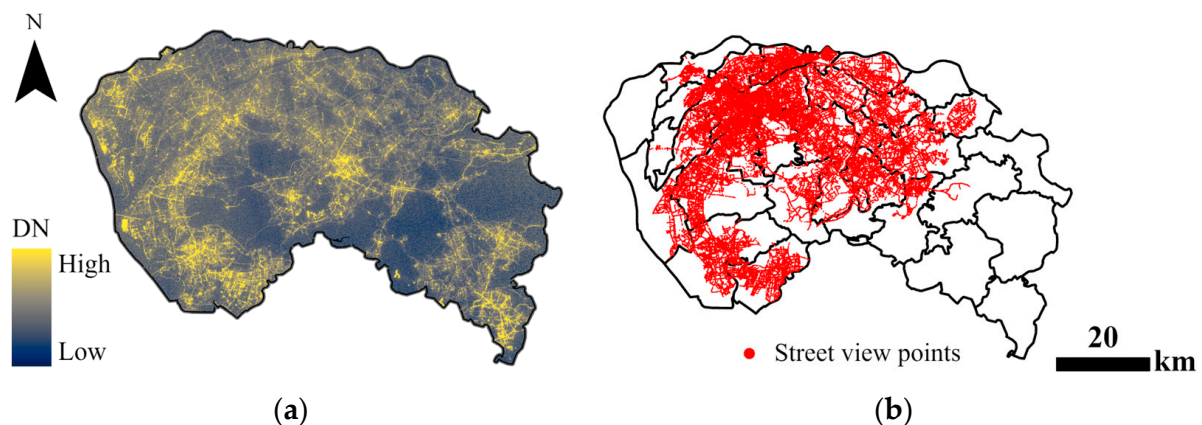


Figure 2. (a) Qimingxing-1 nighttime light and (b) street-view imagery data.

The setting of the minimum threshold was based on Landsat-8 OLI imagery, using the average brightness values of light-free areas (e.g., reservoirs and lakes) as references. Pixels with brightness values below this average were set to zero, thereby further eliminating background noise and irrelevant information unrelated to economic activities [28]. In the data-correction phase, to improve geolocation accuracy, the Qimingxing-1 data were subjected to noise reduction, followed by geometric correction and reprojection. Specifically, the coordinate system was unified to WGS 1984 UTM Zone 49N, and the regional trans-

portation network was used as the reference for geometric registration. This process refined the spatial correction, ensuring both spatial consistency and high-precision geolocation.

According to previous studies [47–49], the characteristics of nighttime lights are measured from four perspectives: central tendency, dispersion degree, distribution characteristics, and spatial characteristics. A total of 12 types of features were identified (Table 1), and the indicators at the town scale were calculated.

Table 1. Nighttime light indicators.

Aspect	Description	Calculation
Central tendency	Average value of pixel light values	$\frac{1}{N} \sum_{i=1}^N X_i$
	Average light index	Number of light pixels/Sum of pixel light values
	Median of pixel light values	-
	Mode of pixel light values	-
Dispersion degree	Variance of pixel light values	$\frac{\sum_{i=1}^N (X_i - \bar{X})^2}{N}$
	Standard deviation of pixel light values	$\sqrt{\frac{\sum_{i=1}^N (X_i - \bar{X})^2}{N-1}}$
Distribution characteristic	Sum of pixel light values	$\sum_{j=1}^{63} B_j m_j$
	Number of light pixels	-
	Range of pixel light values	-
	Maximum of pixel light values	-
	Minimum of pixel light values	-
Spatial characteristic	Local Moran index	$\frac{\sum_{j=1, j \neq i}^n W_{ij} (y_i - \bar{y})(\bar{y} - y_j)}{\sum_{i=1}^N (Y_i - \bar{Y})^2 / n}$

2.2.3. Street-View Imagery (SVI)

Unlike conventional remote sensing imagery, SVI can provide detailed urban environmental information from a human perspective [37,50]. In this study, Baidu Maps was selected as the data source. To ensure comprehensive spatial coverage, SVI collection points were systematically placed at 50 m intervals along the road network, with four images captured at each midpoint in four cardinal directions (0°, 90°, 180°, and 270°) to achieve a complete 360-degree view. All spatial data, including the administrative boundaries of Dongguan and the SVI collection points, were reprojected to the WGS84 coordinate system to ensure spatial consistency. Data quality control involved rigorous manual screening to exclude blurred images and heavily occluded views (e.g., blocked by vehicles or vegetation).

The study area lies in a subtropical region where vegetation types are relatively stable and landscape changes in the urban center are minimal. Therefore, we assumed that the SVI data collected during 2013–2022 remained highly consistent over time. After preprocessing, a total of 2,668,200 high-resolution images were obtained from 667,050 sampling points, providing a rich data foundation for an in-depth urban environment analysis (Figure 2b). The subsequent steps, including semantic segmentation and feature extraction, are detailed in Section 3.1.

2.2.4. Points of Interest (POI)

The POI data used in this study were sourced from Gaode Maps in March 2022. First, we removed incomplete and inconsistent data, including POI entries outside Dongguan’s administrative borders and duplicate records. Next, we utilized the “Kernel Density” tool in ArcGIS Pro 3.1 to calculate the density of POIs across 14 major categories (e.g., food

and beverage). For this analysis, we set a search radius of 500 m and a cell size of 1000 m. Then, we calculated the average kernel density for each category at the town scale using zonal statistics. The results are shown in Figure 3, which highlights differences in economic activity across areas.

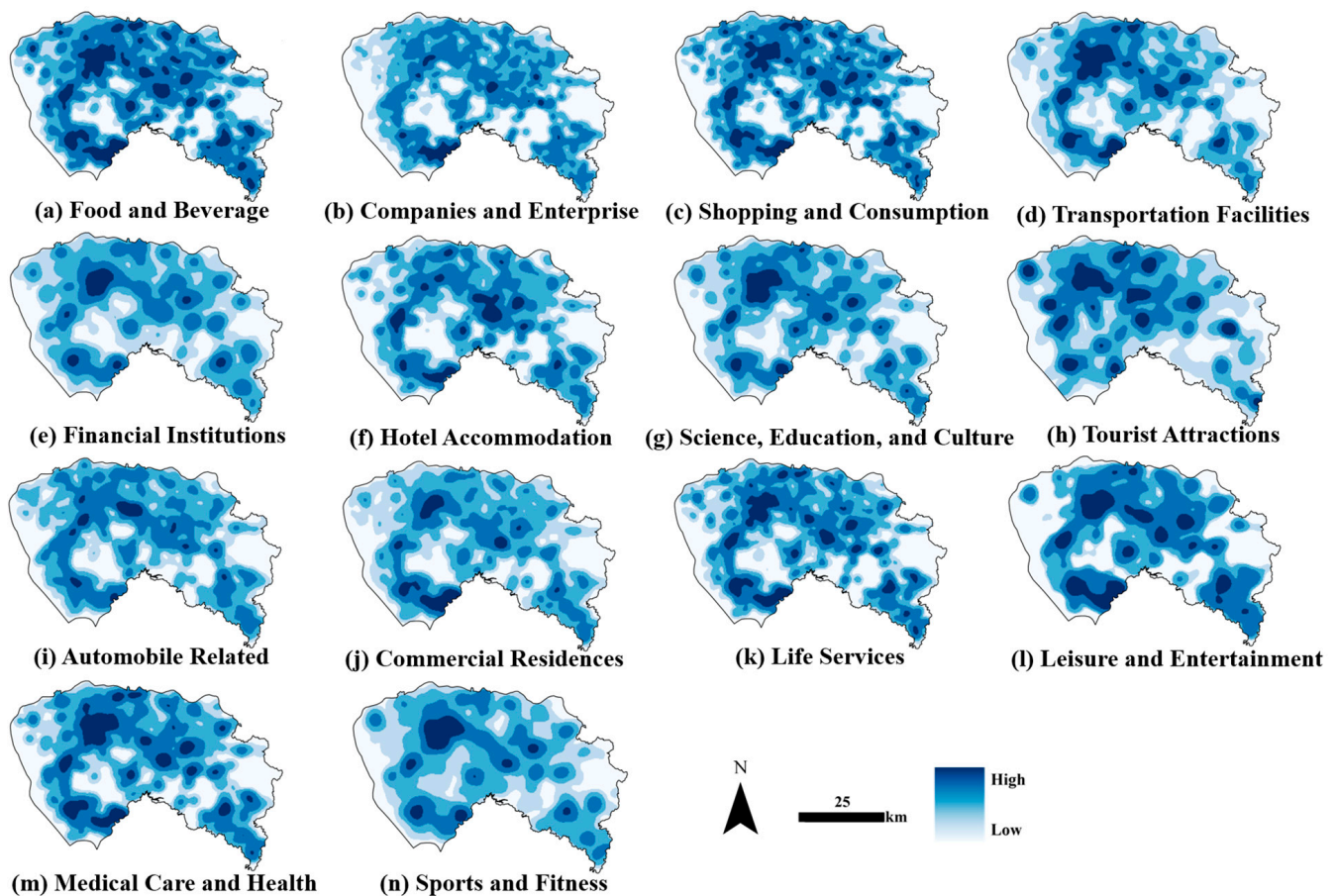


Figure 3. POI indicators.

3. Method

In this study, we first obtained the GDP data for Dongguan at the town scale in 2022, along with the Qimingxing-1 nighttime light, street-view, and POI data. Then, the Qimingxing-1 nighttime light data were processed through noise reduction, threshold setting, and geometric correction to derive the nighttime light indicators. For the SVI, we used semantic segmentation to extract the SVI indicators. The POI data were cleaned by removing incomplete and inconsistent entries, allowing us to extract the POI indicators. Subsequently, we constructed both random forest and decision tree models using GDP as the dependent variable and the Qimingxing-1 nighttime light, POI, and SVI indicators as the independent variables. The results of three different random forest models were then compared and analyzed to validate the effectiveness of the model integrating the Qimingxing-1 nighttime light, SVI, and POI indicators. Finally, the model was further evaluated using the Friedman test and SHAP values, and the best-performing random forest model was compared with the 1 km gridded GDP dataset, thereby enhancing its reliability (Figure 4).

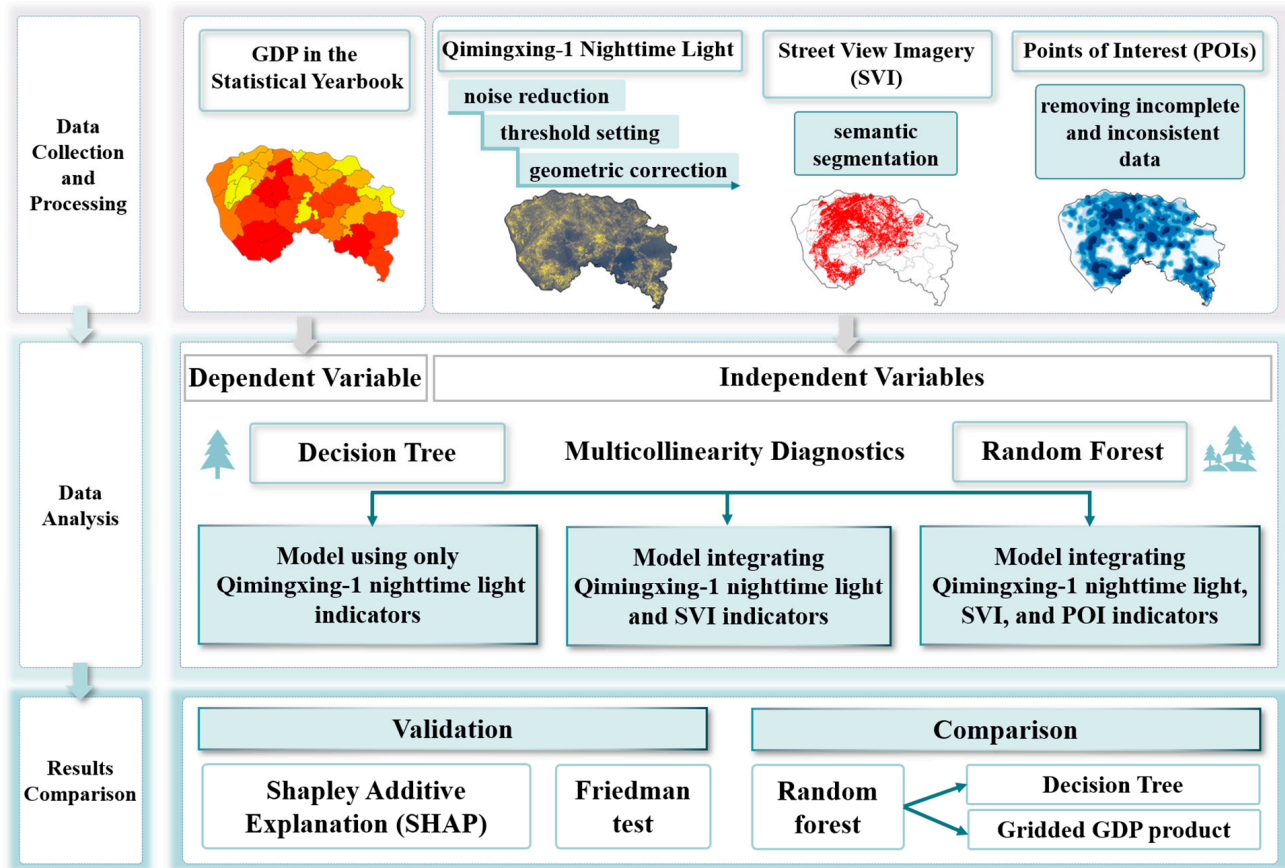


Figure 4. Framework of this study.

3.1. Semantic Segmentation

We employed a semantic segmentation method based on the SegFormer-B0 model, a lightweight yet high-performance Transformer architecture characterized by a low computational cost and a high accuracy [51]. Initially, the SegFormer-B0 model was pre-trained on the Cityscapes dataset, which contains rich urban-scene label information and is well suited for semantic segmentation tasks. After the model was trained, the pre-trained SegFormer-B0 performed pixel-wise semantic segmentation on street-view imagery, extracting the distribution of 19 semantic classes [50,52]. Specifically, when an SVI is input, the model first extracts initial features using a convolutional neural network (CNN). Subsequently, the features are encoded and interacted through a multi-scale self-attention (MSA) mechanism to enhance the model's ability to capture global information. In the final stage, a multi-layer perceptron (MLP) is used to classify each pixel, generating a corresponding class probability distribution. Through this process, each input image generates a pixel-level class proportion map, where the proportion of each class is calculated using the following formula:

$$s_n^0 = \text{CNN}(i_n) \quad (1)$$

$$s_n^{l1} = f_{seg} \left(\text{MSA} \left(\text{LN} \left(s_n^{l-1} \right) \right) \right), l = 1, 2, \dots, L \quad (2)$$

$$l_n = \left[\frac{0 \inf_{seg}(s_n^{l1})}{total\ pixels}, \frac{1 \inf_{seg}(s_n^{l1})}{total\ pixels}, \dots, \frac{18 \inf_{seg}(s_n^{l1})}{total\ pixels} \right] \quad (3)$$

where f_{seg} represents the multi-layer perceptron used for pixel-wise classification, and each l_n is the pixel label mapping of i_n . CNN denotes the convolutional neural network. Each label mapping l_n includes the pixel-wise ratios of each object category in the street-view

imagery. Through this method, the pixel distribution features of various targets in SVI can be accurately extracted, providing reliable data support for subsequent research. Finally, we calculated the average values of the 19 SVI indicators at the town scale in Dongguan (Figure 5).

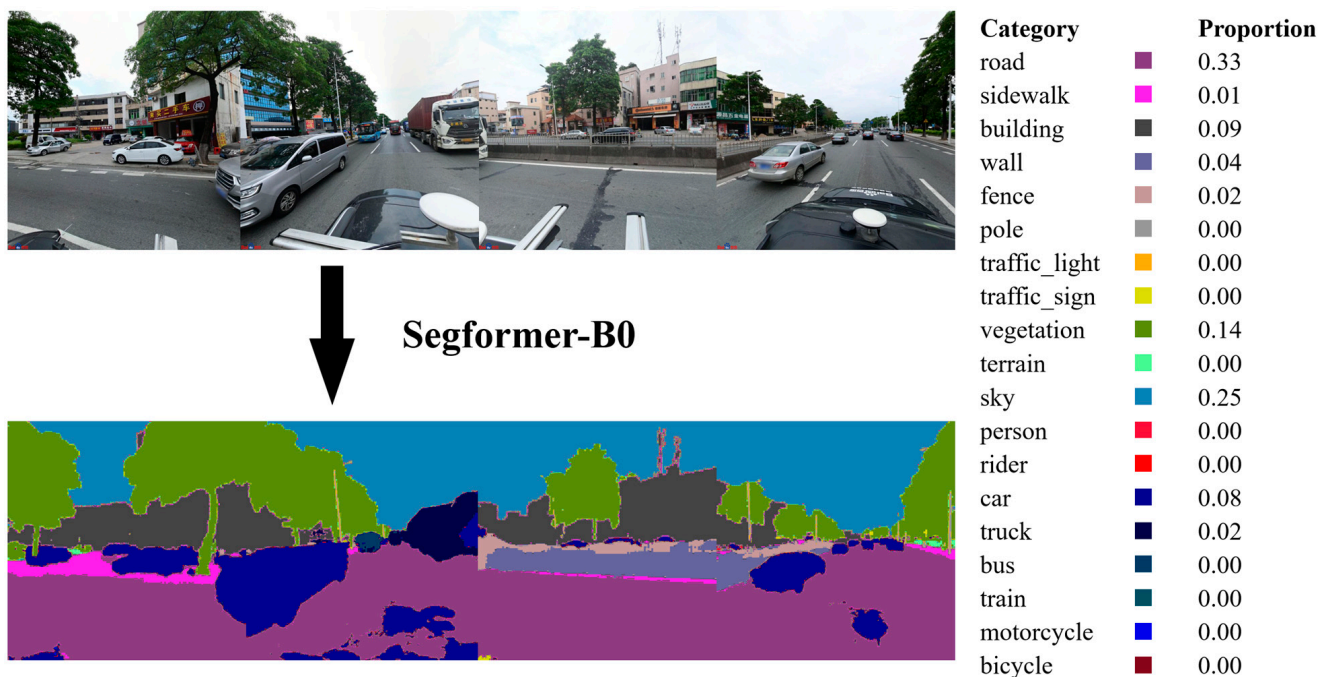


Figure 5. Street-view indicators.

3.2. Random Forest

Although gradient-boosting methods have the potential to offer higher accuracy, their feature importance calculations are based on split gain rather than permutation importance [53–55]. Additionally, the sample-size requirements for deep learning models (typically requiring $N > 10,000$) exceed the scale of our current dataset [56,57]. Therefore, in this study, we employed the random forest model to estimate GDP. Random forest is an ensemble learning algorithm based on decision trees. It constructs multiple decision trees and combines them through voting or averaging to make predictions. This approach is known for its strong resistance to noise and good generalization ability [58,59]. The data features mainly included street-view imagery elements, POIs, and nighttime light features. The street-view features consisted of the proportions of 19 categories, which can reflect a region's economic activities and environmental conditions. POI features were extracted into indicators, such as “food and beverage”, based on kernel density. The nighttime light features were extracted from remote sensing imagery and quantified with indicators such as the “average value of pixel light values” and “standard deviation of pixel light values”, serving as proxy variables for regional economic activities. Before analyzing the model, we performed multicollinearity diagnostics to remove variables with significant multicollinearity ($VIF > 10$), which can ensure the independence of input variables for the model (Table 2).

We used Weka 3.8.6 software to build and evaluate the random forest model. During training, multiple decision trees were constructed by randomly selecting samples and features to reduce the risk of overfitting and enhance the stability of the estimates. We assessed the model's predictive capability and generalization performance by using metrics such as the mean absolute error (MAE) and root mean squared error (RMSE).

Table 2. The results of multicollinearity diagnostics.

Model	Indicator	Tolerance	VIF
Using only Qimingxing-1 nighttime light	range of pixel light values	0.2800	3.5715
	average value of pixel light values	0.4600	2.1739
	sum of pixel light values	0.3567	2.8038
	mode of pixel light values	0.6846	1.4606
	local Moran index	0.8672	1.1532
Integrating Qimingxing-1 nighttime light and SVI	range of pixel light values	0.2757	3.6268
	average value of pixel light values	0.3803	2.6297
	sum of pixel light values	0.3413	2.9297
	mode of pixel light values	0.6538	1.5294
	local Moran index	0.7539	1.3264
	building	0.1452	6.8854
	terrain	0.6336	1.5783
	truck	0.4074	2.4546
	motorcycle	0.1877	5.3289
	range of pixel light values	0.2095	4.7744
Integrating Qimingxing-1 nighttime light, SVI, and POI	average value of pixel light values	0.3023	3.3079
	sum of pixel light values	0.3064	3.2640
	mode of pixel light values	0.5258	1.9019
	local Moran index	0.6953	1.4383
	building	0.1074	9.3148
	terrain	0.5257	1.9023
	truck	0.2276	4.3946
	motorcycle	0.1314	7.6076
	hotel accommodation	0.2459	4.0662
	tourist attractions	0.1765	5.6650
	automobile related	0.2833	3.5297
	commercial residences	0.2334	4.2840

3.3. Decision Tree

A decision tree is a supervised machine learning algorithm used for both classification and regression tasks. It operates by recursively partitioning the feature space into subsets based on the values of input features, aiming to maximize the homogeneity of the target variable within each subset [60–62]. The algorithm selects the optimal feature and split point at each node using criteria such as Gini impurity, information gain, or variance reduction. The process continues until a stopping criterion is met, such as reaching a maximum tree depth or a minimum number of samples per leaf. The final model is represented as a tree structure, where internal nodes represent decision rules, branches represent the outcomes of those rules, and leaf nodes represent the final predictions.

In this study, the decision tree model is employed as a baseline method to evaluate the performance of the random forest model. A random forest is an ensemble of multiple decision trees. It combines their predictions using bagging and feature randomization to reduce overfitting and improve generalization [63]. By comparing the decision tree and random forest models, we demonstrate the advantages of ensemble methods. These advantages include improved predictive accuracy, better resistance to noise, and a greater ability to capture nonlinear relationships.

4. Results

4.1. Comparison Among Different Models

As shown in Table 3, the random forest model outperformed the decision tree model across all evaluation metrics. Notably, after integrating the SVI and POI indicators, the performance of the random forest model improved further. It achieved a correlation coef-

ficient of 0.9796, compared to 0.8018 for the decision tree model. In addition, each error metric demonstrated that the random forest model exhibited higher accuracy and stability in predicting regional economic activities (Figure 6). These results highlight the distinct advantages of the random forest model in handling complex datasets, particularly in capturing nonlinear relationships, resisting noise interference, and enhancing generalization capabilities. By comparing the outcomes of the decision tree and random forest models, the superiority of the latter in GDP prediction was evident.

Table 3. Estimation performance of each model.

Model	Metric	Using Only Qimingxing-1 Nighttime Light	Integrating Qimingxing-1 Nighttime Light and SVI	Integrating Qimingxing-1 Nighttime Light, SVI, and POI
Random Forest	Correlation coefficient	0.9604	0.9710	0.9796
	Mean absolute error	510,894.5	468,248.5	456,649.8
	Root mean squared error	734,278.6	671,378.0	671,332.6
	Relative absolute error	0.3119	0.2859	0.2788
	Root relative squared error	0.3575	0.3268	0.3268
	Correlation coefficient	0.6997	0.7442	0.8018
Decision Tree	Mean absolute error	1,064,221.8	992,372.8	830,477.2
	Root mean squared error	1,467,605.8	1,372,162.2	1,227,661.4
	Relative absolute error	0.6497	0.6059	0.5070
	Root relative squared error	0.7145	0.6680	0.5976

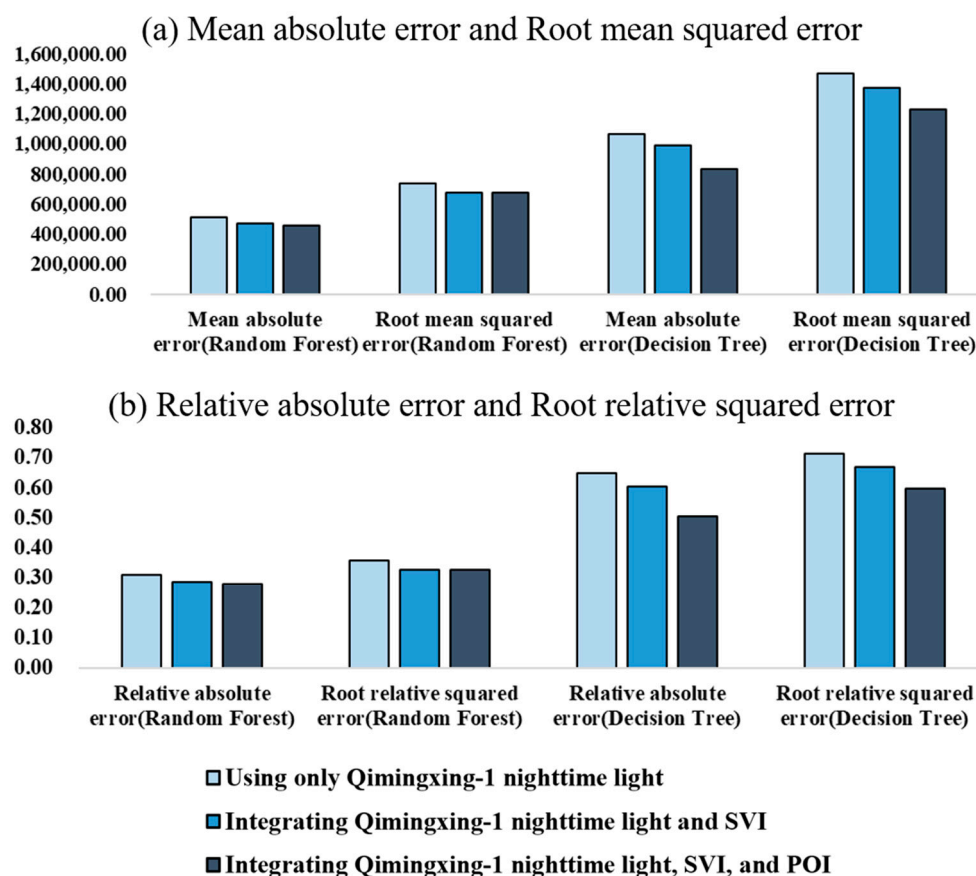


Figure 6. Comparison of model error metrics.

To further analyze the performance of the random forest model, we used the Friedman test to compare it under three different feature combinations. In non-parametric testing, the p -value indicates the probability of observing the current sample result, or one more

extreme, under the assumption that the null hypothesis is true. According to the Friedman test results, the p -value was less than 0.05, leading to the rejection of the null hypothesis. This result shows that there was a statistically significant difference among the three models [64–66].

4.2. Random Forest Model Using Only Qimingxing-1 Nighttime Light Indicators

In estimating Dongguan's GDP at the town scale using only Qimingxing-1 nighttime light indicators, the model demonstrated a certain degree of efficacy (Table 3). The correlation coefficient was 0.9604, indicating a strong positive relationship between the nighttime light indicators and GDP. However, substantial errors were observed, including a mean absolute error of 510,894.5 and relative absolute errors exceeding 30%, suggesting limited precision for practical applications. Figure 7 shows that the model's estimates, derived solely from nighttime light indicators, generally align with the actual GDP values. Overestimation occurred in areas with high nighttime light intensity, likely due to the dataset's bias toward capturing aggregate economic activity.

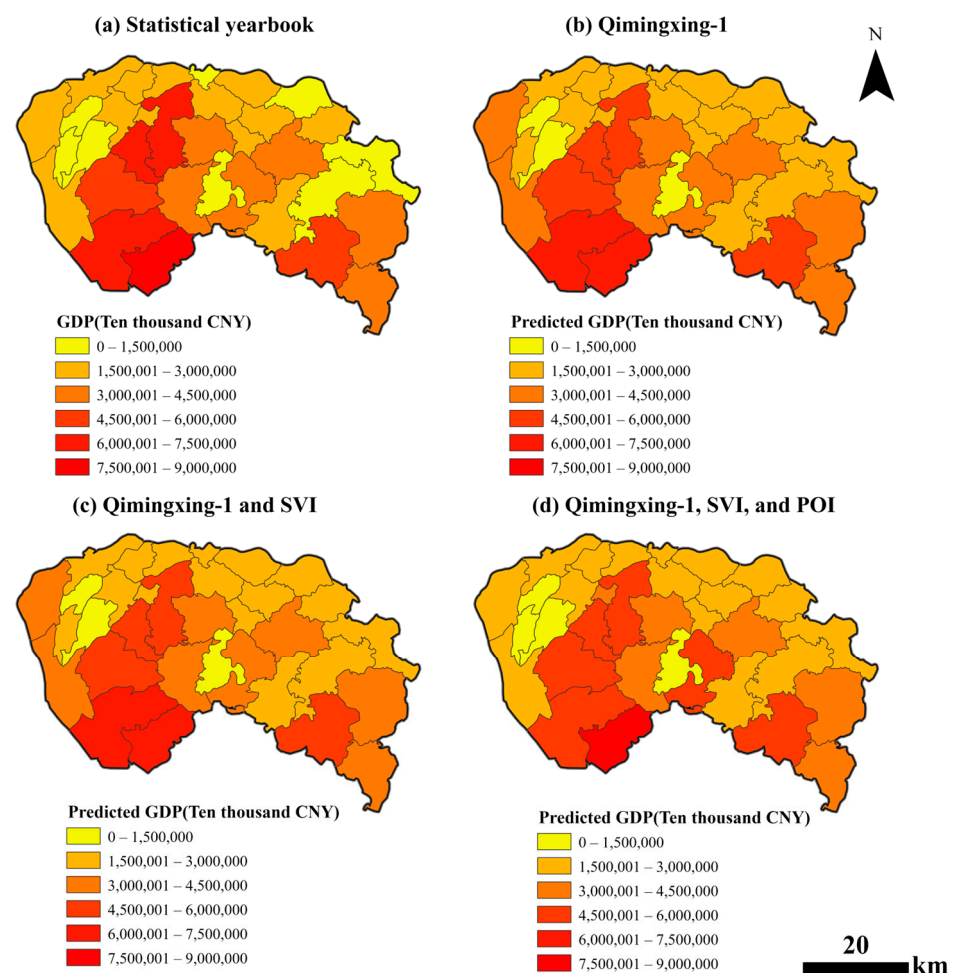


Figure 7. GDP estimation results of each random forest model.

In Figure 8, the importance of Qimingxing-1 nighttime light indicators in GDP estimation is demonstrated. After performing collinearity diagnostics, we identified five key nighttime light indicators that reflect the economic development of town areas from multiple perspectives. The two key indicators, the “local Moran index” and the “sum of pixel light values” accounted for 67.02% of the total importance. These indicators effectively identify economic clusters and quantify overall nighttime productivity.

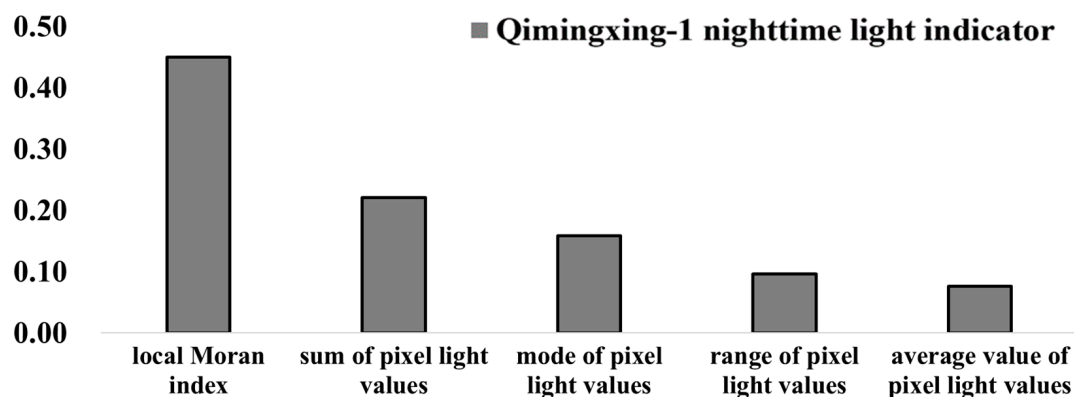


Figure 8. The importance of each indicator after normalization in the random forest model using only Qimingxing-1 nighttime light indicators.

4.3. Random Forest Model Integrating Qimingxing-1 Nighttime Light and SVI Indicators

The model combining Qimingxing-1 nighttime light and SVI indicators demonstrated significantly improved performance (Table 3 and Figure 7c). The addition of SVI reduced the error by 8–12% (e.g., the mean absolute error decreased from 510,894.5 to 468,248.5), and the correlation coefficient increased to 0.9710. Nighttime light data capture the overall distribution of urban economic activities, reflecting the general economic scale and activity. In contrast, street-view data provide detailed micro-level information. Figure 9 illustrates the relative ranking of the Qimingxing-1 nighttime light and SVI indicators in GDP estimation. After collinearity testing, the integrated model revealed that the “truck” and “motorcycle” indicators accounted for 20.87% of the total importance. Vehicle density reflects commercial activity and traffic flow, while building types (commercial, residential, and industrial) reveal land-use patterns related to economic functions. By combining macro-level nighttime light data with micro-level SVI features, the model achieved a more detailed understanding of economic activity at the town scale.

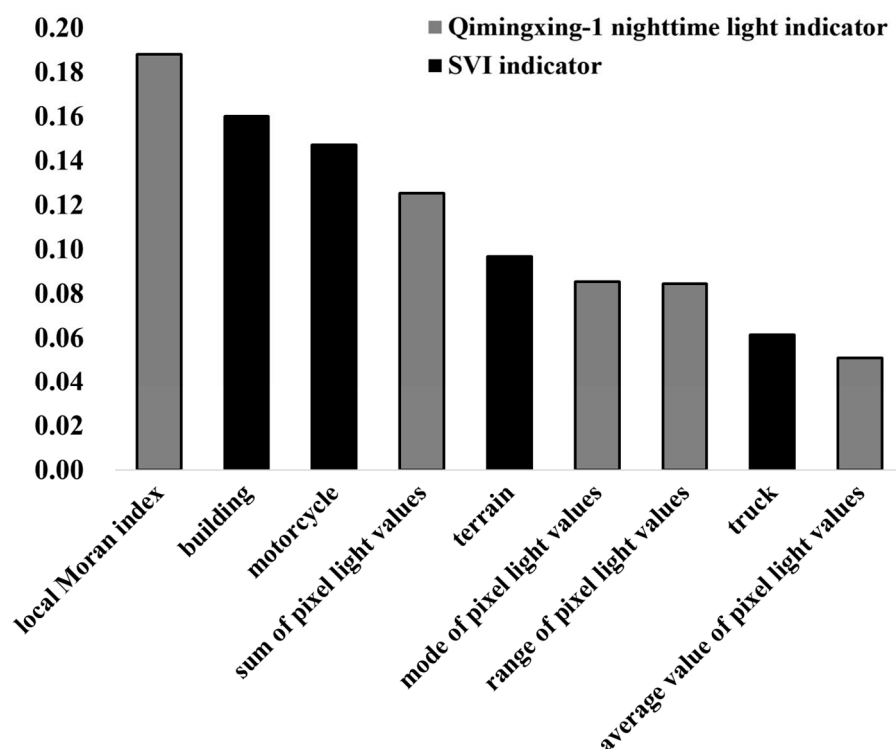


Figure 9. The importance of each indicator after normalization in the random forest model integrating Qimingxing-1 nighttime light and SVI indicators.

4.4. Random Forest Model Integrating Qimingxing-1 Nighttime Light, SVI, and POI Indicators

The integrated model combining Qimingxing-1 nighttime light, SVI, and POI indicators showed a further significant improvement in the GDP estimation (Table 3 and Figure 7d). The correlation coefficient increased to 0.9796, and the errors further decreased. To address the limited coverage of street-view data, we incorporated POI indicators into the model. For instance, POI categories such as “commercial residences”, “tourist attractions”, and “hotel accommodation” complement the “building” indicator from the street-view data. Together, they reflect the economic vitality and consumer attractiveness of towns. Similarly, the “automobile related” POI indicators combined with the “motorcycle” and “truck” indicators from the street-view data reveal the link between traffic flow and industrial activity (Figure 10). “Commercial residences” and “hotel accommodations” indicate the strength of the real estate and service sectors, while the “tourist attractions” and “automobile related” points capture tourism and industrial consumption patterns. These categories bridge the macro-level economic signals from the nighttime light data with the micro-level human activities observed in the street-view data, thereby enhancing the model’s capacity to capture complex socioeconomic interactions.

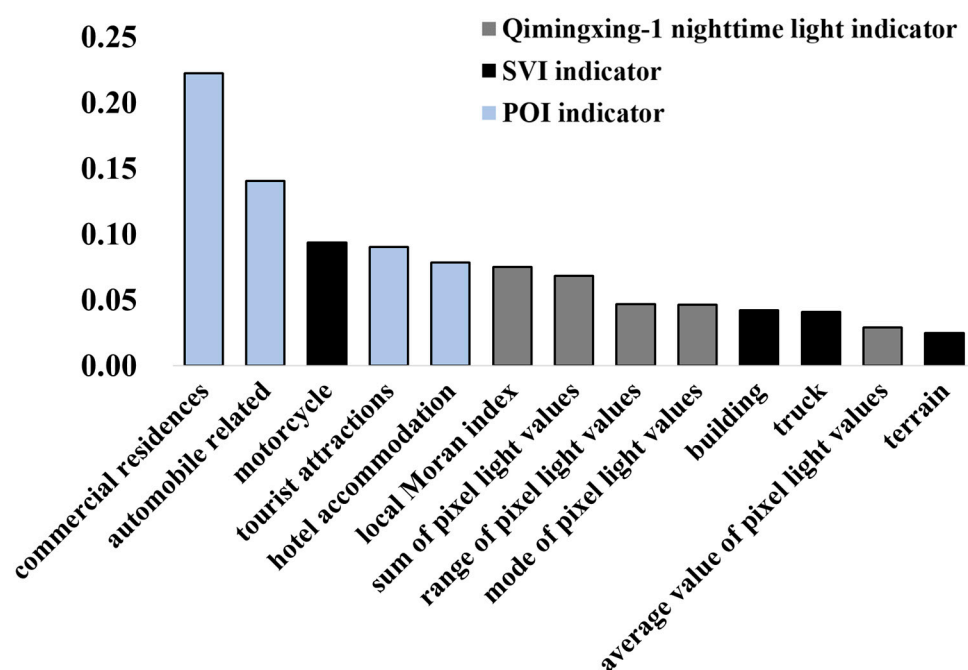


Figure 10. The importance of each indicator after normalization in the random forest model integrating Qimingxing-1 nighttime light, SVI, and POI indicators.

In Figure 11, SHAP (Shapley Additive Explanation) values are used to demonstrate how 13 features affect town-level GDP in Dongguan. Each data point represents the contribution of a single feature to an individual sample [67,68]. All features exhibit positive SHAP values, indicating their positive role in driving economic growth. The two most influential factors are “commercial residences” (SHAP = 593,590.2) and “sum of pixel light values” (SHAP = 511,260.7), which reflect Dongguan’s economic characteristics. In addition, “automobile related” (SHAP = 255,544.1) highlights the importance of transportation infrastructure and industrial zones, consistent with Dongguan’s identity as a manufacturing hub. The street-view imagery reflects human activities and preferences at various times and locations. The POI data show the distribution of buildings such as commercial residences. The Qimingxing-1 nighttime light data identify spatial hotspots of various activities. Therefore, the SHAP values further explain the behavior of the random forest model.

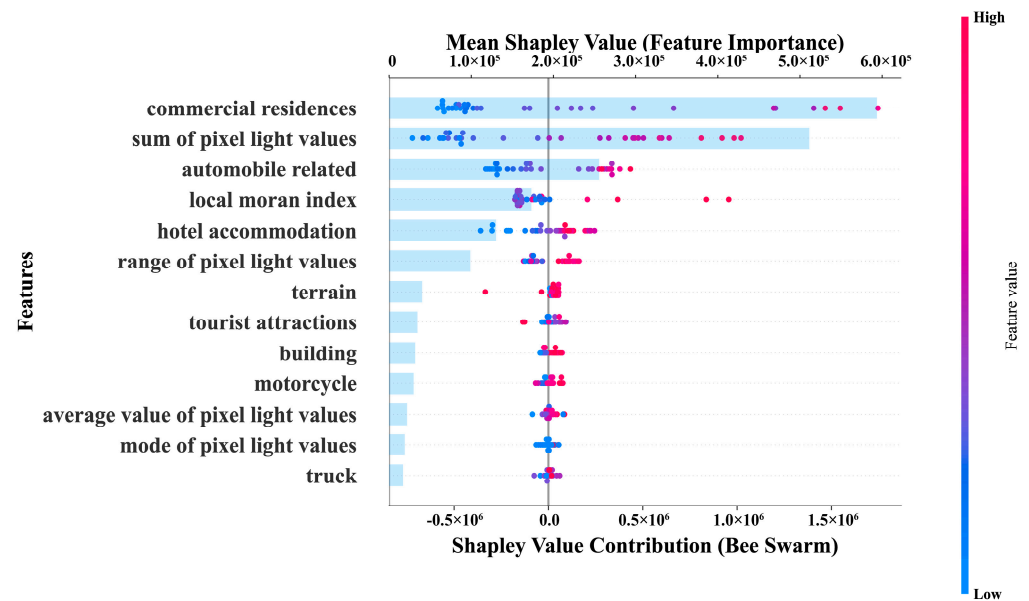


Figure 11. SHAP values of the random forest model integrating Qimingxing-1 nighttime light, SVI, and POI indicators.

4.5. Comparison of the Optimal Random Forest Model Integrating Qimingxing-1 Nighttime Light, SVI, and POI Indicators with Gridded GDP

A comparative analysis reveals that our integrated model aligns with the 2020 gridded GDP dataset in overall spatial distribution trends, with high-value clusters concentrated in southeastern and southwestern Dongguan. However, the 2020 dataset indicates higher GDP values in western Dongguan. Because the model used in the gridded dataset relies on county-level statistical data during training, it is limited in capturing spatial heterogeneity at the town scale [43] and is easily influenced by highly developed western areas, such as Guangzhou, resulting in overestimation. In contrast, our model integrates nighttime light, POI kernel density, and SVI features, achieving higher precision in reflecting spatial gradients of economic activity at the town scale (Figure 12).

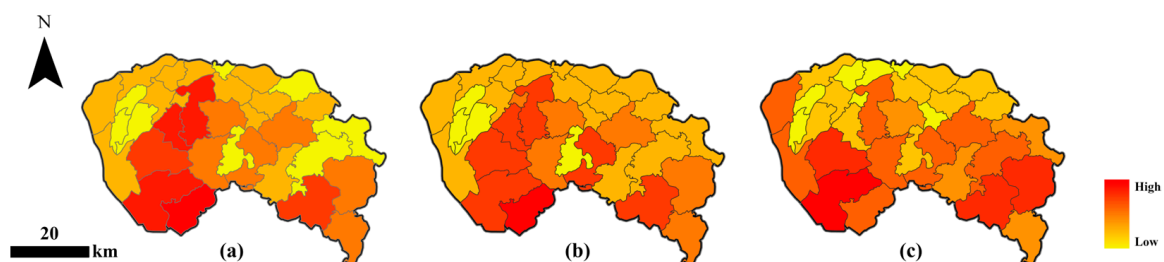


Figure 12. Comparison of different GDP results: (a) Statistical Yearbook; (b) Qimingxing-1, SVI, and POI; (c) 1 km gridded GDP dataset.

5. Discussion

5.1. Main Contributions of This Study

This study makes the following three contributions by comparing different GDP estimation models based on high-resolution nighttime light, SVI, and POI indicators: First, it quantifies the potential value of street-view data in revealing the economic development level of towns. Previous urban economic studies have primarily focused on predicting individual economic indicators, such as total GDP and industrial structure share [69,70]. However, urban economic development involves multiple dimensions. This study demonstrates that SVI not only adds detail to microeconomic activities at the street level but also,

when integrated with high-resolution nighttime light and POI data, plays an important role in reflecting the economic scale, activity, and diversity of economic activities across towns. In measuring economic activity, street-view indicators of pedestrian and vehicle flow complement the brightness distribution of nighttime lights and the economic types and scales represented by POIs, offering a more comprehensive perspective on economic activity estimation.

Second, by comparing the performance of the model using only Qimingxing-1 nighttime light indicators, the model combining Qimingxing-1 nighttime light and SVI indicators, and the model integrating Qimingxing-1 nighttime light, SVI, and POI indicators, this study finds that the latter model shows higher correlation coefficient and lower error measures, highlighting its significant advantage. While high-resolution nighttime light data better reveal the overall distribution of macroeconomic activities, they mainly reflect the current state of the nighttime economy, with less insight into daytime activities. Moreover, the coverage of street-view data is inherently constrained, and adding POI indicators helps to complement these data. By leveraging a broader range of data sources, the integrated model better captures economic development and the complex relationships between various indicators, making it a more effective tool for urban economic research. A higher accuracy in regional GDP estimation enables policymakers to identify economic disparities between towns, allocate resources more equitably, and design targeted interventions (e.g., infrastructure investment in underdeveloped regions). Moreover, precise estimates can help prioritize regions requiring industrial diversification or poverty alleviation programs, thereby promoting sustainable development and reducing regional inequalities.

Finally, at the data application level, integrating high-resolution nighttime light, street-view, and POI data provides new perspectives on urban economic data collection and analysis. Previous studies have typically relied on a single data source or simple data overlays, often failing to explore the deeper connections between different datasets. This study highlights the significant potential of multi-source data integration in enhancing the accuracy of economic estimation. By integrating high-resolution nighttime light, street-view, and POI data to construct models, this study provides a valuable data-processing approach for future urban economic studies.

5.2. Advantages and Shortcomings of This Study

The model integrating Qimingxing-1 nighttime light, SVI, and POI indicators offers clear advantages in urban economic analysis: (1) In terms of data, the model overcomes the limitations of traditional models that rely on a single data type. It combines the macro-level distribution of nighttime light economic activities with the micro-level details of street-view environments and the economic characteristics captured by POI data. For example, indicators such as “motorcycle” and “building” in street-view imagery facilitate a more detailed analysis of the economic functions of an area. These SVI indicators compensate for the lack of daytime information in nighttime light data and work alongside the economic activity types shown by POI data. This integration provides a more comprehensive understanding of the economic characteristics of towns. (2) Regarding performance, the model integrating Qimingxing-1 nighttime light, SVI, and POI indicators has lower error rates. This means that the model is more accurate and stable. It provides a stronger basis for understanding urban economies, which can help city managers control the dynamics of the economic development of towns more accurately and formulate more scientific and reasonable economic strategies.

Nevertheless, this study has several limitations: (1) In terms of data quality, the coverage and timeliness of the street-view data are limited. They do not fully cover all town areas and fail to capture the most recent changes in urban development and economic

activities. This limitation may result in missing information in certain areas, which could affect the model's accuracy. Additionally, in low-density regions, the model's performance may be weakened due to insufficient SVI sampling points and infrequent POI updates. For instance, emerging informal economies or small-scale commercial activities in rural towns may not be captured by limited street-view imagery, thereby leading to estimation biases [39]. (2) Regarding feature selection, although we removed highly collinear variables using VIF testing, redundancy among the remaining features may still reduce the model's interpretability.

In future research, we will attempt to reconstruct missing regions using imputation or interpolation techniques while broadening the range of data sources and utilizing multimodal data (e.g., crowdsourced data) to estimate GDP more accurately. Furthermore, we will apply more advanced feature-selection techniques, such as integrating a principal component analysis with SHAP for feature-importance interpretation or recursive feature elimination, dimensionality reduction, and feature relevance. These approaches would minimize redundancy and further enhance model performance.

6. Conclusions

Accurate GDP estimation is crucial for effective urban planning and sustainable development. Traditional economic surveys often encounter challenges such as over-reporting [71,72]. Moreover, previous studies have mostly relied on a single data source and have not fully exploited the integrated and complementary potential of high-resolution nighttime light, street-view, and POI data. In this study, we aimed to fill this gap by exploring how a model integrating high-resolution nighttime light, street-view, and POI data can improve GDP estimation at the town scale in Dongguan. We compared three models using both the random forest and decision tree methods: one using only Qimingxing-1 nighttime light indicators; one combining Qimingxing-1 nighttime light and SVI indicators; and one integrating Qimingxing-1 nighttime light, SVI, and POI indicators. Our findings demonstrate that the random forest model using all three types of indicators performed the best. The correlation coefficient increased from 0.9604 to 0.9710 and then to 0.9796. This result demonstrates that the integrated model provides a more complete view of economic activity and significantly improves the accuracy of GDP estimation. However, potential errors may come from the insufficient coverage of SVI/POI in low-density areas and inherent statistical biases in GDP data. Despite these limitations, our integrated model reduces estimation bias and offers a robust framework for urban economic analysis, supporting sustainable development through data-driven insights.

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