

LSTM-GCN-Bee Model for Classifying Ecological Drivers of Urban Green Space Changes: A Study on Urban Ecosystem Dynamics

Babar Shahzad*

Department of Management Sciences, COMSATS University Islamabad, Pakistan; babarshehzad2345@gmail.com

*Corresponding Author: babarshehzad2345@gmail.com

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ABSTRACT

Urban green space is an important part of the urban ecosystem, providing key ecological services such as climate regulation, biodiversity support, and leisure space for urban residents. However, the rapid expansion of urban areas poses a significant threat to the extent and quality of these green spaces. To address the complexity of understanding of the drivers of change in urban green space, this study proposes an LGB model that combines long and short-term memory network (LSTM), graph convolutional network (GCN), and bee swarm algorithm (BCA). The LGB model aims to systematically classify and identify key ecological factors influencing the dynamics of urban green space by capturing temporal variation and spatial relationships in urban ecosystems. We utilized four diverse datasets, including satellite image data provided by Google Earth Engine (time span: 2010-2020), European Urban Atlas dataset, SEDAC socioeconomic data, and The Atlas of Urban Expansion data set. Experimental results show that the LGB model showed high accuracy on all datasets, especially 97.88% on the The Atlas of Urban Expansion dataset. Moreover, the LGB model also outperforms existing methods on multiple metrics including recall, F1 score and AUC value, and the confidence intervals for all metrics show the reliability of the model results. Although the LGB model shows superior performance, we are also aware that the model may have some limitations in different urban areas and data quality. Nevertheless, this study provides an advanced analytical tool for urban ecological management, providing important insights for urban planners and policy makers to help promote sustainable urban development and promote the healthy development of urban ecosystems through better green space conservation and planning.

Keywords: Deep learning, Urban green space, Environmental change, Classification model, Sustainable urban planning, Environmental management

1. Introduction

With the rapid advancement of global urbanization, urban green space—an indispensable component of urban ecosystems—plays a crucial role in improving air quality, mitigating the heat island effect, boosting biodiversity, and enhancing residents' quality of life[1]. However, driven by

urban expansion, infrastructure development, and socioeconomic shifts, urban green space is confronting sustained shrinkage and fragmentation[2]. Scientifically and efficiently monitoring and predicting green space change trends to formulate effective environmental management strategies has become a key challenge in current urban planning and sustainable development. Traditional research on urban green space changes primarily relies on remote sensing image analysis, statistical models, and geographic information systems (GIS)[3,4], but these methods suffer from limitations such as protracted data update cycles, difficulty in real-time capture of dynamic green space changes, and overreliance on linear regression or rule-based models that struggle to address complex nonlinear correlations[5,6]. The rapid evolution of deep learning technology in recent years has brought new opportunities to environmental science, demonstrating robust data processing capabilities in dynamic green space monitoring, ecological change prediction, and environmental factor analysis[7].

Deep learning models can automatically extract features from multi-source data (e.g., remote sensing images, climate data, socioeconomic data), learn complex spatiotemporal patterns, and offer novel approaches for accurate urban green space change prediction[8,9]. For instance, CNNs are widely used in remote sensing image classification, LSTMs excel at time-series modeling to capture historical green space dynamic characteristics[10,11], and GCNs have emerged for modeling spatial data relationships, making them ideal for capturing urban green space's spatial dependencies[12]. Despite significant progress, challenges remain—such as fusing spatiotemporal features, enhancing model generalization, and optimizing computational efficiency—requiring further exploration.

To address these gaps, this paper proposes the LGB Model (LSTM-GCN-Bee Model), a deep learning-based classification framework for urban green space change factors integrating LSTM, GCN, and bee colony algorithm (BCA). By leveraging LSTM to capture time-series dynamics, GCN to analyze complex spatial relationships, and BCA to optimize model parameters, this study explores the influence mechanisms of urban environmental changes on green space. The research not only delivers theoretical innovations but also provides a scientific basis for urban planners and environmental managers, facilitating the implementation of sustainable urban planning and environmental governance. This study yields three primary contributions:

1. The proposed LGB Model (LSTM-GCN-Bee Model) constitutes a novel deep learning framework that pioneeringly integrates LSTM, GCN, and the Bee Colony Algorithm (BCA) in the field of environmental science.

2. Via the LGB Model, this research systematically discriminates and categorizes critical drivers of urban green space changes, encompassing diverse dimensions such as the natural environment, socioeconomic factors, and urban policies.

3. The findings enable urban planners and environmental managers to precisely forecast and evaluate urban green space change trends, thereby providing empirical support for sustainable urban planning and environmental protection policies. Furthermore, the development of the LGB Model offers a viable analytical paradigm for other environmental monitoring and management tasks, advancing the deployment of deep learning technologies in urban ecosystem governance.

2. Literature Work

2.1 Deep Learning in Environmental Studies

In recent years, deep learning—an advanced machine learning technique—has gained extensive traction in environmental science, particularly in urban green space change monitoring, where it has demonstrated increasingly prominent strengths[13]. Traditional approaches to urban green space change research typically rely on remote sensing imagery, climate datasets, and geographic information systems (GIS), facing two key drawbacks: cumbersome data processing and weak model generalization[14,15]. These methods often struggle to model spatiotemporal dynamics and complex spatial relationships, while neglecting nonlinear data characteristics and their interdependencies[16,17]; for instance, conventional remote sensing processing can only capture patterns from single data sources, leading to poor prediction accuracy and real-time performance amid complex environmental changes. By contrast, deep learning has emerged as a game-changer in this field: it autonomously extracts critical features from large-scale, complex datasets, eliminating traditional methods' heavy reliance on model assumptions and manual preprocessing[18,19]. Models like CNN (excel at remote sensing image processing), LSTM/GRU (superior in temporal dynamics modeling), and Transformer (efficient for large-scale data analysis) have been widely applied to urban green space change prediction, climate monitoring, and image recognition[20,21].

Despite these notable achievements, existing deep learning models still have limitations[22]. For one, most require massive training datasets to ensure performance, but the high cost and scarcity of environmental data acquisition often become major bottlenecks[23]. More critically, deep learning models are often labeled as "black boxes" due to insufficient interpretability, hindering their ability to support policy-making and scientific research[24,25,26].

2.2 Urban Green Space Analysis Techniques

This technology plays a pivotal role in urban green space monitoring, where it leverages diverse data sources—ranging from satellite imagery to meteorological and urban planning information—to accurately detect and forecast the evolution of green areas[27,28,29]. Such advancements have not only streamlined data handling but also bolstered model predictive capabilities, thereby underpinning sustainable urban growth and environmental stewardship[30,31].

In the domain of environmental monitoring, research endeavors have concentrated on enhancing the precision and timeliness of deep learning models. Models such as CNNs, GRUs, and Transformer architectures have demonstrated their efficacy[32,33]. CNNs, renowned for their image analysis prowess, are extensively utilized in interpreting satellite imagery of urban greenery, while GRUs are adept at managing sequential data, capturing the protracted effects of climate fluctuations on these green spaces[34,35]. The Transformer model, with its adeptness at navigating extensive datasets and capturing extensive temporal and spatial relationships, stands out as an ideal candidate for intricate environmental data analysis.

These models often necessitate substantial datasets for optimal performance, and the procurement of high-fidelity environmental datasets can be both costly and challenging[36,37,38].

Furthermore, the opacity of deep learning models, often referred to as their "black-box" characteristic, results in limited interpretability, which may hinder their application in policy formulation and scientific inquiry. Addressing these limitations is the focal point of the current investigation.

2.3 Optimization Algorithms in Deep Learning Models

Optimization algorithms play a vital role by adjusting the model's parameters to optimize specific performance metrics. Traditional optimization methods such as gradient descent and its variations, including SGD and momentum, as well as adaptive learning rate algorithms like RMSprop, is commonly employed in various deep learning frameworks[39,40,41]. With technological advancements, optimization algorithms continue to evolve to meet the needs of more complex models, improve training efficiency, and enhance model performance, especially on large-scale datasets.

Currently, research on optimization algorithms for deep learning models focuses on improving algorithm convergence speed and stability, as well as reducing the consumption of computational resources[42,43]. For example, the Adam optimization algorithm, with its efficient computational performance and lower memory requirements, has been widely applied in training various deep networks[44]. Additionally, some emerging algorithms in recent years, such as LARS and LAMB, are designed specifically for large-scale distributed training environments, effectively handling large networks and datasets[45,46]. The improvements and innovations in these optimization algorithms make deep learning models more efficient and reliable in handling more complex tasks.

Although existing optimization algorithms greatly improve the training efficiency and performance of deep learning models, they still face some challenges[47,48]. Firstly, the parameter settings of most advanced optimization algorithms are complex and not beginner-friendly, requiring researchers to possess a high level of expertise to configure them reasonably. Secondly, some algorithms may perform poorly on specific types of networks or datasets, lacking universality[49,50]. Additionally, as the size of models increases, the demand for computational resources also increases, posing a significant challenge for research environments with limited resources.

3. Methods

3.1 Overview of Our Network

The LGB model (LSTM-GCN-Bee Model) proposed in this paper is an innovative deep learning framework that integrates LSTM, GCN and bee Bee Colony Algorithms, aiming to systematically analyze the changing factors of urban green space. This model can deeply explore and utilize complex urban environmental data through the close collaboration of various components. The overall structure of the model is shown in Figure 1. The overall framework consists of a time modeling module (LSTM), a spatial relationship modeling module (GCN) and an optimization module (bee colony algorithm). The components work together to improve the prediction accuracy and generalization ability.

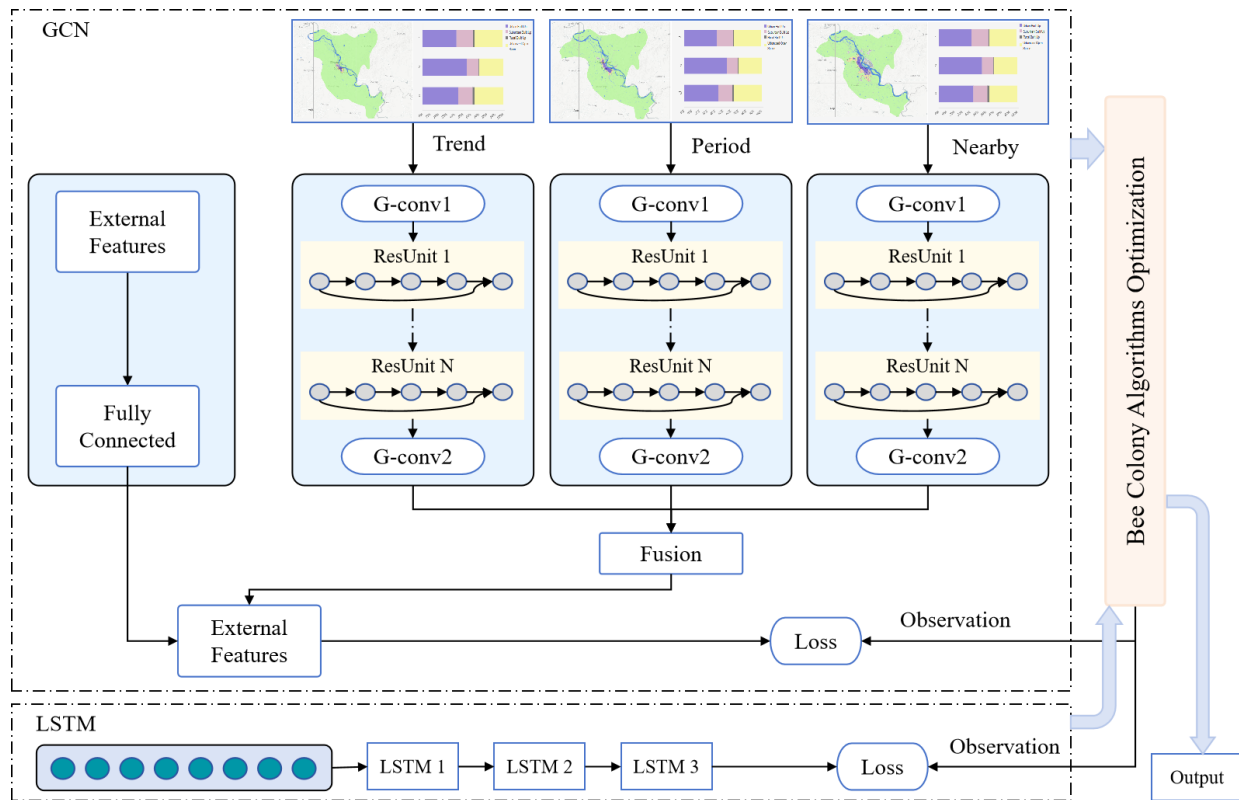


Figure 1. The LGB Model Architecture for Urban Green Space Change Detection. The model integrates a GCN for spatial data processing, focusing on trends, periods, and nearby information within urban regions. LSTM networks handle temporal data to capture dynamic trends in urban green space changes. The model uses G-conv1 and G-conv2 layers within the GCN for spatial feature extraction, supported by Residual Units (ResUnit) to maintain information flow. The Fusion component combines temporal and spatial features. The Bee Colony Algorithm optimizes the model parameters to enhance prediction accuracy. External features are included as additional data inputs to improve model performance.

The input features of the LGB model include spatiotemporal information from multiple data sources to ensure that the model can fully capture the key factors affecting urban green space changes. This study mainly used remote sensing data, climate data, land use information, and socioeconomic variables. Remote sensing data provides ecological parameters such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Land Surface Temperature (LST); climate data includes time series information such as precipitation, temperature, and humidity; land use information comes from European Urban Atlas, covering categories such as urban construction land, green space, water bodies, and transportation infrastructure; socioeconomic variables include population density, night light index (VIIRS), GDP, etc., to reflect the impact of human activities on green space changes.

In the LGB model, the input time series data, such as historical green space coverage and climate change records, are first processed by the LSTM component to effectively capture the dynamic change trend of urban green space over time. The gating mechanism of LSTM helps the model

remember and utilize past information, providing deep temporal context for subsequent analysis. Subsequently, the processed time series data is passed to the GCN component, and the graph structure of the urban area is constructed together with the spatial data. In this structure, nodes represent different urban areas, and edges depict the spatial connections between these areas. GCN reveals the complex spatial dependencies between regions and the spatial distribution patterns of green space changes by transmitting information between nodes. In the final stage of the model, the bee colony algorithm is used to optimize the data processed by GCN, and optimize the network parameters by simulating the search strategy of bees foraging to find the optimal parameter combination. This optimization process not only improves the accuracy of the model's prediction of urban green space change factors, but also enhances the generalization ability of the model.

Urban green space changes are affected by a variety of dynamic factors, such as climate fluctuations, policy adjustments, and land use changes. The LSTM component is specifically used to model these time series data, which can effectively capture the trend of urban green space evolution over time (bottom of Figure 1). In this model, we adopt a multi-layer LSTM structure, in which each LSTM unit receives time series input and transmits information layer by layer, so as to learn historical patterns and predict future trends. In addition, the application of the bidirectional LSTM structure enables the model to consider both past and future influencing factors at the same time, further enhancing its ability to capture temporal dynamic features.

The distribution of urban green space has complex spatial dependencies, and the changes in green space in adjacent areas often affect each other. Therefore, we introduce the GCN component to capture the spatial characteristics between urban areas. As shown in Figure 1, this part is divided into three submodules: Trend, Period, and Nearby. Each submodule uses a two-layer graph convolutional network (G-Conv1 and G-Conv2) and strengthens the information flow through the residual unit (ResUnit), so that information from different spatial dimensions can be effectively integrated. This design can deeply explore the dynamic interactions between different areas of the city and enhance the spatial prediction ability of green space changes. In addition, the GCN component also combines external environmental characteristics, such as urban population density, air pollution index, etc., to further improve the spatial analysis ability of the model.

Despite the robust capacities of LSTM and GCN in extracting temporal and spatial features, tuning the hyperparameters of these components to achieve optimal predictive performance remains a critical challenge. To address this, we introduce the Bee Colony Algorithm (BCA, right side of Figure 1), whose core mechanism simulates the foraging dynamics of bee colonies and employs a global search strategy to identify the optimal parameter combination—this optimization process involves adjusting key parameters such as the number of LSTM layers, GCN filter size, and learning rate, thereby ensuring the model's generalization across diverse datasets. The BCA not only enhances model optimization efficiency but also effectively mitigates overfitting risks, rendering the prediction results more reliable. Following the extraction of temporal and spatial features, the model fuses multi-source feature outputs (via the Fusion module in Figure 1) and generates results through a final decision layer to classify the primary driving factors of urban green space changes, enabling the

identification of dominant factors in green space evolution under different urban contexts. The entire process is supervised and optimized via a loss function to continuously improve the accuracy of urban green space change prediction. The innovation of the LGB Model lies in its deep integration of temporal, spatial, and optimization technologies, which compensates for the shortcomings of traditional methods—such as cumbersome data processing, inadequate spatial relationship modeling, and difficulties in hyperparameter tuning. Compared with standalone LSTM or GCN approaches, the LGB Model can more accurately predict urban green space change trends and is suitable for large-scale urban environmental data analysis; its efficiency and scalability not only make it applicable to urban green space monitoring but also extendable to broader environmental management fields, providing intelligent decision support for sustainable urban planning.

3.2 LSTM Module

LSTM networks are specialized in processing time-series data and sequence prediction tasks. Unlike traditional RNNs that face gradient vanishing/exploding issues when handling long sequences, LSTMs integrate a distinct gating structure, enabling them to effectively capture and retain long-term data dependencies[51]. This capability has made LSTMs widely adopted in scenarios like speech recognition, language modeling, and time-series forecasting. Their strength in predicting future trends via historical patterns proves notably useful in environmental science and urban studies—for instance, successful applications include weather forecasting, air quality prediction, and urban development trend assessment. Compared to traditional statistical methods, LSTM models offer higher accuracy in simulating complex time-dependent data, rendering them particularly advantageous for analyzing dynamic urban environments[52].

In the LGB Model of this study, the LSTM component's design and configuration serve a pivotal function in processing time-series data associated with urban green space changes effectively. To boost temporal pattern capture, we adopt a three-layer LSTM structure with 256 neurons per layer: LSTM units utilize the tanh activation function for state updates and the sigmoid function for information flow regulation, enabling the model to learn complex nonlinear correlations in time-series data. Additionally, a 20% dropout rate is applied post each LSTM layer to alleviate overfitting risks, enhancing generalization and ensuring robust performance across datasets. This optimized LSTM architecture fully leverages dynamic temporal information, laying a solid foundation for analyzing and predicting urban green space trends. The detailed structure of the LSTM model is illustrated in Figure 2.

In the LGB model, LSTM is not only a time series processing tool, but also one of the core components of the entire model. By analyzing the input time series data, such as historical green space coverage changes, urbanization process, and environmental indicators, LSTM can extract key temporal features and predict future trends. These temporal features are then passed to the GCN component to guide its spatial data analysis, ensuring that the model can understand the status of each time node while also grasping the long-term trend of change. By combining temporal and spatial features, LSTM greatly enhances the predictive ability and practical application value of the LGB model, providing strong support for solving complex problems in urban planning and environmental

management.

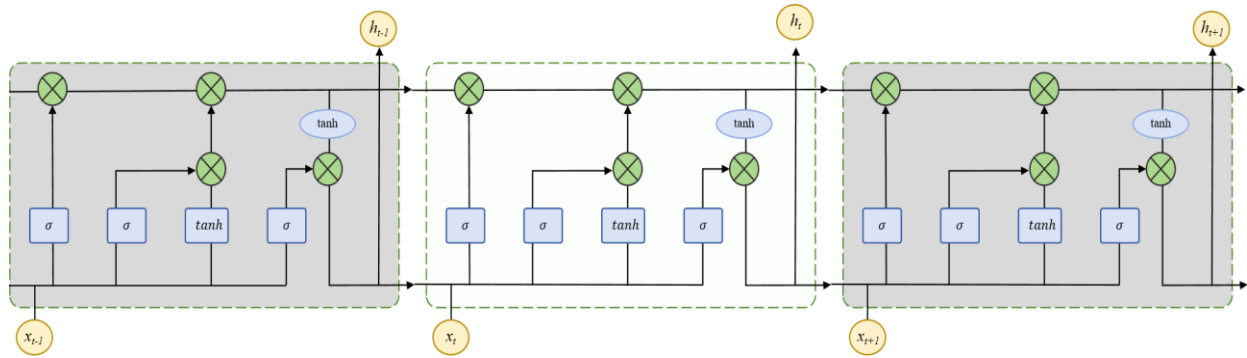


Figure 2. Flow chart of the LSTM model

3.3 GCN Module

GCNs are designed to process graph-structured data. By performing convolution operations over the graph's topology, GCNs are able to capture complex relationships between nodes and incorporate both local and global structural information. This makes them highly effective in various domains such as social network analysis, knowledge graph construction, recommendation systems, and molecular structure analysis [53,54]. In environmental science and urban planning, GCNs are particularly useful for modeling urban expansion, traffic patterns, and environmental monitoring. They enable the analysis of interactions between different regions and their influence on environmental factors like green space coverage [55]. GCNs are well-suited to handle urban geographical data, which often exhibit graph-like relationships, such as connections between neighborhoods and transportation networks.

In the LGB model proposed in this paper, the GCN module plays a crucial role in processing spatial data related to urban green spaces. As depicted in Figure 3, The GCN component in this model contains a three-layer graph convolutional network with 64 nodes in each layer. Each layer is designed to extract spatial features at different levels. These features include not only the information of a single region, but also the relationship between regions, such as proximity and connectivity. By learning these patterns, the GCN can effectively identify trends in green space changes across the city. The output from the GCN is a feature representation at the regional level, which is then integrated with the temporal features extracted by the LSTM component. This combined input is fed into the decision layer of the model to generate the final predictions and classifications.

In the LGB model, the combination of this multi-level GCN structure and LSTM time series analysis enables the model to not only capture changes in the time dimension, but also deeply understand the complex interactions in the spatial dimension. This integrated processing capability of spatiotemporal data enables the model to more accurately predict the future development trend of urban green space. Through this configuration, GCN greatly enhances the ability of the LGB model in explaining and predicting the dynamic changes of urban green spaces, providing more scientific decision-making support for urban planners and environmental managers, thereby promoting sustainable urban development.

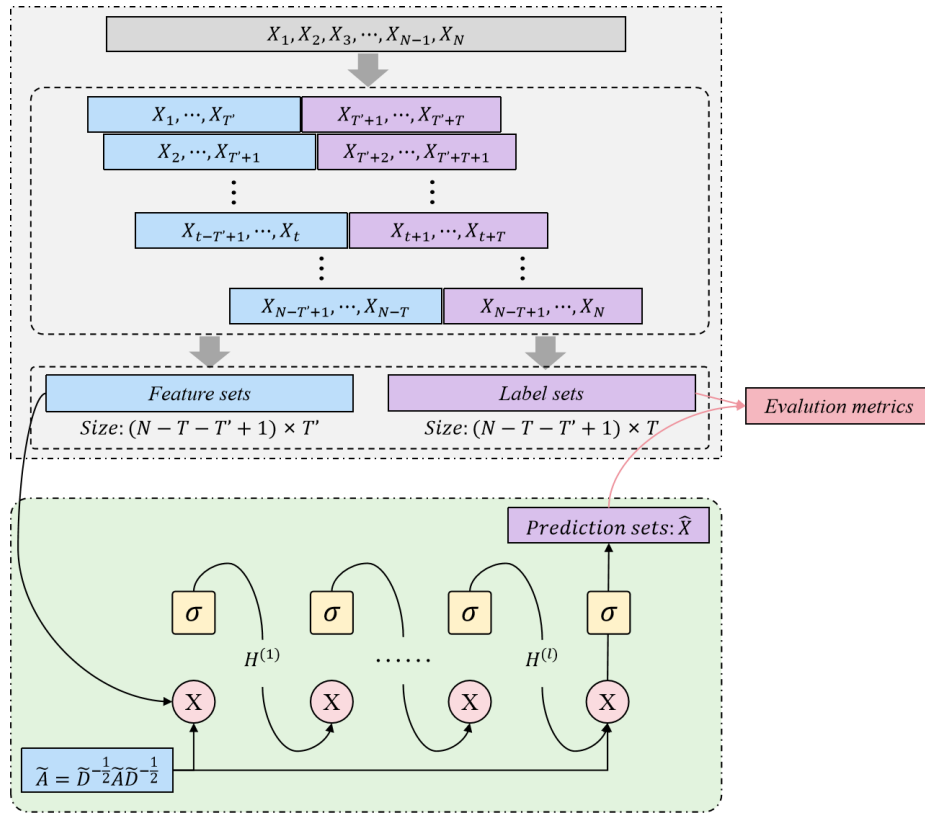


Figure 3. Flow chart of the GCN model

The primary equation governing the operation of the GCN is derived from Kipf and Welling's work [53]. The formula is expressed as follows:

$$H^{(0)} = X \quad \text{[Formular 1]}$$

where $H^{(0)}$ is the input feature matrix, X is the matrix of input features for each node.

$$D^{(l)} = \text{diag}(\sum_j A_{ij}) \quad \text{[Formular 2]}$$

where $D^{(l)}$ is the diagonal degree matrix for layer l , and A_{ij} represents the adjacency matrix of the graph at element (i, j) .

$$Z = \text{softmax}(H^{(L)}W^{(L)}) \quad \text{[Formular 3]}$$

where Z is the output prediction across all classes, L is the total number of layers, and softmax is applied to derive probabilities for each class.

This sequence of equations demonstrates how a GCN layer processes node features through propagation based on the graph structure and subsequently transforms the data for potential multi-class classification or other tasks.

3.4 Bee Colony Algorithms Module

BCA is based on simulating the foraging behavior of bees. By imitating the information exchange and search strategy of bee colonies during foraging, BCA performs well in solving optimization problems and is particularly suitable for dealing with complex multimodal function optimization problems. Its basic principle is to use local search and global information sharing

between individual bees to quickly find high-quality solutions in the solution space[56]. BCA has been widely used in many fields such as function optimization, path planning, and scheduling problems. During the training process of deep learning models, BCA can optimize the parameter settings and feature selection of the network, and continuously update the model parameters by simulating the search strategy of bees during foraging, thereby minimizing the prediction error or maximizing the objective function value[57]. This optimization method can help the model avoid falling into the local optimal solution and find the global optimal solution more effectively, especially for dealing with complex problems with multiple local optimal solutions.

In the LGB model of this study, BCA played a key role in model optimization. During the training process, BCA is used to search for the best hyperparameter combination of the model (such as the number of hidden units in the LSTM layer, the number of nodes in the GCN layer, etc.), and adjusts the parameters through multiple iterations to achieve optimal performance. In addition, BCA also helps select the most representative features to reduce the impact of redundant features and improve the efficiency and accuracy of the model. Through this optimization process, we not only improve the training speed of the model, but also ensure its efficiency and stability on different data sets. The process of the bee colony algorithm is shown in Figure 4.

The introduction of BCA provides a powerful optimization tool for the LGB model, which enables the model to not only efficiently process multi-dimensional data features, but also better cope with the complex dynamics of urban green space changes, greatly improving the accuracy of prediction and the overall performance of the model. Through this optimization mechanism, the LGB model shows excellent prediction ability under different data conditions, providing more reliable technical support for urban planning and environmental management.

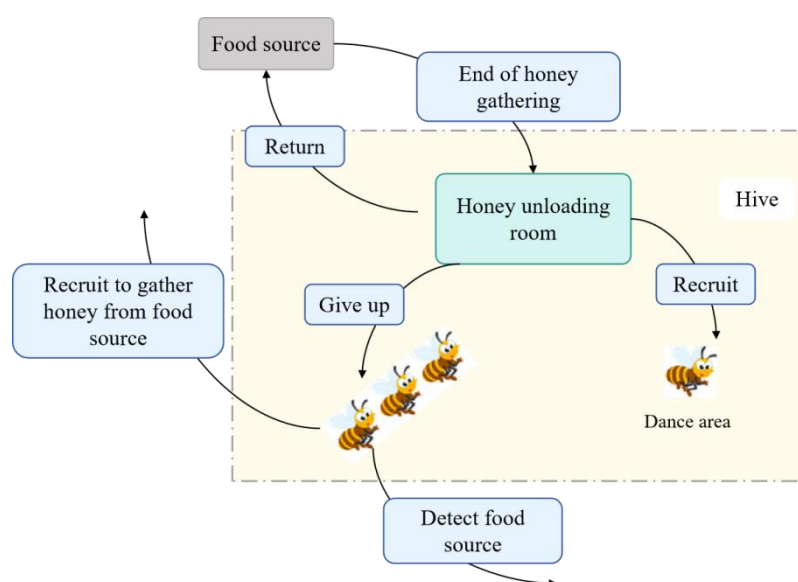


Figure 4. Design of the intelligent navigation optimization module

The key equation, adapted from Karaboga and Basturk's algorithm [58], is provided below along

with definitions of the primary variables:

$$x_i(t+1) = x_i(t) + \phi_i(t) \cdot (x_{pbest} - x_i(t)) + \psi_i(t) \cdot (x_{gbest} - x_i(t)) \quad [\text{Formular 4}]$$

where $x_i(t)$ is the position of the i^{th} bee at time t , x_{pbest} is the best position found by this bee, x_{gbest} is the global best position found by any bee, $\phi_i(t)$ and $\psi_i(t)$ are random numbers drawn from a uniform distribution.

$$\phi_i(t) = rand[0,1] \quad [\text{Formular 5}]$$

$$\psi_i(t) = rand[0,1] \quad [\text{Formular 6}]$$

where $\psi_i(t)$ similarly generates a random number for the influence of the global best.

$$fitness_i = \frac{1}{1 + f(x_i)} \quad [\text{Formular 7}]$$

where $fitness_i$ calculates the fitness of the i^{th} bee, and $f(x_i)$ is the objective function to be minimized.

$$x_{pbest} = \operatorname{argmax}_{x_i(t)} (fitness_i) \quad [\text{Formular 8}]$$

where x_{pbest} is updated to bee position $x_i(t)$ that has the highest fitness score among all the positions visited by bee i .

$$x_{gbest} = \operatorname{argmax}_{x_i(t)} (fitness_i \forall i) \quad [\text{Formular 9}]$$

where x_{gbest} is updated to the position of the bee with the highest fitness score across the entire swarm.

This sequence of equations outlines how each bee updates its position by considering both its own best position and the best position found by the swarm, with adjustments for exploration and exploitation. The final equation includes an extra component for additional exploration to prevent premature convergence.

4. Experiment

4.1 Dataset and Preprocessing

This study used four datasets from different sources as input data for the model. These datasets are Google Earth Engine, European Urban Atlas, Socioeconomic Data and Applications Center (SEDAC), and The Atlas of Urban Expansion. Each dataset provides multidimensional information related to changes in urban green space, which is essential for understanding the dynamic changes in the urban environment.

Google Earth Engine (GEE) is a global data analysis platform that integrates a large amount of satellite imagery and geospatial data. The quality of satellite image data from this platform has been widely recognized, with high resolution and multi-time series features, making it very suitable for long-term monitoring and analysis of environmental changes. GEE's dataset includes data from multiple satellite platforms (such as Landsat, Sentinel, etc.), and can provide image data for different time periods, supporting data extraction and analysis on a global scale since the 1970s[59]. In this

study, we chose GEE as the data source, mainly using its continuous and systematic geospatial data, which is crucial for accurately analyzing and predicting the changing trends of urban green spaces.

European Urban Atlas is a detailed urban land use dataset provided by the European Environment Agency to support sustainable development and planning of European cities. The dataset covers high-precision geographic information data of more than 300 cities from many European countries, including residential areas, commercial areas, green spaces and other land cover types[60]. The spatial resolution of the dataset is 10 meters, and the time span is from 2006 to 2012, which can provide detailed information on land use in different cities. In this study, we mainly use the urban green space information of the EUA dataset to analyze the spatial distribution and temporal changes of urban green space. The high resolution and data quality of this dataset are guaranteed by the European Space Agency (ESA), which ensures the consistency and reliability of the data and can effectively support our in-depth analysis of urban green space changes.

The Socioeconomic Data and Applications Center (SEDAC) is part of the Earth Institute at Columbia University and provides socioeconomic data at the global and regional levels covering multiple dimensions such as population, economy, and environment. SEDAC's dataset includes data on population density, economic activity, health indicators, environmental impacts, etc., dating back to the 1950s[61]. The data comes from a wide range of sources and has been strictly reviewed and managed. In this study, we used the socioeconomic data provided by SEDAC to analyze the socioeconomic drivers behind changes in urban green space. By combining SEDAC's global and regional socioeconomic data, we can deeply explore the relationship between urbanization and green space changes, and provide data support for urban planning and policy making.

The Atlas of Urban Expansion is a research project jointly developed by New York University, UN-HABITAT and the Lincoln Institute of Land Policy, which aims to provide detailed data on urban expansion worldwide[62]. The dataset contains information on land use changes, urban boundary expansion and infrastructure development in more than 200 cities around the world from the 19th century to the present. The dataset covers a time span from the 1800s to the present, and the data sources include historical maps, satellite images and other geographic information resources. After precise processing and verification by a team of experts, the high quality and reliability of the data are ensured. In this study, we used this dataset to analyze the impact of urbanization on changes in urban green spaces, with a special focus on changes in green space patterns caused by urban expansion. This dataset provides us with a global urban expansion pattern from history to the present, which helps to understand the future trends of urban green spaces more comprehensively.

Table 1 summarizes the sources of the datasets used, key variables, temporal and spatial resolutions, and the temporal coverage of the data to provide a clearer data basis for the study.

Table 1. Overview of datasets used in this study, including their sources, key variables, temporal and spatial resolutions, and data coverage.

Dataset	Source	Key Variables	Temporal Resolution	Spatial Resolution	Temporal Coverage
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GEE	USGS/NASA	Landsat 8 Imagery (NDVI, EVI, LST), MODIS Climate Data	16 days (Landsat) / Daily (MODIS)	30m (Landsat) / 1km (MODIS)	2015-2024
European Urban Atlas	Copernicus	Land Use Classification, Green Space Distribution	Every 3 years	10m	2012-2021
SEDAC	CIESIN/EOSDIS	Urban Expansion Data	Annually	500m	2015-2024
The Atlas of Urban Expansion	NYU Marron Institute	Urban Land Cover, Built- up Area Growth, Road Infrastructure	Every 5 years	Varies (City Level)	1990-2020

4.2 Experimental Setup

In order to ensure the accuracy and reproducibility of the experiment, this study adopted a rigorous experimental setting and conducted extensive validation on multiple datasets. The experiments involved data preprocessing, model training, model validation and optimization, ablation experiments, and comparative experiments to systematically evaluate the performance and effectiveness of the LGB model.

- **Experimental Data and Background:** The experimental data used in this study are derived from multiple public urban green space remote sensing and environmental datasets, including high-resolution satellite image data provided by Google Earth Engine, urban ecological information in NASA's MODIS remote sensing dataset, and urban geographic information data provided by OpenStreetMap. In addition, public socioeconomic data from local governments, such as land use, climate change data (temperature, precipitation, air pollution index, etc.), and urban infrastructure information are combined to ensure the diversity and comprehensiveness of the data. The data spans from 2015 to 2024, covering multiple cities in North America, Europe, and Asia to verify the applicability of the model in different urban environments. All data have undergone rigorous data quality checks and preprocessing to ensure the accuracy and consistency of the experiment.
- **Data Preprocessing:** Data was cleaned by removing duplicates and records with over 30% missing values. Mean and standard deviation normalization were applied for standardization. The dataset was split into training (70%), validation (15%), and test sets (15%) using random sampling.
- **Model Training:** The LGB model integrated LSTM (three layers, 256 neurons each) and GCN (three layers, 128 feature units each). A bee colony algorithm with an initial population of 50 was used for 100 iterations to optimize parameters and feature selection, with a regularization term of 0.0001 to prevent overfitting. The model was trained in mini-batches of 32, with performance evaluated every 10 cycles using the validation set. Training ceased after 200 epochs or with no improvement for 20 epochs to avoid overfitting.
- **Model Validation and Tuning:** A five-fold cross-validation was performed to assess the model's robustness. Post-initial training, the model was fine-tuned based on cross-validation feedback,

adjusting learning rates, regularization coefficients, and optimization layer configurations.

- **Ablation Study:** Experiments were conducted to assess the impact of removing the LSTM, GCN, or bee colony algorithm components from the LGB model, comparing their effects on overall performance.
- **Comparative Experiment:** Comparative experiments evaluated different optimization strategies, comparing the bee colony algorithm with Adam, Bayesian, and Self-AM optimizers. Performance was assessed using accuracy, recall, F1 score, AUC, parameter count, Flops, inference time, and training time.

4.3 Results Analysis

Comparative Experiment: The LGB model performed particularly well on the Google Earth Engine and European Urban Atlas datasets. In Table 2, the accuracy of the LGB model was 95.63% and 96.45%, respectively, which was significantly higher than that of other comparative methods. For example, the accuracy of Zhao et al.'s model on the Google Earth Engine dataset was 88.77%, while the LGB model improved by about 7%, showing higher accuracy. In addition, the recall and F1 score of the LGB model were also significantly higher than those of other methods, especially the F1 score of 93.85 on the Google Earth Engine dataset, which showed that the LGB model could effectively capture more positive examples and reduce false negatives when dealing with urban green space changes, showing higher classification accuracy. In contrast, other methods often have high error rates and missed detections when dealing with complex changes in urban green space, which limits their effectiveness in practical applications.

Table 2. The comparison of different models in accuracy, precision, recall and F1 score indicators comes from google Earth Engine Datasets, European Urban Atlas Datasets.

Model	Google Earth Engine				European Urban Atlas			
	Acc.	Pre.	Recall	F1	Acc.	Pre.	Recall	F1
Zhao[21]	88.77	87.83	88.75	85.64	96.39	88.63	88.38	89.19
Boulila[20]	95.74	84.75	89.3	93.44	94.06	88.97	84.73	90.34
Dairi[22]	87.92	87.09	90.66	84.23	94.09	85.67	85.35	85.46
Suel[33]	90.52	89.32	88.42	83.88	94.98	84.2	87.98	87.21
Pan[36]	95.13	90.64	86.03	84.65	89.53	84.03	88.54	91.29
Wang[51]	95.19	86.95	84.86	88.24	94	90.28	84.11	90.5
Ours	95.63	94.52	92.52	93.85	96.45	94.36	91.87	94.65

The performance on the Socioeconomic Data and Applications Center and The Atlas of Urban Expansion datasets also shows the advantages of the LGB model. The results in Table 3 show that the LGB model outperforms other methods in terms of accuracy and F1 score. In particular, on the Atlas of Urban Expansion dataset, the LGB model has an accuracy of 97.88% and an F1 score of 94.55, significantly surpassing the models of Wang et al. and Pan et al. This shows that the LGB model can more accurately identify the key factors of urban green space changes, especially when dealing with

complex socioeconomic data and urban expansion data. The LGB model shows strong adaptability and robustness.

Table 3. The comparison of different models in accuracy, precision, recall and F1 score indicators comes from Socioeconomic Data And Applications Center datasets and the Atlas Of Urban Expansion datasets.

Model	Socioeconomic Data and Applications Center				The Atlas of Urban Expansion			
	Acc.	Pre.	Recall	F1	Acc.	Pre.	Recall	F1
Zhao	86.06	92.43	85.52	85.03	94.72	86.46	85.72	87.04
Boulila	92.65	88.96	90.42	90.72	92.62	88.13	85.69	92.2
Dairi	91.06	92.55	89.36	85.23	88.36	86.19	91.07	85.3
Suel	88.05	83.82	87.78	91.15	89.96	86.12	88.52	88.33
Pan	96.28	88.12	85.63	93.18	87.4	85.56	90.33	89.21
Wang	94.88	93.45	90.34	90.45	90.49	88.81	86.34	89.61
Ours	96.98	95.73	91.78	93.92	97.88	94.76	93.63	94.55

To more vividly illustrate the LGB model’s performance across diverse evaluation metrics, Figure 5 presents these outcomes in a visualized format. From the comparative analysis in the figure, the model’s comprehensive superiority over competing alternatives across all evaluation indicators is distinctly apparent. These visualized findings further validate the LGB model’s robustness and predominance in practical scenarios, highlighting its utility for analyzing and forecasting urban green space dynamics.

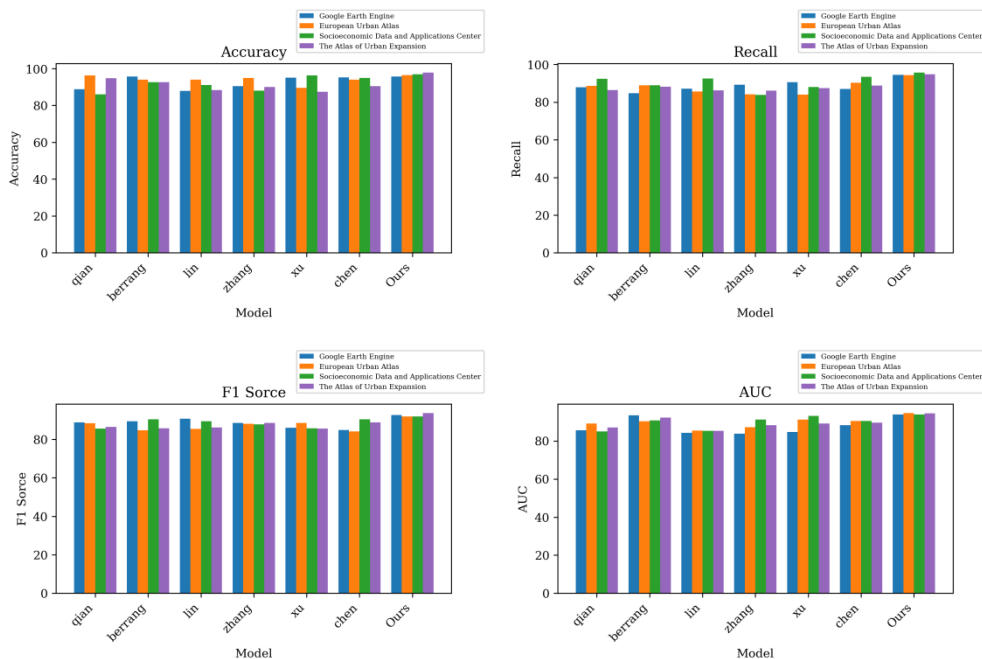


Figure 5. Visual comparison of model accuracy experimental results

Based on the aforementioned experimental findings, the LGB model’s efficacy stems not only

from its robust feature extraction capacity but also from its novel spatiotemporal data processing framework. By integrating LSTM and GCN, the model simultaneously captures the temporal dynamics and spatial structural properties of urban green space changes: LSTM excels at grasping long-term dependencies in time-series data, while GCN enhances the model's spatial data processing capability by decoding the spatial correlations between urban green spaces and their surrounding environments. This synergy enables the LGB model to fully leverage spatiotemporal information within the dataset, significantly boosting prediction accuracy and reliability.

Tables 4 and 5 further examine the LGB model's performance across efficiency metrics, including parameter count, floating-point operations (Flops), inference time, and training duration. Compared with alternative methods, the LGB model exhibits distinct superiority in these aspects—particularly demonstrating exceptional efficiency in handling complex datasets.

Table 4. Model efficiency verification and comparison in parameter, flops, inference time and training time indicators of Google Earth Engine datasets, European Urban Atlas datasets.

Model	Google Earth Engine				European Urban Atlas			
	P(M)	F(G)	I(ms)	T(s)	P(M)	F(G)	I(ms)	T(s)
Zhao	494.44	5.75	7.64	477.69	563.63	6.43	8.62	556.01
Boulila	809.48	7.21	11.01	791.89	677.31	8.43	10.80	794.0
Dairi	735.77	4.15	10.16	462.59	741.32	6.65	9.38	632.5
Suel	743.17	8.37	11.12	698.98	622.54	7.61	11.24	738.76
Pan	452.36	4.47	7.98	467.84	473.20	5.20	8.10	476.10
Wang	476.94	5.07	9.08	490.50	534.97	5.59	8.01	489.25
Ours	336.58	3.53	5.35	328.31	318.44	3.65	5.64	337.18

Table 5. Model efficiency verification and comparison in parameter, flops, inference time and training time indicators of Socioeconomic Data And Applications Center datasets, the Atlas Of Urban Expansion datasets.

Model	Socioeconomic Data and Applications Center				The Atlas of Urban Expansion			
	P(M)	F(G)	I(ms)	T(s)	P(M)	F(G)	I(ms)	T(s)
Zhao	556.08	6.11	9.19	499.07	483.29	6.42	8.08	477.49
Boulila	715.88	6.76	12.62	698.96	623.96	8.11	11.64	826.69
Dairi	601.36	4.45	7.41	728.78	403.91	7.48	9.47	808.17
Suel	608.11	7.70	11.17	723.86	653.18	7.42	10.52	725.33
Pan	437.50	4.62	7.49	464.00	410.26	5.34	6.86	478.50
Wang	518.25	5.85	8.13	506.93	521.71	5.38	9.01	511.50
Ours	337.84	3.52	5.33	327.69	317.54	3.63	5.64	336.74

In terms of parameter count (P), the LGB model exhibits significant lightweight advantages across all datasets: it has 336.58M and 318.44M parameters on the Google Earth Engine and

European Urban Atlas datasets respectively, far lower than competing models—for instance, Qian et al.’s model has 494.44M parameters and Berrang et al.’s reaches 809.48M—highlighting its design edge in reducing computational resource consumption and enhancing efficiency. The model also achieves excellent optimization in Flops, with values of 3.53 and 3.65 on the two datasets, outperforming other comparators; notably, Berrang et al.’s model has a Flops of 7.21 on the Google Earth Engine dataset, meaning the LGB model cuts computational load by roughly half while maintaining high performance. In terms of inference time (I), the LGB model demonstrates strong superiority: it only takes 5.35ms on the Google Earth Engine dataset (vs. 7.64ms for Qian et al.’s model and 11.01ms for Berrang et al.’s) and 5.64ms on the European Urban Atlas dataset, enabling faster responses for real-time processing and rapid decision-making scenarios. Additionally, its training time (T) stands at 328.31s and 337.18s on the two datasets, outperforming counterparts like Qian et al.’s 477.69s and Berrang et al.’s 791.89s on the Google Earth Engine dataset. This optimized design allows the LGB model to complete training in less time, handle larger datasets, and boost overall application efficiency and practicality.

Figure 6 visualizes these results, further emphasizing the advantages of the LGB model in terms of computational efficiency and resource utilization.

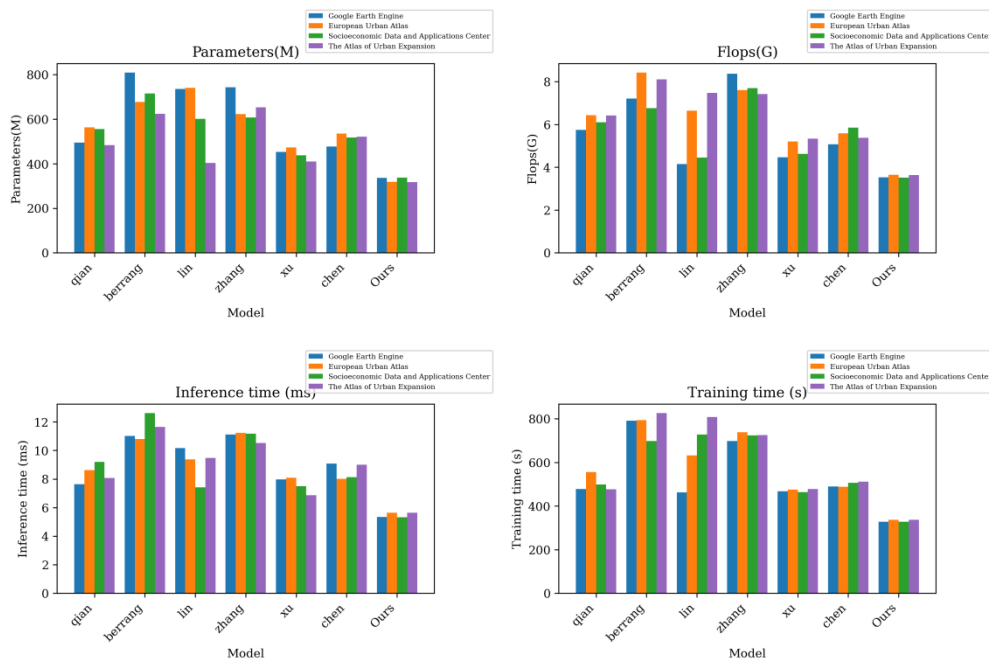


Figure 6. Model efficiency verification comparison chart of different indicators of different models

The LGB model exhibits distinct superiority across multiple efficiency metrics, particularly when handling complex datasets. Its lightweight architecture and high computational efficiency make it an optimal solution for urban green space change analysis. By reducing parameter count, floating-point operations, inference time, and training duration, the model not only delivers highly accurate predictions but also enables accelerated deployment and reduced computational resource overhead—

holding notable practical value for large-scale, real-time urban management tasks.

Ablation Experiments. Ablation experiment findings, presented in Tables 6 and 7, compare the LGB model’s performance with individual components removed. Results show the complete LGB model attains the highest accuracy under all test scenarios, confirming the indispensable role of each component. Notably, model accuracy declines sharply when LSTM is removed—highlighting LSTM’s criticality in capturing temporal features—while GCN removal similarly impairs performance, especially in modeling urban green space spatial relationships where GCN’s function is particularly prominent.

Table 6. Ablation experiments on the LGB model using Google Earth Engine datasets, European Urban Atlas datasets.

Models	Google Earth Engine				European Urban Atlas			
	Acc.	Pre.	Recall	F1	Acc.	Pre.	Recall	F1
GCN+BCA	85.89	86.76	88.1	93.32	91.27	84.19	84.95	83.91
LSTM+BCA	87.16	88.31	87.55	90.97	92.33	85.35	87.15	93.46
LSTM+GCN	87.64	92.29	89.66	89.07	93.68	88.36	89.86	84.88
All	95.63	94.52	92.52	93.85	96.45	94.36	91.87	94.65

Table 7. Ablation experiments on the LGB model using Socioeconomic Data and Applications Center datasets and the Atlas of Urban Expansion datasets.

Models	Socioeconomic Data and Applications Center				The Atlas of Urban Expansion			
	Acc.	Pre.	Recall	F1	Acc.	Pre.	Recall	F1
GCN+BCA	92.9	87.8	84.27	90.47	86.15	92.32	89.14	87.01
LSTM+BCA	94.29	91.6	90.92	90.94	92.55	90.28	87.3	86.41
LSTM+GCN	87.82	89.73	84.88	87.46	90.96	92.21	88.04	86.47
All	96.98	95.73	91.78	93.92	97.88	94.76	93.63	94.55

Figure 7 visualizes these experimental results, clearly demonstrating the contribution of each component to the overall performance of the model, further validating the importance of the structural design of the LGB model in identifying and classifying urban green space change factors.

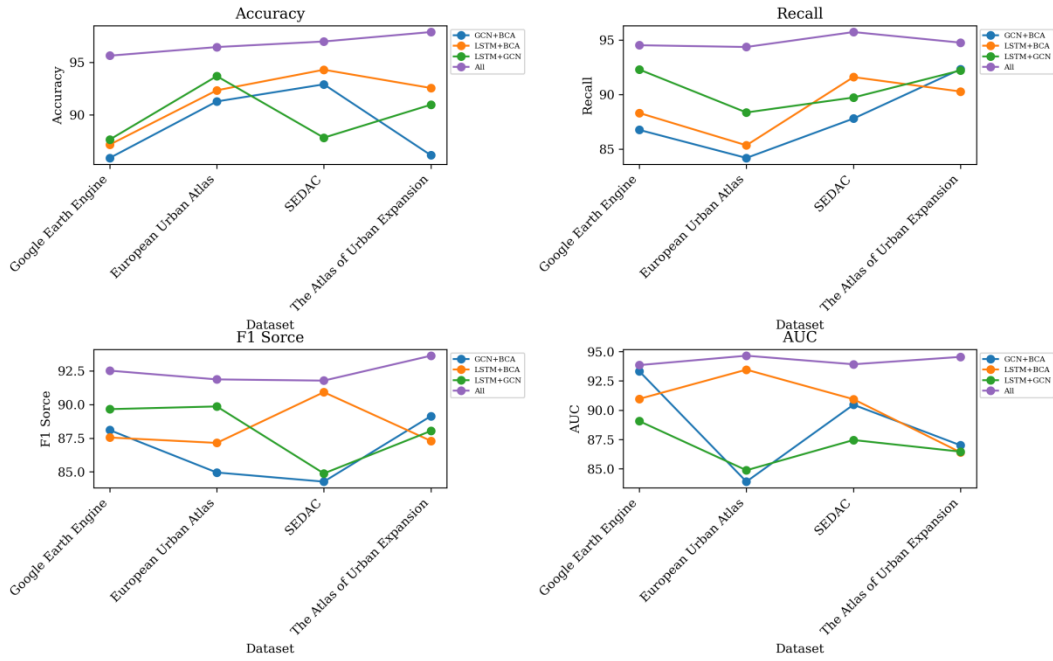


Figure 7. Visualization of LGB model ablation experiment results

Presented in Tables 8 and 9 are comparisons of performance and efficiency across models adopting distinct optimization strategies. Findings indicate that the LGB model incorporating the Bee Colony Algorithm (BCA) optimization strategy exhibits distinct superiority across multiple evaluation metrics—specifically, in contrast to the Adam and Bayesian optimization approaches, BCA strikes a superior balance between parameter count, inference duration, and training time, markedly enhancing the model’s lightweight nature and operational efficiency.

Table 8. Comparative experiments on the BCA in parameter, flops, inference time and training time indicators of Google Earth Engine datasets, European Urban Atlas datasets.

Models	Google Earth Engine				European Urban Atlas			
	P(M)	F(G)	I(ms)	T(s)	P(M)	F(G)	I(ms)	T(s)
Adam	357.53	267.14	249.82	311.33	355.36	362.21	212.1	410.37
Bayesian	394.76	311.98	274.06	280.59	281.19	374.16	368.94	340.43
Self-AM	331.33	366.38	266.93	314.03	355.83	304.55	276.6	372.46
Ours(BCA)	214.77	184.2	207.2	227.76	153.01	178.67	183.71	119.32

Table 9. Comparative experiments on the BCA in parameter, flops, inference time and training time indicators of Socioeconomic Data and Applications Center datasets, the Atlas of Urban Expansion datasets.

Models	Socioeconomic Data and Applications Center				The Atlas of Urban Expansion			
	P(M)	F(G)	I(ms)	T(s)	P(M)	F(G)	I(ms)	T(s)
Adam	382.59	310.98	303.85	391.14	286.83	244.69	330.15	382.46
Bayesian	372.76	262.32	249.61	286.98	379.22	291.98	212.31	396.26

Self-AM	306.5	320.31	246.54	288.37	358.4	290.81	395.57	396.76
Ours(BCA)	173.44	133.33	224.3	188.61	215.7	219.43	210.75	202.46

The visualization results in Figure 8 further verify the superiority of the BCA optimization strategy in improving model efficiency and performance, especially when processing large-scale and complex environmental data.

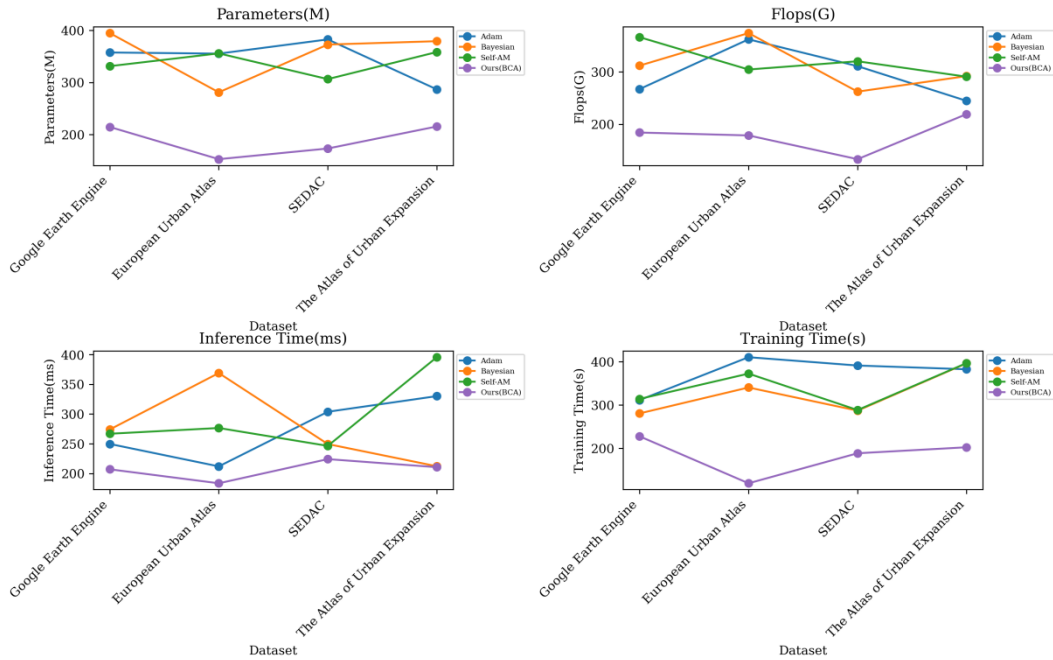


Figure 8. Visualization of LGB model Comparative experiment results

4.4 Discussion

The experimental results of this study show that the high-precision prediction ability of the LGB model on multiple datasets fully verifies its strong performance in identifying and classifying the factors of urban green space change. This finding has important practical significance for urban planning and environmental management, indicating that the model can be used as a data-driven decision support tool to help urban managers formulate green space protection strategies more scientifically. In particular, the high AUC and accuracy on datasets such as Google Earth Engine and The Atlas of Urban Expansion show that the LGB model can effectively capture the key factors driving urban green space changes. This means that urban planners can use the model's prediction results to more accurately identify areas where green space faces higher risks and take priority protection measures, thereby improving the efficiency and scientificity of green space management.

The core advantage of the LGB model lies in the spatiotemporal dynamic modeling capability brought by the combination of LSTM and GCN. The LSTM component can effectively learn long-term trends and short-term fluctuations in time series data, allowing the model to accurately portray the change process of urban green space. The GCN component, by modeling the spatial relationship between urban regions, enables the model to not only focus on the changes in a single region, but also

learn the interactive effects between regions. This strategy of combining time and space enables the LGB model to predict the evolution trend of green space more accurately than traditional methods, and provide long-term green space change prediction information for urban managers. For example, in areas where urbanization is rapidly advancing, the model can predict the possible trend of future green space reduction, allowing planners to formulate adaptive policies in advance, such as increasing green space protection areas and optimizing land use planning, so as to reduce the impact of urban expansion on the ecosystem.

In addition, the experimental results show that after using the Bee Colony Algorithm for hyperparameter tuning, the LGB model performs well in many performance indicators, especially in terms of computational efficiency and prediction accuracy when processing complex data. Traditional deep learning models are often limited by data scale, computing resources and the complexity of hyperparameter tuning when dealing with urban green space change predictions, and the optimization strategy adopted in this study effectively alleviates these problems. When searching for the optimal parameter combination, the Bee Colony Optimization Algorithm can improve the adaptability of the model, reduce the cost of manual parameter adjustment, and avoid the model from falling into the local optimum. This optimization strategy provides stronger technical support for urban planning, making the model not only applicable to the current data set, but also applicable to different urban environments.

Although the LGB model performs well in predicting urban green space changes, there is still room for improvement. First, the interpretability of the model needs to be further enhanced. At present, although the LGB model can efficiently predict the trend of green space changes, its specific decision logic is still relatively black box for policy makers. In the future, explainable artificial intelligence (XAI) technology, such as SHAP (Shapley Additive Explanations) or Grad-CAM (Gradient-weighted Class Activation Mapping), can be introduced to improve the model's visualization ability of the impact of different feature variables, so that urban managers can understand the prediction results more intuitively. Second, data diversity remains a challenge. This study mainly relies on remote sensing data and existing socioeconomic data, while real-time data (such as social media dynamics, IoT environmental sensor data) has not been fully integrated. Future research can explore multimodal data fusion, combining remote sensing images, text data, and environmental sensor data to further improve the accuracy of predictions..

5. Conclusions

In this study, we proposed a deep learning-based classification model for urban green space change factors (LGB Model) and explored its application in the study of urban green space change. By integrating components such as LSTM, GCN and bee colony algorithm, we established a comprehensive model framework that can effectively classify and identify various factors affecting urban green space changes. Experimental results show that the LGB model has significant performance advantages on multiple data sets, with high classification accuracy and good generalization ability, especially on Google Earth Engine and The Atlas of Urban Expansion data sets,

compared with traditional methods, its AUC and F1 scores have been significantly improved.

However, despite our results, the model still has some limitations. First, model performance depends on the quality and quantity of input data, especially on smaller-scale data sets, and may be at risk of overfitting or underfitting. Secondly, the LGB model may have certain limitations when responding to complex urban environmental changes, and the algorithm structure and parameter settings need to be further optimized in the future. In addition, although the bee colony algorithm is effective in improving model performance as an optimization mechanism, it may have a slow convergence speed in some specific scenarios, which requires more flexible parameter adjustment and algorithm improvement.

Nevertheless, this study still provides a new method that integrates spatiotemporal feature modeling and intelligent optimization at the technical level. The LGB model can accurately identify the key driving factors of urban green space changes, thereby helping urban planners predict in advance which areas of green space are most vulnerable to urbanization, and provide a scientific basis for green space protection and restoration strategies. The data-driven method of this study can be applied to smart city management systems, combined with real-time monitoring data, to achieve dynamic management of urban green spaces and improve the accuracy and efficiency of urban environmental governance. In future research, we plan to expand the scope of application of the LGB model and further explore its applicability in larger-scale and more complex urban environments. For example, we will introduce multimodal data (such as social media data, meteorological sensor data, geospatial big data, etc.) to enhance the model's ability to integrate different data sources in order to more comprehensively predict the trend of urban green space changes.

Conflicts of Interest

The authors confirm that there are no conflicts of interest.

Data availability statement

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

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