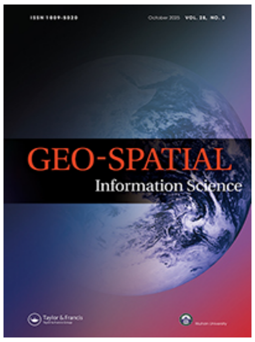

Geo-spatial Information Science

ISSN: 1009-5020 (Print) 1993-5153 (Online) Journal homepage: www.tandfonline.com/journals/tgsi20

Land cover simulation and analysis for the Greater Bay Area of China in the context of the 2035 development plan

Gomal Amin, Majid Nazeer & Man Sing Wong

GEO-SPATIAL INFORMATION SCIENCE
https://doi.org/10.1080/10095020.2025.2548360

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

Land cover simulation and analysis for the Greater Bay Area of China in the context of the 2035 development plan

Gomal Amin [a], Majid Nazeer [a] and Man Sing Wong [a,b,c]

[a]Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong, China; [b]Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Hong Kong, China; [c]Research Institute for Land and Space, The Hong Kong Polytechnic University, Hong Kong, China

ABSTRACT

This study focuses on the Guangdong-Hong Kong-Macao Greater Bay Area (GHM-GBA) for simulating Land Use Land Cover (LULC) considering the development plan for 2035. The research aims to quantify LULC change and simulate future LULC scenarios based on policy implications for 2035. In this study, Patch-Generating Land Use Simulation (PLUS) model was used to project future LULC under different scenarios. These scenarios include, Natural Increase Scenario (NIS), Ecological Conservation Scenario (ECS) and Urban Development Scenario (UDS). The China Land Cover Dataset (CLCD) from 2010–2022 along with eighteen driving factors for both historical and recent time periods and planning data were used to simulate the future succession of LULC patterns for 2035. This multifaceted methodology represents significant advancement over previous LULC simulation studies in GBA, which often relied on a more limited set of historical and development factors. The analysis revealed several key trends across the LULC categories. The simulation results (for 2022–2035) reveal that the cropland is expected to experience a modest increase of approximately 1.38%, indicating potential expansion of agricultural activities in future. However, the projections show declines in natural land covers, with forested areas decreasing by 2.44%, shrubland by 19.57%, grassland by 22.26%, water bodies by 9.15%, and barren land by 10.54%. Conversely, impervious surfaces are expected to increase by an average of 13.16%, suggesting urban development and infrastructure expansion. The findings provide valuable insights for regional environmental planning and sustainable development. The comparative analysis of the PLUS model's performance across different policy scenarios can aid in improving LULC change projections. A significant contribution of this current study is the comparative analysis of the PLUS model's performance under different policy-driven scenarios, which can aid in improving LULC simulations and projections.

ARTICLE HISTORY
Received 9 November 2024
Accepted 11 August 2025

KEYWORDS
PLUS model; land simulation; land use change; GBA; multi-scenario simulation

1. Introduction

Land Use Land Cover (LULC) is a fundamental aspect of human activity, shaping the natural and built environment in which we live, work, and interact (Zhao et al. 2023). LULC can be significantly modified by a variety of factors, including but not limited to rapid population growth, urbanization, intensive agricultural expansion, and the overexploitation of natural resources (Amin et al. 2024). Moreover, LULC patterns can aggravate resource and energy consumption and cause serious environmental problems (Cao et al. 2024), as it has potential to alter the carbon stocks and fluxes (Kang, Zhang, and Dang 2024), land surface temperature (Ghaderpour et al. 2024) and water resources (Entezami et al. 2024). Therefore, as global population continues to grow, the need to effectively plan, manage, and simulate LULC in multiple scenarios has become increasingly critical (Wang, Liu, et al. 2024; Wu, Wang, and Gou 2024). Importantly, LULC simulation and scenario analysis provide crucial insights to guide decision makers in navigating complex land use conversion and spatial planning. This helps governments to strategically allocate and govern land resources to balance social, economic, and environmental priorities (Amin et al. 2024; Chen and Ma 2023; Li et al. 2022; Wang et al. 2019).

Over the past few decades, China has achieved remarkable progress in its development, positioning the country as a global economic powerhouse. The "Framework Agreement on Deepening Guangdong-Hong Kong-Macao Cooperation in the Development of the Greater Bay Area" signed in 2017 by the National Development and Reform Commission and the governments of Guangdong, Hong Kong, and Macao (GHM) laid the foundation for strategic collaboration. In line with this agreement, the "Outline Development Plan for the Greater Bay Area" was promulgated in 2019. This comprehensive plan

CONTACT Majid Nazeer majid.nazeer@connect.polyu.hk

establishes key development areas and outlines the cooperative efforts aimed at fostering the integrated growth and sustainable development of the Greater Bay Area (GBA) for 2035 (Li 2021).

The Development Plan for GBA has a primary objective of promoting economic integration and development among the target core cities. This ambitious plan entails substantial infrastructure development, such as the construction of roads, railways, and ports, which has the potential to greatly impact the region's LULC pattern. Thus, to comprehend the dynamic process of Land Use Land Cover Change (LULCC), the utilization of LULC simulation models becomes crucial (Li et al. 2022; Tabassum et al. 2023). These models enable the examination of different scenarios and aid in the promotion of sustainable land use patterns that strike a balance between economic growth and environmental protection, especially during policy implementation (Guo et al. 2023).

Researchers have explored methods and models using remote sensing data to predict future LULCCs (e.g. Amgoth, Rani, and Jayakumar 2023; Shahi, Karimi, and Jafari 2020). These include single/quantity and hybrid/spatial simulation models. The former, such as Markov Chain (MC), Agent-Based Model (ABM), Cellular Automata (CA), regression analysis, and System Dynamics (SD) model, focus on quantifying land demand but neglect transformation rules and spatial distribution, making them insufficient for simulating complex surface evolution scenarios (Lin et al. 2023; Yang et al. 2023; Rahaman et al. 2022; Zhang, Kwan, and Yang 2023). To overcome these limitations, hybrid models have been proposed to meet the requirements of complex surface evolution simulations (Koko et al. 2023). Hybrid models leverage historical LULCCs and driving factors to estimate LULC demand and their distribution probabilities, hence, enabling the simulation of future spatiotemporal LULC patterns.

Examples of such hybrid models include CA-Markov, Patch-generating Land Use Simulation (PLUS), Conversion of Land Use and its Effects at Small extent model (CLUE-S), and Land Transformation Model (LTM) (Liang et al. 2021; Liu et al. 2017). Several regional studies have utilized these hybrid models to determine the future dynamics of LULC (Shahi, Karimi, and Jafari 2020; Wang, Guan, et al. 2023; Zhong et al. 2023). Among these, PLUS model has been widely employed in regional studies for a variety of applications such as to assess flood risk probability (Wang, Guan, et al. 2023), carbon storage simulation (Yue, Ji, et al. 2023), prediction of ecological carrying capacity, and for monitoring urban expansion (Yu, Zhao, et al. 2023).

In the context of GBA for instance, research has focused on ecosystem services assessment (Liao and Zhang 2023; Wang, Oguchi, and Liang 2023), climate risk assessment (Wang, Liu, et al. 2024), habitat quality (Wang, Oguchi, and Liang 2023), terrain gradient (Chen et al. 2023) and coastal vulnerability (Wang and Chen 2022) to simulate LULC scenarios for future. However, these or similar studies have not used the "Outline Development Plan for the GHM-GBA" as a reference, nor have they incorporated the spatial planning layers within their modeling approach specific to GBA. This represents a gap that the current study aims to address as a whole for future LULC scenario.

The GHM-GBA represents unique case study due to its rapid urbanization and significant infrastructure development. The 2019 Outline Development Plan for GBA puts forward the vision of transforming the GBA into a globally renowned urban cluster and a prime example of exceptional livability with high-quality development. Considering this strategic vision, it is crucial to conduct a comprehensive examination of the transformations in LULC patterns within the GBA, as well as simulate the potential future trajectory of LULC in light of relevant policies. However, previous LULC simulation and scenario analysis studies for GBA have largely overlooked the implications of this comprehensive development plan, instead focusing on understanding the drivers of urban expansion and habitat quality changes. Conducting research in the GBA will address the existing gap by explicitly aligning the LULC simulation with the strategic objectives outlined in the region's 2035 development plan (Li et al. 2022). Such an investigation can provide valuable insights into the potential influence of planned transportation networks, development zones, and urban expansion on the dynamics of land use and cover in the region.

Therefore, this study selects the GHM-GBA region as a case to investigate the projected LULCCs for the year 2035 under multiple scenarios aligned with the "Outline Development Plan for the GHM-GBA" policy document. Also, this study aims to incorporate the latest and historical factors to refine the probability of land use transitions and minimize errors in the overall simulation process. The objectives of this research are (i) to quantify the LULCCs that occurred in the GHM-GBA region from 2010 to 2022, (ii) to using PLUS model to simulate and analyze different future LULC scenarios under the influence of development policy, to provide valuable insights for decision making on sustainable land use planning and management.

2. Materials and methods

2.1. Study area

GBA is a city agglomeration consisting of nine cities, including Dongguan, Foshan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhuhai, Zhongshan, Zhaoqing, Hong Kong and Macao (Figure 1). With an approximate administrative land area of 57,000 km^2, it had a population of over 86 million in 2020 (Li, Chen, et al. 2023). Recognized as one of China's most economically advanced and densely populated urban agglomerations, the GBA recorded a GDP of USD 1668.8 billion in 2020, based on annual data from Guangdong Province, the Hong Kong Special Administrative Region Government (SARG), and the Macao SARG (Wang, Wu, et al. 2021).

2.2. Datasets

2.2.1. China Land Cover Dataset (CLCD)

Considering the characteristics of GBA as a mega-urban agglomeration, and to ensure high accuracy, we acquired the LULC data (2010–2022) from the annual China Land Cover Dataset (CLCD) (J. Yang and Huang 2021). The relevant data for CLCD was produced using the Landsat imagery for each period as the main data source at a spatial resolution of 30 m. According to the CLCD image classification, the LULC classes for the GBA region encompass Barren, Cropland, Grassland, Forest, Shrub, Water, and Impervious. These categories represent the various types of land cover observed in the region.

The CLCD used in this research has been widely adopted in various LULC simulation studies in China due to its high accuracy and comprehensive coverage (Fan et al. 2023; Ji et al. 2023; Zhao et al. 2023; Zhu et al. 2023). CLCD has been evaluated for its data quality in various studies which confirmed the overall accuracy could essentially reach about 76% (Zhao et al. 2023). Moreover, in its original paper the rate of accuracy for CLCD dataset was about 79.31%, which was greater than the mean accuracy of the MODIS (Moderate Resolution Imaging Spectroradiometer) land cover product (MCD12Q1), European Space Agency-Climate Change Initiative (ESACCI) land cover product, and GlobalLand30 datasets (Yang and Huang 2021). In the context of GBA, CLCD has been successfully employed for multi-scenario simulations which shows its high reliability and applicability for this research (Ding et al. 2022; Wu, Wang, and Gou 2024). Based on these studies, we are confident that the CLCD data is of sufficient quality and has suitability for the LULC simulation and scenario analysis undertaken in the study area.

2.2.2. Driving factors

Taking into account the data availability and a review of existing relevant studies (Guo et al. 2021; Huang et al. 2023; Li, Li, et al. 2023; Wang et al. 2022), 18 driving factors were selected from geographical, climatic, socioeconomic, location aspects (Table 1 and Figure 2). Among these driving factors, slope and aspect were derived using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM). The location factors for the years 2010 and 2022 were obtained from Open Street Map (OSM) archives. While the future planning data collected includes information on three factors, i.e. distance to expressway, distance to railroads, and airports.

3. Method

The method proposed in this work aims to simulate the LULC and spatial patterns by considering the influence of development plan of GBA for 2035 by employing the PLUS model (Figure 3). Moreover, as part of the preprocessing stage, all input data underwent projection transformation to ensure uniformity, aligning it with the desired coordinate system (WGS 1984 UTM Zone 49N). Subsequently, resampling

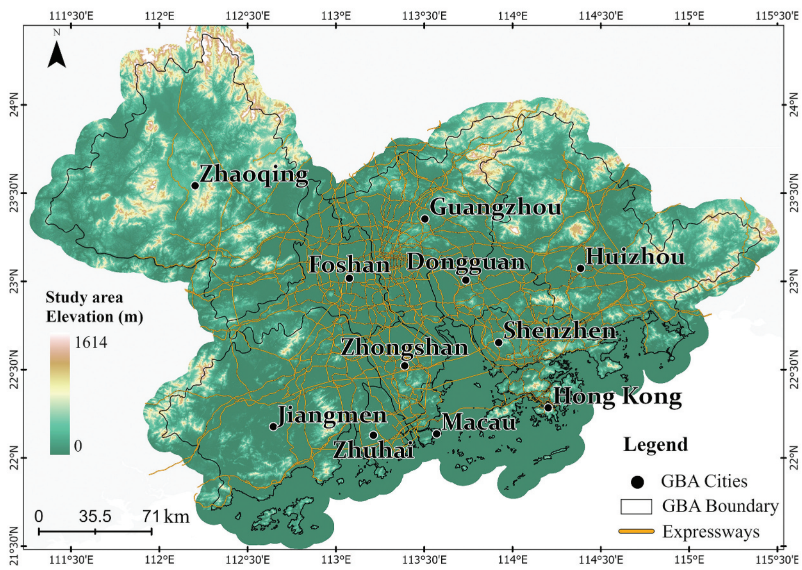

Figure 1. Map of study area with buffer of 10 km around the administrative boundaries of cities.

Table 1. Information of the input driving factors data. Where KD and ED represent the Kernal density and Euclidean distance, respectively.

Category	Spatial data	Analysis	Year	Original Resolution	Source
Geographical factors	Slope	–	2013	30 m	ASTER GDEM- USGS
	Aspect	–	2013	30 m	ASTER GDEM- USGS
	DEM	–	2013	30 m	ASTER GDEM- USGS
	Soil	–	1995	1 km	FAO -Harmonized World Soil Database
Climatic factors	Temperature	–	2010, 2022	0.5°	MERRA
	Precipitation	–	2010, 2022	0.05°	CHIRPS Pentad
Socioeconomic factors	population density	–	2010, 2022	100 m	GHS-POP-JRC
	GDP	–	2010, 2022	1 km	RESDC China
Location factors	Hotel distribution density	KD	2022	30 m	Open Street Map
	Supermarket density	KD	2010, 2022	30 m	Open Street Map
	Distance to city center	ED	2022	30 m	Open Street Map
	Distance to town center	ED	2022	30 m	Open Street Map
	Distance to expressway	ED	2010, 2022	30 m	Open Street Map
	Distance to waters streams	ED	2022	30 m	Open Street Map
	Distance to primary roads	ED	2022	30 m	Open Street Map
	Distance to railroad	ED	2022	30 m	Open Street Map
	Distance to bus stops	ED	2010, 2022	30 m	Open Street Map
	Distance from Airports	ED	2022	30 m	Open Street Map
Restricted areas	Open water/Inland water	–	2022	30 m	ESRI-ArcGIS Hub
	Nature reserves	–	2022	30 m	Protected Planet/HKSARG
	Protected areas	–	2022	30 m	Protected Planet/HKSARG
Planning data	Distance to expressway	ED	Planned	30 m	Bay area-HKSARG
	Distance to railroad	ED	Planned	30 m	Bay area-HKSARG
	Airports	ED	Planned	30 m	King & Wood Mallesons

techniques were applied to achieve a consistent grid size of 30 m. This uniform grid size, along with the matching row and column numbers, served as fundamental requirements for the subsequent modeling procedures. Multiple analyses such as, Euclidean Distance (for proximity analysis), kernel density (for hotel distribution density, and supermarket density data), and rasterization (for soil data) were also performed. These processing steps ensured the harmonization among all input data layers in terms of pixel size and coverage, enabling their seamless integration into the PLUS model.

Compared to other LULC simulation models, PLUS model distinguishes itself through the integration of multiple advanced components. These include a CA based on multi-type random patch seeds (CARS), the land expansion rule mining framework (LEAS), along with the multi-type stochastic seed mechanism. Through this integration, the PLUS model achieves highly accurate and detailed simulations of land use changes at patch level, as verified by previous studies (Wang and Chen 2022; Wang, Guan, et al. 2023). To address the allocation of optimal land demand for various scenarios in the year 2035, we employed both Linear Regression (LR) and Markov Chain (MC) models, leveraging historical data (2010–2022) and planning information to establish individual projections for the future demand matrix of each LULC class.

In this study, we commissioned a two-step approach to generate the LULC conversion patterns. Initially, 18 drivers were selected (Table 1) and the Random Forest (RF) model was used to predict the LULC conversion patterns across the study area. After establishing the land demand, we proceeded to implement the LULC conversion rules, which incorporated the neighborhood parameter and the land use conversion cost matrix. The neighborhood parameter played a crucial role in determining the ease of LULC type conversion, with higher values indicating a lower probability of such conversions occurring. This parameter helps capture the spatial relationships and influences between different land use types in the modeling process. These parameter values were defined based on the LULC transfer rate observed between 2010 and 2022, resulting in assigned values of 0.26, 0.30, 0.01, 0.01, 0.03, 0.01, and 0.40 for cropland, forest, shrub, grassland, water, barren, and impervious land use types, respectively. Moreover, we employed the cost matrix (Table 2) for each scenario, which restricted the conversion of LULC classes based on the values (1, 0). The value of "1" signifies that a particular LULC type can be transformed to another type, whereas a value of "0" shows that a specific LULC type cannot be transformed to another type. Additionally, in the current study, we converted protected areas, nature reserves, and open water/inland water to a raster with a value of 0, effectively treating them as restricted areas (Liang et al. 2018). This setting of restricted areas reflects the actual situation of the study area, where certain zones are designated as exclusion zones and land use conversion is prohibited (Peng et al. 2023).

Subsequently, we added the aforementioned parameters (Table 1) and the LULC data for GBA in PLUS model. To assess the model's performance, we conducted historical testing and optimization using LULC data from 2010 to 2022. Calibration of the PLUS model was considered successful when the Kappa Coefficient (KC) and Overall Accuracy (OA) for the year 2022 simulated LULC pattern exceeded 90% (Liu et al. 2024). With the

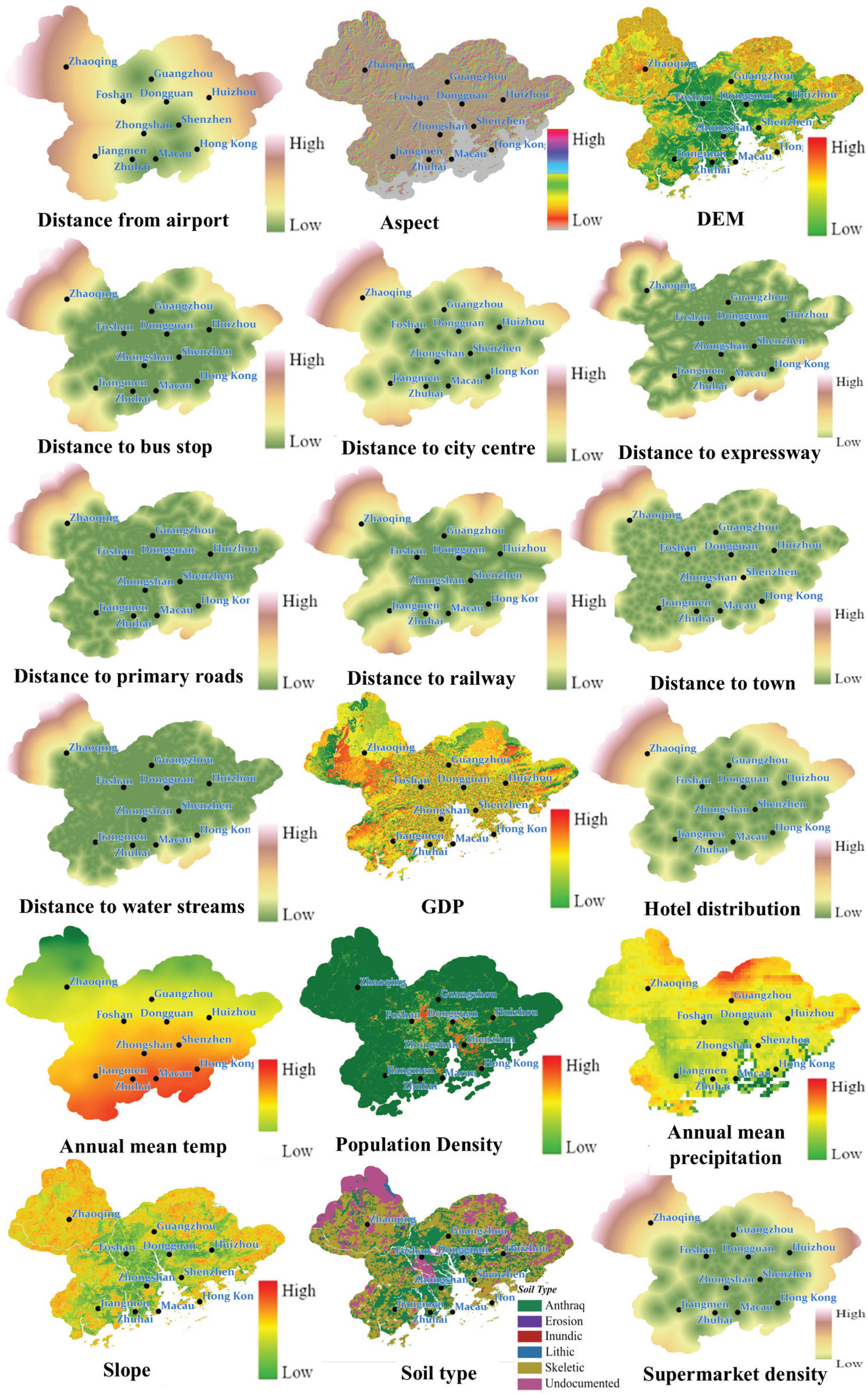

Figure 2. Driving factors used in the study.

best-fit model parameters in place, we proceeded to examine the future simulation of LULC patterns.

3.1. Patch-generating land use simulation model

As discussed, PLUS model is a powerful stand-alone simulation program that combines the LEAS module along with CA model by using multi-class random patch seeding (Liang et al. 2021). The spatial characteristics of land use expansion and the underlying driving forces at different stages of LULCC are evaluated. The model utilizes the RF algorithm to sample land expansion and calculate the probability of development for each land type. The overall probability of comprehensive LULCC is determined using an adaptive inertial competition mechanism known as roulette. The final LULC pattern is optimized by integrating random patch generation, a transition matrix, and a threshold decline

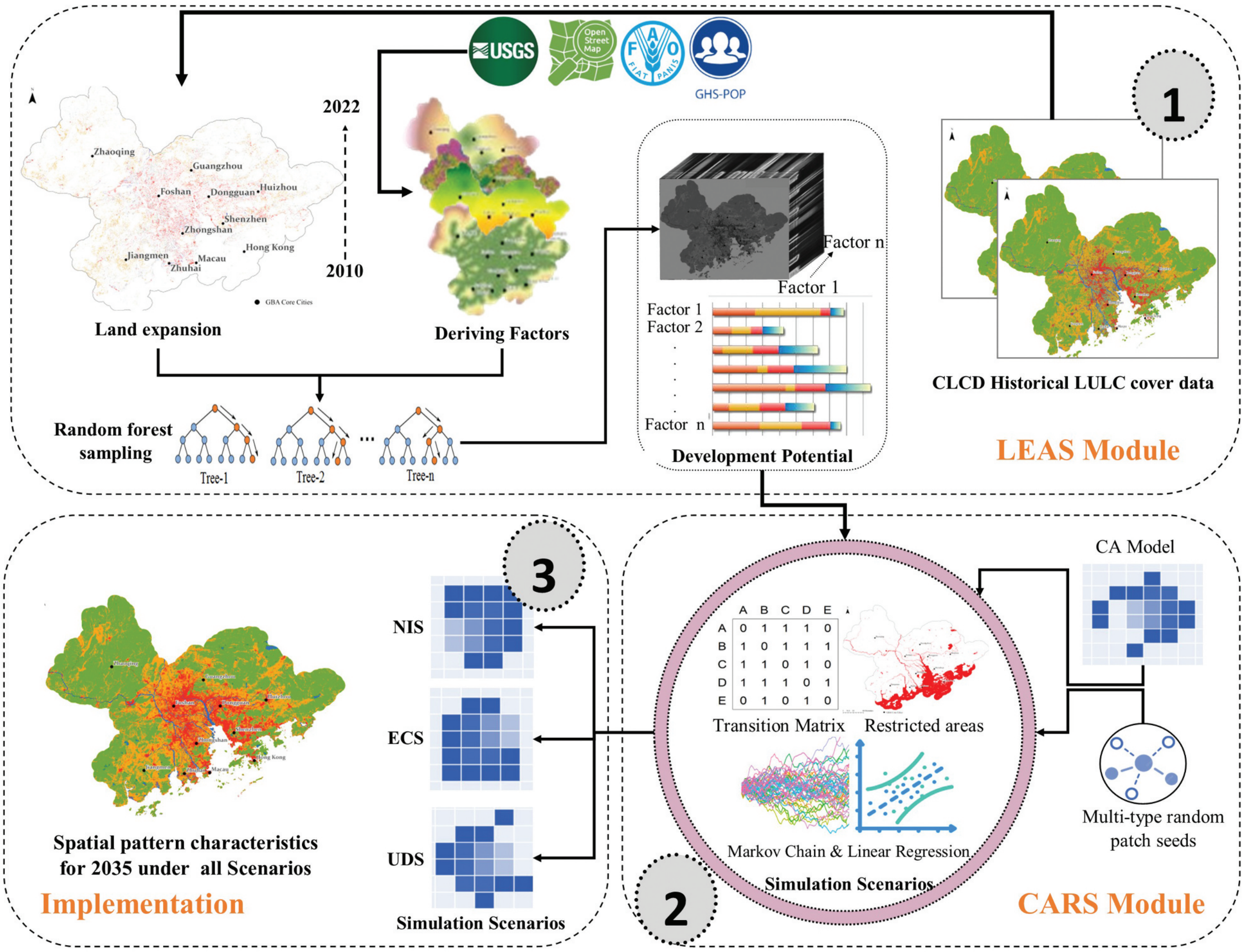

Figure 3. Simulation model framework based on PLUS for the GBA considering multiple scenarios.

Table 2. The cost matrix for three scenarios developed in this study.

	NIS							ECS							UDS						
Scenario Setting	Cl	Fr	Sh	Gl	Wr	Br	Ip	Cl	Fr	Sh	Gl	Wr	Br	Ip	Cl	Fr	Sh	Gl	Wr	Br	Ip
Cl	1	1	1	1	0	0	1	1	1	1	0	0	1	1	1	1	1	1	0	0	1
Fr	1	1	0	0	0	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	1
Sh	1	1	1	1	0	0	1	1	1	1	1	1	0	1	0	0	1	0	0	0	1
Gl	1	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	1	0	0	1
Wr	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1
Br	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0	0	0	0	1	1
Ip	1	1	1	1	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1

Note: The "NIS" stands for Natural Increase Scenario, "ECS" is Ecological Conservation Scenario and "UDS" is Urban Development Scenario. Where the values "1" or "0" denote whether cell conversion is allowed or not allowed, respectively. Cropland (Cl), Forest (Fr), Shrub (Sh), Grassland (Gl), Water (Wr), Barren (Br), and Impervious (Ip) represent the respective LULC type.

mechanism. This approach allows for a thorough and dynamic analysis of land use changes in the designated area.

3.1.1. LEAS (land expansion analysis strategy)

The LEAS module of the PLUS model employs the RF algorithm to analyze the factors influencing the expansion of individual LULC categories. It enables the estimation of probabilities associated with specific drivers contributing to land use expansion over time. The RF algorithm handles high-dimensional data, multicollinearity, and provides growth probabilities.

3.1.2. CA model based on multi-type random patch seeds (CARS)

The CARS module includes a patch-generation mechanism which integrates "top-down" factors, such as global land use demands, and "bottom-up" factors, including local land use competition (Liang et al. 2021). The CARS module also incorporates a stochastic seed mechanism that considers various factors, such as neighborhood weights, transformation cost matrices, and decreasing thresholds. This combination enables a comprehensive analysis of complex interactions in LULC dynamics, capturing the influence of different scales on LULCCs.

3.2. Scenario design

Three scenarios were developed for LULC simulation including the (i) Natural Increase Scenario, (ii) Ecological Conservation Scenario, and (iii) Urban Development Scenario. These scenarios depict potential futures for the GBA in which development is guided by a comprehensive land use framework, and they are closely aligned with the development strategies outlined in the 14th Five-Year National Strategy and GBA Development Outline Plan for 2035.

The process of developing these scenarios involved parameterization of the transition cost matrix within the PLUS model, where the assigned values reflect the hypothetical policies and priorities associated with each scenario, considering factors such as agricultural needs, ecological conservation, urban development goals, and preservation of key ecosystems.

3.2.1. Natural increase Scenario

In this scenario, the cropland conversion was permitted for agricultural support, while forest conversion was allowed to meet the increasing demand for land. Shrub conversion was allowed for diverse vegetation and wildlife habitat. Water body conversion was not allowed to protect aquatic ecosystems and water resources. Barren land conversion was permitted for various uses, including infrastructure. Impervious surface conversion (e.g. buildings, roads) was allowed for urban development and human activities. In the simulation, we assumed that the historical growth pattern would persist, which led to the absence of significant constraints or restrictions.

3.2.2. Ecological conservation Scenario

This scenario signifies a commitment to foster sustainable development practices and protecting the ecological environment for present and future generations. In this scenario, we implemented a reduction in the probability of converting forest and grassland into other types of land, while permitting the conversion from cropland, barren land, or impervious to forest, grassland, or water.

3.2.3. Urban development Scenario

In UDS, the priority was given to facilitate the economic growth of urban areas by expanding the construction land. To achieve this, we permitted the conversion of cropland, forest, grassland, or water into impervious category. Additionally, we decreased the likelihood of conversion from built-up areas to any other land types. This scenario reflects a concentrated emphasis on urban development, where the preservation of impervious surfaces such as buildings and roads take precedence over the preservation of other LULC types.

4. Results

4.1. Model validation and testing

The PLUS model implementation consisted of two simulation periods: model calibration and validation, and scenario simulation. The model was calibrated and validated from 2010 to 2022 to assess the performance of the Random Forest Classifier (RFC) and to ensure accurate simulation results. Following this, the scenario simulation was conducted specifically for the period from 2022 to 2035, utilizing the calibrated model parameters determined through a trial-and-error method (Liang et al. 2021). This phase ensured that the model produces reliable and precise results.

The two trials, Trial#1 and Trial#2 were conducted with varying parameter values (Table 3), except for the neighborhood cell size and mTry value which correspond to number of features for training the RF were kept constant. In Trial#1, the model was configured with 20 trees, a sampling rate of 0.01, and a thread value set at 1. This configuration resulted in a KC of 0.82 and an OA of 0.89, indicating a relatively good performance. However, in Trial#2, certain adjustments were made to enhance the modeling of LULC dynamics. Such as, the number of RF trees were increase to 50, allowing for more comprehensive and refined analysis. Additionally, the sampling rate was adjusted to 0.05 (5%), indicating a denser data collection, and the number of threads used for the simulation was also reduced to 1.

The results of Trial#2 demonstrated a significant improvement in performance compared to Trial#1. The model achieved an OA of 0.98 and KC of 0.96 during calibration, indicating higher accuracy and agreement with actual data. This improvement can be attributed to the increased number of trees and thread values in the model, which allowed for a more thorough exploration of the parameter space and a better representation of the underlying dynamics. These findings also highlight the importance of parameter selection in land simulation models, emphasizing the need for careful consideration and optimization to achieve the best possible results.

The validation results (Figure 4) show the model's robust performance in predicting various land cover classes. Cropland classification achieved a high

Table 3. Comparison of parameter configurations in Trial#1 and Trial#2 for PLUS model.

Module	Parameters	Trial#1	Trial#2
LEAS	Uniform sampling	Yes	Yes
	Forest regression trees	20	50
	Sampling rate	0.01	0.05
	mTry	18	18
	Thread	3	1
CARS	Neighborhood size	3	3
	Patch generation threshold	0.2	0.5
Accuracy	OA	0.89	0.98
	KC	0.82	0.96

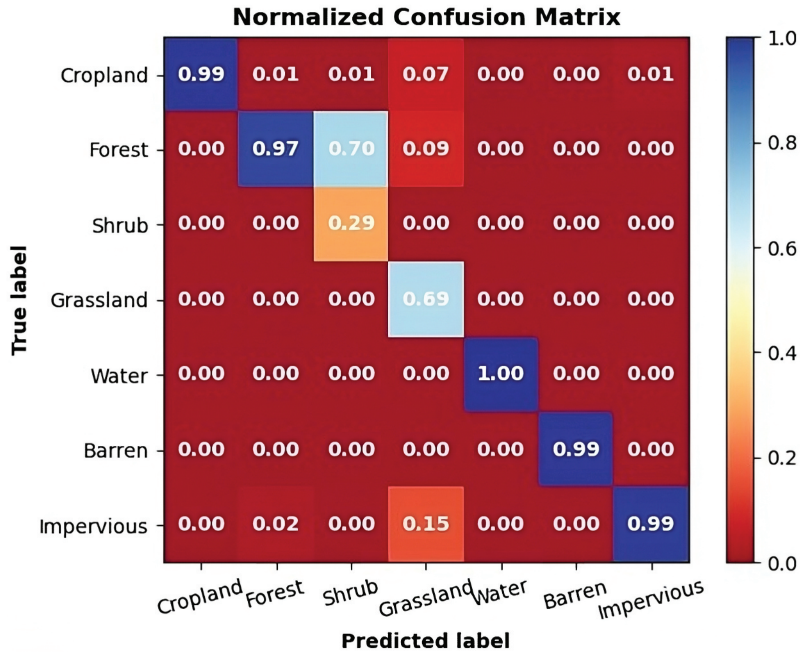

Figure 4. Confusion matrix of the predicted (simulated) land use pattern versus the true (actual) pattern in 2022 for trial#2.

normalized accuracy of 0.99, while the model's forest and barren class prediction exhibited equally strong results, reaching a normalized accuracy of 0.99. Furthermore, the model displayed commendable accuracy in differentiating between shrub and grassland classes, with values of 0.98 and 0.99, respectively. Remarkably, the model attained perfect accuracy in predicting water, as indicated by a value of 1.00 in the corresponding diagonal elements. The impervious class also registered a relatively higher accuracy of 0.86. The model achieved a KC of 0.96 and an OA of 97.93%, demonstrating its higher accuracy in simulating future land cover types.

Figure 5 shows the visualization of the land use pattern for the year 2022, depicting both the actual (Figure 5(a)) and the simulated LULC (Figure 5(b)). By comparing these two figures, it becomes possible to assess the accuracy and effectiveness of the simulation in capturing the real-world land use dynamics. This visualization aids in evaluating the model's performance and provides valuable insights into the simulated land use pattern for the specified year.

Table 4 displays the evaluation metrics for different LULC categories, namely cropland, forest, grassland, shrub, barren land, water, and impervious areas. The metrics include the Root Mean Square Error (RMSE) and the Out-of-Bag RMSE (OOB RMSE). The RMSE values indicate the average prediction error for each land cover category, with lower values indicating higher accuracy, while OOB RMSE values represent the prediction error for the out-of-bag samples.

The simulated LULCC model for 2022 demonstrated favorable performance, with lower errors observed for forest and shrubland classes compared to cropland. The RMSE analysis indicated that the model achieved relatively low errors for specific land use classes. The cropland class had RMSE of 0.13, suggesting a moderate level of error in predicting this land use category. The Forest class exhibited a slightly better performance than Cropland with RMSE of 0.10, indicating a relatively lower level of error in predicted forested areas. Notably, the Shrub class demonstrated the highest accuracy, indicated by RMSE of 0.00, signifying precise prediction of shrubland. Similar trends were observed in the OOB RMSE metric, where the cropland class had the highest value of 0.38, indicating a larger margin of error. The forest class showed a lower prediction error with an OOB RMSE of 0.30. Once again, the shrub class exhibited excellent performance with an OOB RMSE of 0.01, indicating high accuracy in predicting shrubland.

4.2. *Spatiotemporal change in LULC (2010–2022)*

The land use dynamics and changes in GBA for different categories were analyzed using classified images acquired from the CLCD, spanning from 2010 to 2022 (Figure 6(a)). The time-series analysis of each LULC showed that the cropland exhibited a consistent upward trend, expanding from 16,522.5 km^2 in 2010 to 17,394.94 km^2 in 2022. This increase reflects the expansion of agricultural activities and potentially indicates shifts in land management practices or changes in land-use policies.

In contrast, the forest category demonstrated a slight decline in area, decreasing from 39,549.74 km^2 in 2010 to 38,719.16 km^2 in 2022. This reduction

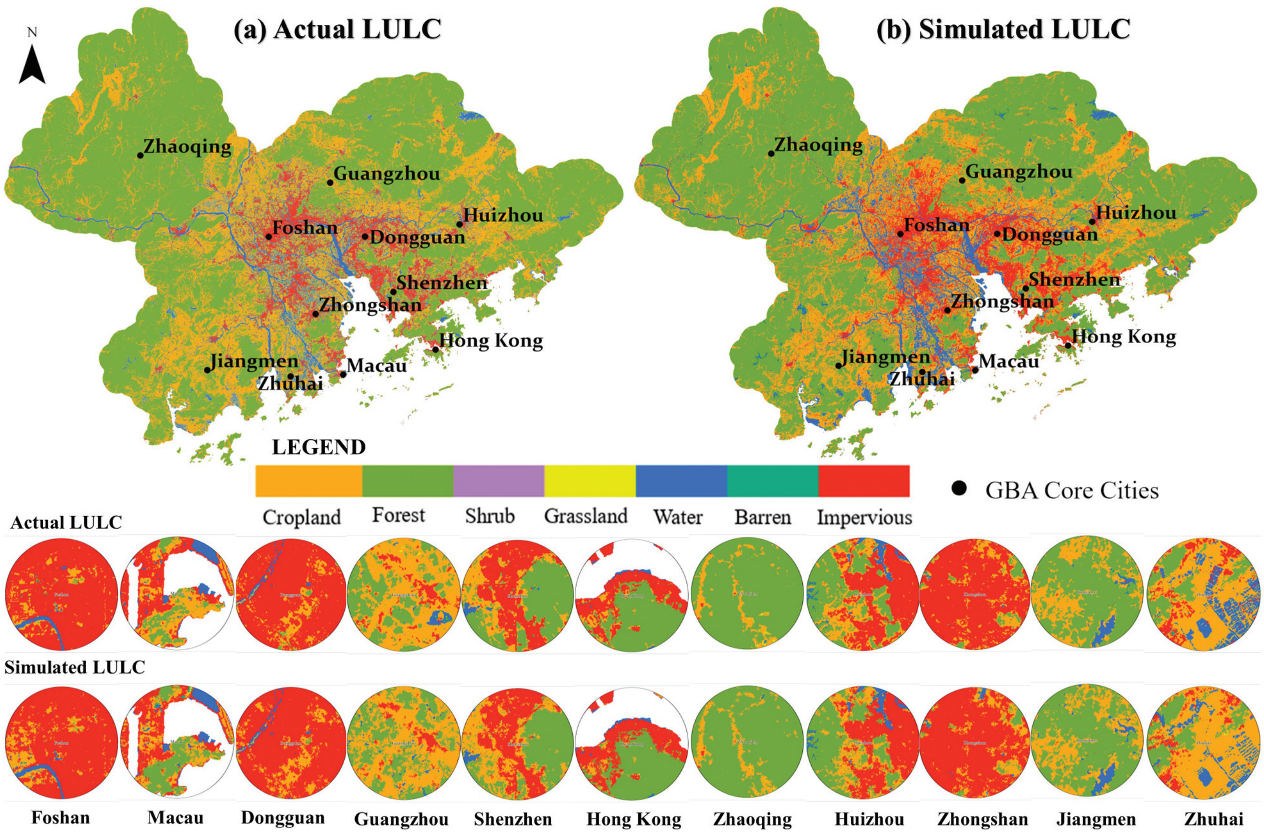

Figure 5. Visualization of land use pattern for the year 2022 with (a) actual LULC and (b) simulated LULC. The circular snippets show the zoomed area of each city center between actual and simulated image.

Table 4. Evaluation metrics for model validation.

Evaluation metric	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
RMSE	0.13	0.10	0.00	0.02	0.04	0.01	0.09
OOB RMSE	0.38	0.30	0.01	0.05	0.11	0.04	0.26

may be attributed to factors such as deforestation, urbanization, or natural disturbances. The shrub category experienced a substantial decrease in area, declining from 16.90 km^2 in 2010 to 7.11 km^2 in 2022 (−58%). This significant reduction raises concerns about the loss of shrubland habitats, which play crucial roles in supporting biodiversity, soil stabilization, and carbon sequestration. Grassland areas also showed a consistent decreasing trend, with the area decreasing from 117.77 km^2 in 2010 to 36.39 km^2 in 2022 (−69%). This decline in grassland area may be attributed to land-use changes, conversion to other LULC types, or alterations in agricultural practices.

Contrarily, the Barren category exhibited a minimal change, shifting from 19.69 km^2 in 2010 to 20.18 km^2 in 2022 (2%). While the area remained relatively constant, it is important to investigate the underlying reasons for this barren land and assess whether it represents degraded or unproductive areas. Finally, the Impervious class, which includes urban and built-up areas, demonstrated a steady growth, increasing from 5,877.64 km^2 in 2010 to 7,276.10 km^2 in 2022 (24%). This expansion reflects urbanization and infrastructure development, with potential implications for land fragmentation, habitat loss, and changes on local scale.

The results (Figure 6) provide some insights–the cropland category demonstrated a consistent expansion conversely the forest and shrub categories exhibited declines, raising concerns about deforestation and habitat loss. While water bodies and barren land showed a relatively stable or minimal changes as compared to the impervious LULC which increased in area over the time suggesting urbanization and infrastructure growth.

4.3. Exploring the driving forces of LULC

The research utilized the PLUS model with the LEAS module to examine the relationship between different LULC and the driving factors behind them. Figure 7 illustrates the outcomes of these influencing factors that shaped LULCC as well as expansion in the GBA from 2010 to 2022. It also provides a visual representation of the impact and significance of these diverse factors on the growth of each LULC type. It was observed that the variables with relatively higher importance across

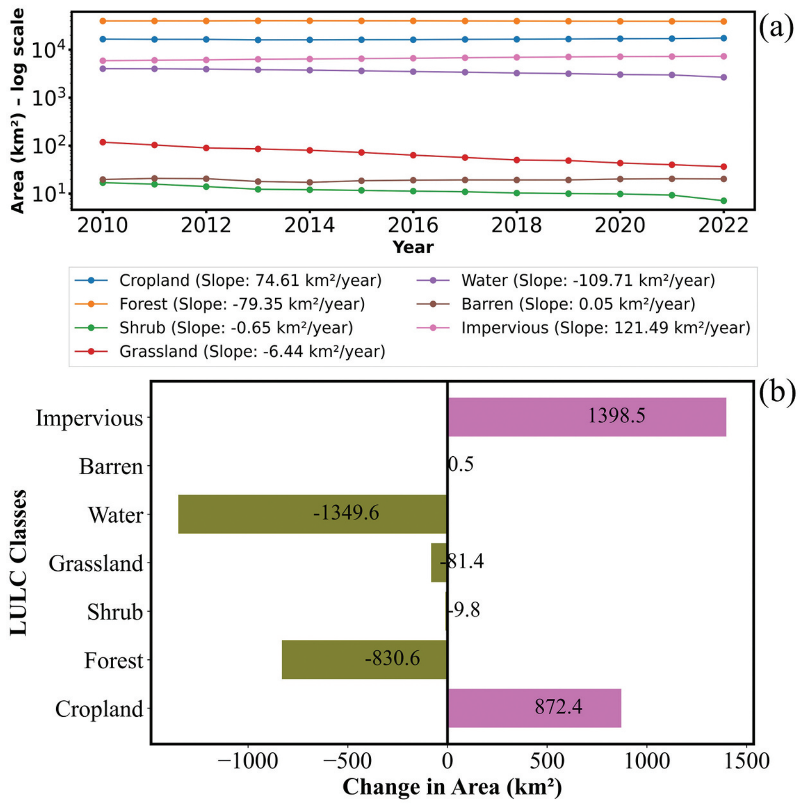

Figure 6. (a) Distribution of land cover classes of GBA from year 2010–2022. (b) Change in LULC area (km^2) between the year 2010–2022. Where olive and orchid color bars indicate decrease and increase in LULC class area, respectively.

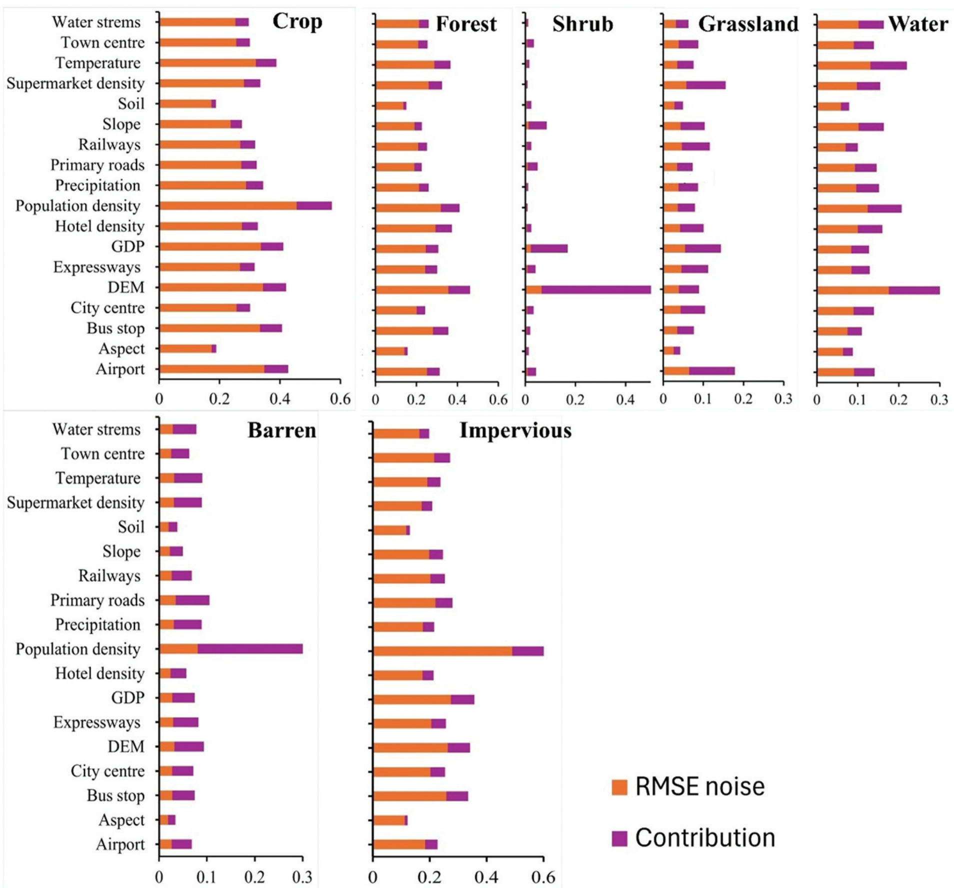

Figure 7. The relative importance and contribution of driving factors in land expansion and growth in GBA between the year 2010–2022.

multiple LULC type include population density, DEM, and GDP. Population density stands out as a significant factor for cropland, forest, grassland, barren land, and impervious surfaces, indicating that the density of the population in an area has a considerable influence on the growth and distribution of these land covers. Moreover, the population density emerges as the most influential factor with a value of 0.18, indicating its significant impact on the growth and distribution of impervious surfaces. Other factors such as distance to bus stop, DEM, GDP, distance to expressway, distance to railroad, distance to primary roads, distance to town center, slope, temperature, and soil also contributed to impervious LULC to a lesser extent, with importance values ranging from 0.01 to 0.08. Factors like aspect, precipitation, supermarket density, hotel distribution density, and distance to water streams have relatively lower importance, with values ranging from 0.03 to 0.08, suggesting a minimal influence on the overall growth and distribution of impervious land cover.

4.4. Simulation of LULC for future scenarios

We simulated the future LULC for three different scenarios (i.e. ECS, NIS, and UDS) under the influence of GBA development plan for 2035 based on MC (Figure 8(a,c,e)) and LR (Figure 8 (b,d,f)) models. The results of the LULC analysis for the year 2035 (Table 5), based on the both models, indicate the predicted values for various LULC categories.

The results of the LULC analysis for the year 2035, based on the Markov Chain model, provide valuable insights into the predicted distribution of various land cover categories for each scenario. Cropland, representing cultivated agricultural land, is projected to cover 17,624.41 km^2 in the ECS 17,624.83 km^2 in the NIS, and 17,622.19 km^2 in the UDS. These values suggest relatively stable cropland across the scenarios. Forest is estimated to occupy 37,996.27 km^2 in the ECS 37,996.18 km^2 in the NIS, and 37,998.34 km^2 in the UDS. Shrubland is projected to cover 6.67 km^2 in the ECS, 3.75 km^2 in the NIS, and 6.85 km^2 in the UDS. These values suggest variability in the extent of shrubland, particularly between the NIS and other scenarios. Grassland is estimated to occupy 30.63 km^2 in the ECS, 27.09 km^2 in the NIS, and 28.84 km^2 in the UDS. These values indicate a potential decrease in grassland area, particularly in the NIS. Water bodies, including lakes, rivers, and reservoirs, are projected to cover 2,343.74 km^2 in the ECS, 2,647.74 km^2 in the NIS, and 2,289.12 km^2 in the UDS. Barren land is estimated to occupy 15.42 km^2 in the ECS, 15.38 km^2 in the NIS, and 15.41 km^2 in the UDS. These values indicate a relatively stable extent of barren land across the scenarios. Moreover, impervious surfaces, such as buildings, roads, and pavement, are projected to cover 8,084.03 km^2 in the ECS, 7,786.21 km^2 in the NIS, and 8,140.41 km^2 in the UDS.

Furthermore, the results of the LULC simulation analysis using the LR model for various scenarios suggest that the estimated area of cropland remains relatively stable, with values of 17,644.14 km^2 in the ECS 17,645.64 km^2 in the NIS, and 17,643.14 km^2 in the UDS. Similarly, the forested areas show consistency, occupying 37,608.52 km^2 in the ECS 37,606.69 km^2 in the NIS, and 37,608.97 km^2 in the UDS. However, the extent of shrubland exhibits variability, with 6.87 km^2 in the ECS, 2.06 km^2 in the NIS, and 6.93 km^2 in the UDS. Grassland shows potential differences, with 30.39 km^2 in the ECS, 24.80 km^2 in the NIS, and 28.11 km^2 in the UDS, indicating minor changes. Water bodies are projected to cover 2,343.77 km^2 in the ECS, 2,647.29 km^2 in the NIS, and 2,280.65 km^2 in the UDS. Barren land remains relatively stable, with values of 20.04 km^2 in both the ECS and NIS, and 20.03 km^2 in the UDS. Impervious surfaces, representing urban and developed areas, are estimated to occupy 8,447.43 km^2 in the ECS, 8,154.64 km^2 in the NIS, and 8,513.34 km^2 in the UDS.

A comparison between LR and MC models reveals interesting differences (Table 5) for land cover projections. The LR model shows relatively consistent estimates for cropland, forests, barren land, and impervious surfaces across the scenarios. In contrast, the MC model predicts slightly lower cropland areas in the UDS and higher shrubland areas in the NIS compared to the LR results. The LULC projections based on the LR model show cropland area increasing by 1.32% to 1.44% across the scenarios, while forest area is expected to decline by −2.87%. Shrubland is estimated to decrease, with notable reductions of −3.38% in the ECS and −71.03% in the NIS. Grassland area is anticipated to decrease, with the largest decline of −31.85% in the NIS. Water body area is projected to decrease in the ECS (−11.47%) and UDS (−13.85%) scenarios, while remaining stable in the NIS. Barren land area is expected to see the most substantial reduction of −23.78% in the NIS, and impervious (built-up) area is predicted to increase between 12.07% and 17%. The MC model projections exhibited similar trends, corroborating the expected changes in land cover across the different categories and scenarios.

5. Discussion

5.1. Analysis of driving factors and their influence on LULCC in GBA

The study utilized LEAS module within the PLUS model to investigate the relationship between LULCC and the driving factors behind them in GBA from 2010

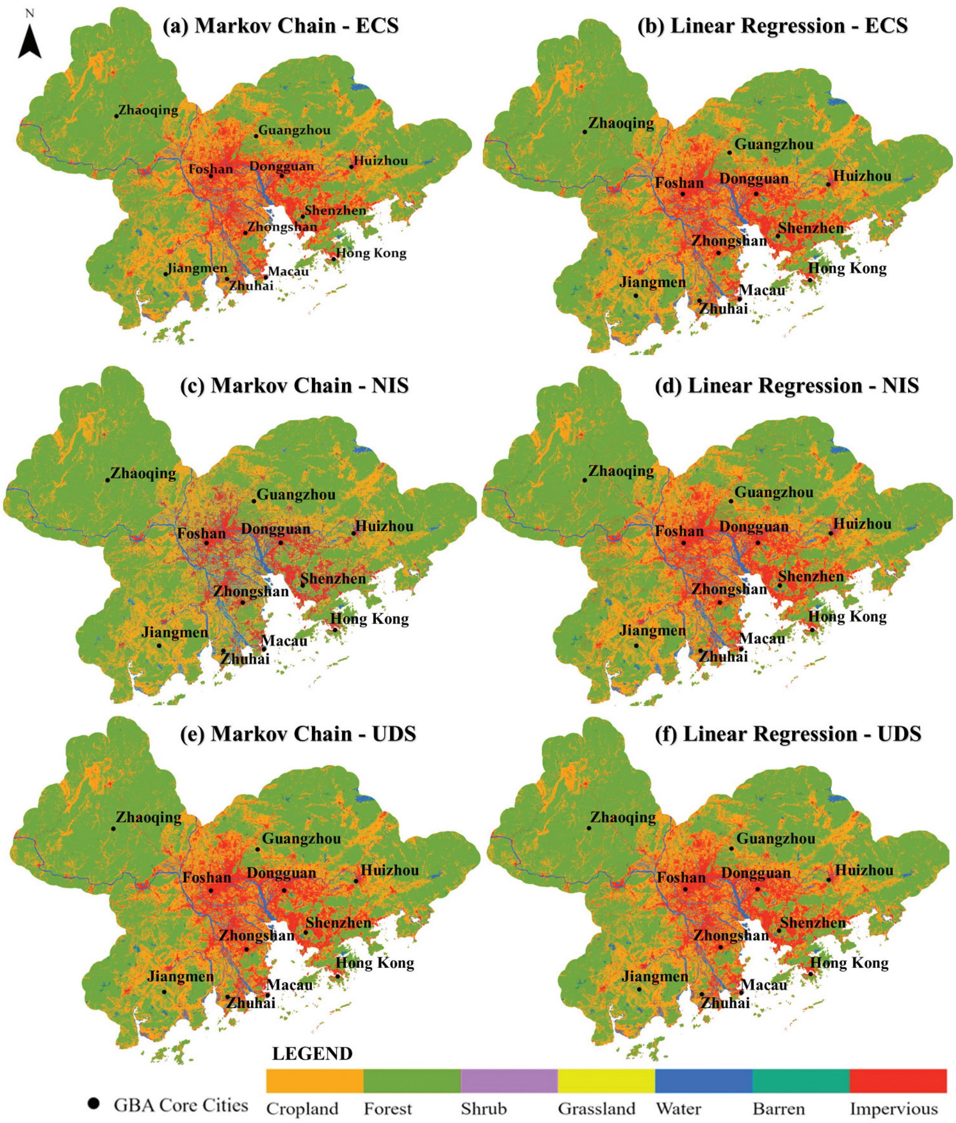

Figure 8. Spatial distribution of simulated LULC in 2035 under three scenarios developed for GBA based on Markov Chain (a, c, and e) and Linear Regression (b, d and f) for ECS, NIS, and UDS.

Table 5. Predicted LULC areas (km^2) in 2035 under different scenarios based on Linear Regression & Markov Chain model, and percentage difference in LULC area between 2022–2035 for ECS, NIS, and UDS.

Model	Scenario	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Linear Regression	ECS (km^2)	17,644.14	37,608.52	6.87	30.39	2343.77	20.04	8447.43
	ECS (%)	1.43	−2.87	−3.38	−16.48	−11.47	−0.68	16.1
	NIS (km^2)	17,645.64	37,606.69	2.06	24.8	2647.29	20.04	8154.64
	NIS (%)	1.44	−2.87	−71.03	−31.85	0.00	−0.68	12.07
	UDS (km^2)	17,643.14	37,608.97	6.93	28.11	2280.65	20.03	8513.34
	UDS (%)	1.43	−2.87	−2.53	−22.75	−13.85	−0.73	17.00
Markov Chain	ECS (km^2)	17,624.41	37,996.27	6.67	30.63	2343.74	15.42	8084.03
	ECS (%)	1.32	−1.87	−6.19	−15.82	−11.47	−23.58	11.1
	NIS (km^2)	17,624.83	37,996.18	3.75	27.09	2647.74	15.38	7786.21
	NIS (%)	1.32	−1.87	−47.26	−25.55	0.02	−23.78	7.01
	UDS (km^2)	17,622.19	37,998.34	6.85	28.84	2289.12	15.41	8140.41
	UDS (%)	1.31	−1.86	−3.66	−20.74	−13.53	−23.63	11.88

to 2022 (Figure 7). Based on the analysis of the contributing factors to changes in each land use class, certain variables demonstrate relatively higher importance across multiple land use types. These variables include population density, DEM, and GDP, which is consistent with previous findings (Guo et al. 2023).

From the driving factors, population density emerges as a significant factor influencing the changes in cropland, forest, grassland, barren land, and impervious surfaces. Higher population densities drive urbanization and agricultural expansion, leading to the conversion of natural land covers into impervious surfaces. Furthermore, the significance of GDP for certain land cover types, such as shrubland, grassland, impervious surfaces, and water, suggests that economic factors and development patterns play a substantial role in shaping land use distribution. As economic growth drives changes in land use, it is crucial to integrate environmental considerations into economic planning processes. This can be achieved through the implementation of green infrastructure initiatives, conservation programs, and smart growth strategies which balance the economic development with the environmental protection. Moreover, the elevation of the terrain, as represented by DEM, emerges as a critical factor influencing the presence and extent of forest, shrubland, water, and impervious surfaces. Areas with high elevations may be more suitable for forest conservation, while low-lying areas may be more prone to impervious surface expansion, as previously observed by He et al. (2023).

Furthermore, this study highlights the varying influence of environmental variables on land cover patterns. Factors such as temperature, distance to primary roads, distance to expressways, distance to railroads, and hotel distribution density exhibit moderate importance in shaping LULC patterns. These variables can be used to identify areas susceptible to specific LULC types and guide targeted conservation efforts or infrastructure planning. However, their overall influence is secondary to population density, economic factors, and elevation. Therefore, a comprehensive understanding of multiple factors is crucial for effective land use management based on promulgation.

5.2. Comparison of simulated LULC under different land demands and scenarios

Comparison between LR and MC models reveals important insights into the anticipated trends in LULC categories. The results indicate an expected increase in cropland area across all scenarios, emphasizing the significance of agricultural activities in the region (Chen et al. 2023; Li et al. 2022; Li, Huang, et al. 2023; Wang, Cong, et al. 2021). However, both land demand models predict a decline in forested areas, raising concerns about the loss of forest cover and the associated ecological services. Shrubland and grassland areas are also projected to decrease, warranting attention to the conservation of these ecosystems. While, the impervious surfaces, representing urban and developed areas, are projected to increase in all scenarios. This finding reflects the ongoing urbanization and infrastructure development trends within the GBA (Chen et al. 2023; Ding et al. 2022). Managing the expansion of impervious surfaces is crucial to minimize the environmental footprint of urban areas, protect natural habitats, and enhance the overall sustainability of the region (Li, Li, et al. 2023). It was revealed by Wang and Chen (2022) that if an economic-first development model is adopted, the ongoing urban expansion in GBA is projected to have a substantial detrimental effect on ecosystem services. It is estimated that by 2035, this development trajectory could lead to a total loss of ecosystem service values amounting to USD 28.1 billion.

The LR model generally showed more consistent estimates across the scenarios, the MC model predicted slightly different distributions. These variations highlight the inherent uncertainties and limitations associated with LULCC modeling, as observed previously in a study by Li, Li, et al. (2023). Thus, it is essential to consider these uncertainties when using model outputs for decision making and to employ a combination of modeling approaches to enhance the accuracy of predictions.

While numerous studies have conducted multi-scenario LULC simulations for GBA with different perspectives and objectives, directly comparing the quantitative results of these studies is challenging. This is primarily due to the differences in the input LULC datasets used, as well as the varying time periods considered for predictions. However, some general insights can be drawn from a qualitative comparison of the simulation results.

For instance, in contrast to a previous study (B. Wang, Oguchi, and Liang 2023) which projected a 42% expansion of the total urban area from 2020 to 2040 using MC model, our model estimates a more modest 12% increase in impervious area from 2022 to 2035. This difference in the magnitude of projected urban growth highlights the importance of aligning land use simulation with the specific development plans and policies outlined for the GBA region. Additionally, the model projections indicate that urban growth will be highly compacted, with a tendency to spread along the current urban peripheries, resulting in the formation of high-density urban clusters. The simulation results from the current study indicate that forest, cropland, and grassland areas are projected to show decreasing trends from 2022 to 2035 under various scenarios. This aligns with the findings of a previous study over GBA by Wang and Chen (2022), who also reported the declining trends for these LULC from 2020 to 2035. Similarly, a recent habitat quality simulation study (Wu, Wang, and Gou 2024) found reductions in cultivated land, forest, and water bodies, except for artificial surfaces which showed continuous increase across multiple scenarios between 2020 and 2030. Another study that simulated urban expansion under multiple scenarios between 2020–2025–2035 also verified the decrease in ecological land cover (e.g. forests and grasslands) and the increase in urban land, with the extent of these changes dependent on the specific restrictions imposed during the modeling process (Liao and Zhang 2023).

While the direct quantitative comparisons of literature may be limited, the overall directional trends observed in these prior studies align with the findings of the current research results. The current study's projections of declining forest, cropland, and grassland areas, coupled with the increase in compact and high-density urban expansion, corroborate the broader patterns of land use change anticipated for the GBA region. This also reinforces the need for comprehensive and coordinated land use planning efforts to balance the economic development and ecological conservation objectives in the rapidly evolving GBA.

5.3. Policy implications on future LULCC in GBA

Policies play a crucial role in fostering overall development of regions and countries (Setturu and Ramachandra 2021). Examining the influence of policy(s) on future LULCC is a significant aspect in understanding the dynamics of development and environmental sustainability within the GHM-GBA. The "Outline Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area" served as the key policy reference for designing the LULC simulation scenarios in this study. This strategic framework aims to enhance connectivity, innovation, and sustainable development within the GBA region. Specifically, the plan promotes the development of green and low-carbon cities, the conservation of natural resources, and the preservation of cultural heritage. It emphasizes the importance of sustainable land use practices, urban planning, and environmental protection in achieving a harmonious and balanced development across the GBA.

While the policy objectives may have a significant influence on future LULCC within the GBA core cities, the plan also provides a comprehensive strategic vision and guidelines for decision-making processes related to economic development, innovation, urban growth, infrastructure planning, and environmental management. Various studies have explored the policy implications on future LULC patterns under different scenarios in other regions (Jin et al. 2023; Wang, Liu, et al. 2023).

Drawing on the insights from the current LULC simulations study, we propose the following policy recommendations to guide the future land use trajectories in the GBA:

(1) The projected increase in cropland area within the GBA region suggests a need to focus on sustainable agricultural development. This trend may be driven by factors such as population growth, rising demand for food, and the region's efforts to enhance food security. Continued implementation of existing policies and initiatives that support precision farming techniques, water management strategies, and agricultural diversification can help optimize land use productivity while maintaining environmental sustainability. For instance, the promotion of high-yielding crop varieties, improved irrigation systems, and diversification into cash crops and specialty agricultural products can contribute to more efficient and ecologically responsible use of the limited land resources in the densely populated GBA. Encouraging the adoption of advanced agricultural technologies and promoting diversification of crop cultivation can further enhance the region's agricultural productivity and resilience.

(2) While the forest coverage within the GBA region appears relatively stable based on the projections, it is important to prioritize forest conservation and sustainable management. This relative stability may be attributable to the region's existing policies and initiatives aimed at protecting and managing its forest resources. However, to maintain healthy forest ecosystems, preserve biodiversity, and support the GBA's carbon neutrality goals by 2030, it is crucial to implement robust forest protection measures, promote afforestation and reforestation efforts, and strengthen overall conservation initiatives. This multi-pronged approach can help ensure the long-term viability of the GBA's forest resources, which play a critical role in climate change mitigation, ecosystem services, and the overall environmental well-being of the region.

(3) The potential decrease in grassland area, particularly under the NIS, raises significant concerns about habitat loss and ecological impacts in the GBA. The simulation results indicate that the reductions in grassland coverage occurred predominantly in areas transitioning to croplands and shrubs, especially in the suburban and peri-urban zones surrounding major metropolitan centers and urban clusters. Several key factors appear to be driving this decline in grasslands. Firstly, the high demand for land to support economic development and agricultural expansion has led to the conversion of grasslands to other more intensive land uses (Qin, Wang, and Meng 2024). Secondly, the improved living standards and increased demand for meat and dairy products in the region have resulted in a larger number of farm animals and intensified grazing practices, which can potentially reduce grassland coverage. To address this issue, it is crucial to implement sustainable land management practices, such as rotational grazing regimes and the rehabilitation of

degraded grasslands. Adopting these strategies can help maintain the ecological integrity of the grassland ecosystems and mitigate the negative impacts on biodiversity and habitat quality within the GBA region.

(4) The projected increase and expansion of impervious surfaces signify major urban developments. For instance, the reference policy document puts emphasis on expediting infrastructural connectivity, including enhancing the international competitiveness of the seaport and airport clusters, and building a rapid transport network in the GBA. This may cause conversion of other LULCs into impervious class, which again may have negative impacts such as urban heat islands, traffic congestion, poor air quality and more. Thus, it is necessary to adopt sustainable urban planning practices to minimize the environmental impact of urbanization. The GHM-GBA should incorporate some modern interventions, also suggested in the relevant policy documents for promotion of green infrastructure, green spaces within urban areas, and implementation of smart growth principles to ensure efficient land use and to reduce the ecological footprint of urban development.

These policy recommendations revolve around promoting sustainable land management practices, conservation efforts, and integrated development strategies for the GBA region. Striking the right balance between economic progress and environmental protection is crucial for achieving long-term sustainability and resilience. By closely aligning the LULC simulation results with the region's development plans, policymakers can make more informed decisions and develop a comprehensive spatial planning framework.

5.4. Uncertainty analysis and limitations

A significant source of uncertainty in the current study arises from input data, particularly remote sensing images. Atmospheric conditions and sensor calibration introduce variability, especially the cloud effect, which alters reflectance values, potentially leading to classification errors in the final LULC product. Additionally, model selection plays a vital role, as different modeling approaches can yield varying outcomes due to unique assumptions and structures. For instance, linear models might oversimplify complex relationships, while more sophisticated models risk overfitting the data. Likewise, uncertainty surrounding model parameters and predicted classes needs careful examination; variations in parameter settings can impact model performance, while classification algorithms often yield probabilistic outputs that may misclassify due to pixel heterogeneity. Another layer of uncertainty stems from the coarse resolution of some socio-economic parameters such as GDP and population, which may not fully capture local variations and context-specific factors critical for accurately assessing LULCC.

A major shortcoming of the current study, however, is the lack of consideration for future climate change scenarios and their potential impacts on regional LULC patterns. To address this limitation, it is suggested that future research incorporate RCPs (Representative Concentration Pathways) projections to deepen the understanding of how climate-driven factors may shape the land use trajectories of the GBA in the years to come.

6. Conclusions

This study analyzed the CLCD LULC patterns and projected future changes in the GHM-GBA, based on the policy "Outline Development Plan for the GHM-GBA" for 2035. To achieve the objectives, we employed PLUS model to simulate LULCCs under three different scenarios, including ECS, NIS, and UDS, and considered eighteen driving factors (historical and recent) from various categories.

The analysis of LULC dynamics from 2010–2022 reveals important trends, indicating an expansion of cropland (1.38%), suggesting stable agricultural practices. However, concerns arise from the decline in forest, grassland and shrubland areas, which raises issues of habitat loss and biodiversity impacts in GBA. The impervious class showed the highest positive change in percentage area from 2010–2022 (13%), attributed to urbanization, which raises concerns about land fragmentation and habitat loss, necessitating sustainable urban planning to mitigate these impacts. Moreover, the results for LULC simulation for 2035 suggest that the Trial#2 demonstrated a significant improvement in performance compared to Trial#1, where the RF trees were increased, and the thread value was reduced to improve the accuracy (> 90%). These findings highlight the importance of carefully selecting parameters and fine-tuning the model to meet the best possible results.

The comparative exploration of the simulated LULC under multiple scenarios in 2035, based on Markov Chain and Linear Regression revealed similarities in their projections. There is a small increase in croplands of around 1.32% to 1.43%, indicating ongoing agricultural expansion. However, they also forecast considerable declines in forests (−2.87% to − 3.38%), grasslands (−16.48% to − 31.85%), and water bodies (−11.47% according to both). Notably, the Markov Chain model predicts a dramatic 71.03% reduction in shrublands. Meanwhile, urban areas may rise substantially by 11% to 16% based on modeling results. These changes underscore both development pressures and threats to critical ecosystems. If unaddressed, such transformations could negatively impact habitat, biodiversity, and ecosystem services.

The findings emphasize the need for sustainable planning and governance to help guide LULC dynamics and promote more effective resource management.

A key contribution of this study is the comprehensive consideration of eighteen driving factors from various categories for two-time intervals (historical and recent). This multifaceted approach represents a significant advancement compared to previous LULC simulation studies in the GBA, which have typically relied only on the factors using recent data. Importantly, the inclusion of both historical and contemporary data for these driving variables provided a robust foundation for the modeling framework, enhancing its ability to accurately simulate future LULCCs. In future, it is recommended to couple the PLUS model with Multi-Objective Programming (MOP) techniques to predict the future economic implications of LULC under different scenarios. These quantitative insights would be invaluable for policymakers in charting the future development goals and priorities for the GHM-GBA region.

Acknowledgments

The authors thank Yang and Huang (2021) for providing open-source land cover dataset (CLCD) (openly accessible at https://zenodo.org/records/8176941.). Authors would also like to thank USGS, Hong Kong, RESDC, OSM, FAO and European Commission, Joint Research Centre (JRC) for providing data (Table 1). The authors would also like to thank the respective institutions for providing the environment and platform for conducting the research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Derived data supporting the findings of this study are available from the corresponding author on request.

Funding

Majid Nazeer was substantially supported by the General Research Fund [Grant No. PolyU-15306224] from the Research Grants Council of Hong Kong, China. Man Sing Wong would like to acknowledge the funding support through the Collaborative Research Fund [Grant No. C5062–21GF] and Young Collaborative Research Fund [Grant No. C6003–22Y] from the Research Grants Council of Hong Kong, China; and the funding support [Grant Nos. BBG2 and CD81] from the Research Institute for Sustainable Urban Development and the Research Institute for Land and Space, The Hong Kong Polytechnic University, Hong Kong, China.

Notes on contributors

Gomal Amin holds a master's degree in Remote Sensing and GIS from COMSATS University, Islamabad, Pakistan. He has served as a research assistant at the Department of Land Surveying & Geo-Informatics, the Hong Kong Polytechnic University (PolyU), China, and worked in humanitarian non-profit sectors. His research focuses on remote sensing, and environmental monitoring.

Majid Nazeer is a research assistant professor at the Department of Land Surveying & Geo-Informatics, the Hong Kong Polytechnic University (PolyU), China. He received his PhD in Remote Sensing and GIS from PolyU, China, in 2016 and has academic experience at institutions in Pakistan, Saudi Arabia, and China.

Man Sing Wong is a professor at the Department of Land Surveying & GeoInformatics, the Hong Kong Polytechnic University (PolyU), China. He is leading several projects, including the application of remote sensing in urban heat island effects, vegetation and ecosystem studies, aerosol retrieval, water quality monitoring, the use of GIS in smart city tree management, and the integration of iBeacon technology to enhance learning experiences.

ORCID

Gomal Amin http://orcid.org/0000-0003-1700-115X
Majid Nazeer http://orcid.org/0000-0002-7631-1599
Man Sing Wong http://orcid.org/0000-0002-6439-6775

References

Amgoth, A., H. P. Rani, and K. V. Jayakumar. 2023. "Exploring LULC Changes in Pakhal Lake Area, Telangana, India Using QGIS MOLUSCE Plugin." *Spatial Information Research* 31 (4): 429–438. https://doi.org/10.1007/s41324-023-00509-1.

Amin, G., I. Imtiaz, E. Haroon, N. U. Saqib, M. I. Shahzad, and M. Nazeer. 2024. "Assessment of Machine Learning Algorithms for Land Cover Classification in a Complex Mountainous Landscape." *Journal of Geovisualization and Spatial Analysis* 8 (2): 34. https://doi.org/10.1007/s41651-024-00195-z.

Cao, X., H. Wang, B. Zhang, J. Liu, J. Yang, and Y. Song. 2024. "Land Use Spatial Optimization for City Clusters Under Changing Climate and Socioeconomic Conditions: A Perspective on the Land-Water-Energy-Carbon Nexus." *Journal of Environmental Management* 349 (11): 119528. https://doi.org/10.1016/j.jenvman.2023.119528.

Chen, L., and Y. Ma. 2023. "Current and Future Characteristics of Land Use Based on Intensity Analysis and PLUS Model: A Case Study of Foshan City, China." *SN Applied Sciences* 5 (3). https://doi.org/10.1007/s42452-023-05298-8.

Chen, Y., W. Chen, J. Gong, and H. Yuan. 2023. "Uncommonly Known Change Characteristics of Land Use Pattern in Guangdong Province–Hong Kong–Macao, China: Space Time Pattern, Terrain Gradient Effects and Policy Implication." *Land Use Policy* 125 (2): 106461. https://doi.org/10.1016/j.landusepol.2022.106461.

Ding, Q., Z. Shao, X. Huang, O. Altan, and B. Hu. 2022. "Time-Series Land Cover Mapping and Urban Expansion Analysis Using OpenStreetMap Data and Remote Sensing Big Data: A Case Study of Guangdong-Hong Kong-Macao Greater Bay Area, China." *International Journal of Applied Earth Observation and Geoinformation* 113 (9): 103001. https://doi.org/10.1016/j.jag.2022.103001.

Entezami, H., F. Mojarrad, H. Shahabi, and E. Ghaderpour. 2024. "Spatiotemporal Variability in Snow and Land Cover in Sefid-Rud Basin, Iran." *Sustainability* 16 (21): 9381. https://doi.org/10.3390/su16219381.

Fan, L. Y., T. Cai, Q. Wen, J. Han, S. Wang, J. Wang, and C. Yin. 2023. "Scenario Simulation of Land Use Change and Carbon Storage Response in Henan Province, China: 1990–2050." *Ecological Indicators* 154:110660. https://doi.org/10.1016/j.ecolind.2023.110660.

Ghaderpour, E., P. Mazzanti, F. Bozzano, and G. Scarascia Mugnozza. 2024. "Trend Analysis of MODIS Land Surface Temperature and Land Cover in Central Italy." *Land* 13 (6): 796. https://doi.org/10.3390/land13060796.

Guo, H., Y. Cai, Z. Yang, Z. Zhu, and Y. Ouyang. 2021. "Dynamic Simulation of Coastal Wetlands for Guangdong-Hong Kong-Macao Greater Bay Area Based on Multi-Temporal Landsat Images and FLUS Model." *Ecological Indicators* 125 (6): 107559. https://doi.org/10.1016/j.ecolind.2021.107559.

Guo, P., H. Wang, F. Qin, C. Miao, and F. Zhang. 2023. "Coupled MOP and Plus-SA Model Research on Land Use Scenario Simulations in Zhengzhou Metropolitan Area, Central China." *Remote Sensing* 15 (15): 1–23. https://doi.org/10.3390/rs15153762.

He, N., W. Guo, H. Wang, L. Yu, S. Cheng, L. Huang, X. Jiao, W. Chen, and H. Zhou. 2023. "Temporal and Spatial Variations in Landscape Habitat Quality Under Multiple Land-Use/Land-Cover Scenarios Based on the PLUS-Invest Model in the Yangtze River Basin, China." *Land* 12 (7): 1338. https://doi.org/10.3390/land12071338.

Huang, X., J. Liu, S. Peng, and B. Huang. 2023. "The Impact of Multi-Scenario Land Use Change on the Water Conservation in Central Yunnan Urban Agglomeration, China." *Ecological Indicators* 147 (3): 109922. https://doi.org/10.1016/j.ecolind.2023.109922.

Ji, X., Y. Sun, W. Guo, C. Zhao, and K. Li. 2023. "Land Use and Habitat Quality Change in the Yellow River Basin: A Perspective with Different CMIP6-Based Scenarios and Multiple Scales." *Journal of Environmental Management* 345 (6): 118729. https://doi.org/10.1016/j.jenvman.2023.118729.

Jin, Y., A. Li, J. Bian, X. Nan, and G. Lei. 2023. "Modeling the Impact of Investment and National Planning Policies on Future Land Use Development: A Case Study for Myanmar." *ISPRS International Journal of Geo-Information* 12 (1): 22. https://doi.org/10.3390/ijgi12010022.

Kang, J., B. Zhang, and A. Dang. 2024. "A Novel Geospatial Machine Learning Approach to Quantify Non-Linear Effects of Land Use/Land Cover Change (LULCC) on Carbon Dynamics." *International Journal of Applied Earth Observation and Geoinformation* 128 (4): 103712. https://doi.org/10.1016/j.jag.2024.103712.

Koko, A. F., Z. Han, Y. Wu, S. Zhang, N. Ding, and J. Luo. 2023. "Spatiotemporal Analysis and Prediction of Urban Land Use/Land Cover Changes Using a Cellular Automata and Novel Patch-Generating Land Use Simulation Model: A Study of Zhejiang Province, China." *Land* 12 (8): 1525. https://doi.org/10.3390/land12081525.

Li, H., Y. Huang, Y. Zhou, S. Wang, W. Guo, Y. Liu, J. Wang, et al. 2023. "Spatial and Temporal Evolution of Ecosystem Service Values and Topography-Driven Effects Based on Land Use Change: A Case Study of the Guangdong–Hong Kong–Macao Greater Bay Area." *Sustainability* 15 (12): 9691. https://doi.org/10.3390/su15129691.

Li, L., J. Li, L. Peng, X. Wang, and S. Sun. 2023. "Spatiotemporal Evolution and Influencing Factors of Land-Use Emissions in the Guangdong-Hong Kong-Macao Greater Bay Area Using Integrated Nighttime Light Datasets." *Science of the Total Environment* 893 (10): 164723. https://doi.org/10.1016/j.scitotenv.2023.164723.

Li, L., S. Ma, Y. Zheng, and X. Xiao. 2022. "Integrated Regional Development: Comparison of Urban Agglomeration Policies in China." *Land Use Policy* 114 (4): 105939. https://doi.org/10.1016/j.landusepol.2021.105939.

Li, P., J. Chen, Y. Li, and W. Wu. 2023. "Using the Invest-Plus Model to Predict and Analyze the Pattern of Ecosystem Carbon Storage in Liaoning Province, China." *Remote Sensing* 15 (16): 4050. https://doi.org/10.3390/rs15164050.

Li, S. 2021. "Legal Instruments for the Integration and Cooperation in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA): Better Implementation of the SDGs." *Sustainability* 13 (22): 12485. https://doi.org/10.3390/su132212485.

Liang, X., Q. Guan, K. C. Clarke, S. Liu, B. Wang, and Y. Yao. 2021. "Understanding the Drivers of Sustainable Land Expansion Using a Patch-Generating Land Use Simulation (PLUS) Model: A Case Study in Wuhan, China." *Computers, Environment and Urban Systems* 85 (1): 101569. https://doi.org/10.1016/j.compenvurbsys.2020.101569.

Liang, X., X. Liu, D. Li, H. Zhao, and G. Chen. 2018. "Urban Growth Simulation by Incorporating Planning Policies into a CA-Based Future Land-Use Simulation Model." *International Journal of Geographical Information Science* 32 (11): 2294–2316. https://doi.org/10.1080/13658816.2018.1502441.

Liao, Z., and L. Zhang. 2023. "Spatio-Temporal Evolution and Future Simulation of Urban Agglomeration Expansion in the Guangdong–Hongkong–Macau Greater Bay Area." *Humanities and Social Sciences Communications* 10 (1): 1–12. https://doi.org/10.1057/s41599-023-01968-5.

Lin, J., X. Li, Y. Wen, and P. He. 2023. "Modeling Urban Land-Use Changes Using a Landscape-Driven Patch-Based Cellular Automaton (LP-CA)." *Cities* 132 (1): 103906. https://doi.org/10.1016/j.cities.2022.103906.

Liu, J., B. Liu, L. Wu, H. Miao, J. Liu, K. Jiang, H. Ding, W. Gao, and T. Liu. 2024. "Prediction of Land Use for the Next 30 Years Using the PLUS Model's Multi-Scenario Simulation in Guizhou Province, China." *Scientific Reports* 14 (1): 13143. https://doi.org/10.1038/s41598-024-64014-7.

Liu, X., X. Liang, X. Li, X. Xu, J. Ou, Y. Chen, S. Li, S. Wang, and F. Pei. 2017. "A Future Land Use Simulation Model (FLUS) for Simulating Multiple Land Use Scenarios by Coupling Human and Natural Effects." *Landscape and Urban Planning* 168 (12): 94–116. https://doi.org/10.1016/j.landurbplan.2017.09.019.

Peng, B., J. Yang, Y. Li, and S. Zhang. 2023. "Land-Use Optimization Based on Ecological Security Pattern—A Case Study of Baicheng, Northeast China." *Remote Sensing* 15 (24): 5671. https://doi.org/10.3390/rs15245671.

Qin, X., S. Wang, and M. Meng. 2024. "SEA for Better Climate Adaptation in the Face of the Flood Risk: Multi-Scenario, Strategic Forecasting, Nature-Based Solutions." *Environmental Impact Assessment Review* 106 (4): 107495. https://doi.org/10.1016/j.eiar.2024.107495.

Rahaman, Z. A., A. A. Kafy, A.-A. Faisal, A. Al Rakib, D. M. A. Jahir, M. A. Fattah, S. Kalaivani, R. Rathi, S. Mallik, and M. T. Rahman. 2022. "Predicting Microscale Land Use/Land Cover Changes Using Cellular Automata Algorithm on the Northwest Coast of Peninsular Malaysia." *Earth Systems and Environment* 6 (4): 817–835. https://doi.org/10.1007/s41748-022-00318-w.

Setturu, B., and T. V. Ramachandra. 2021. "Modeling Landscape Dynamics of Policy Interventions in Karnataka State, India." *Journal of Geovisualization and Spatial Analysis* 5 (2): 22. https://doi.org/10.1007/s41651-021-00091-w.

Shahi, E., S. Karimi, and H. R. Jafari. 2020. "Monitoring and Modeling Land Use/Cover Changes in Arasbaran Protected Area Using and Integrated Markov Chain and Artificial Neural Network." *Modeling Earth Systems and Environment* 6 (3): 1901–1911. https://doi.org/10.1007/s40808-020-00801-1.

Tabassum, A., R. Basak, W. Shao, M. M. Haque, T. A. Chowdhury, and H. Dey. 2023. "Exploring the Relationship Between Land Use Land Cover and Land Surface Temperature: A Case Study in Bangladesh and the Policy Implications for the Global South." *Journal of Geovisualization and Spatial Analysis* 7 (2): 25. https://doi.org/10.1007/s41651-023-00155-z.

Wang, B., T. Oguchi, and X. Liang. 2023. "Evaluating Future Habitat Quality Responding to Land Use Change Under Different City Compaction Scenarios in Southern China." *Cities* 140 (9): 104410. https://doi.org/10.1016/j.cities.2023.104410.

Wang, H., H. Xue, W. He, Q. Han, T. Xu, X. Gao, S. Liu, R. Jiang, and M. Huang. 2024. "Spatial-Temporal Evolution Mechanism and Dynamic Simulation of the Urban Resilience System of the Guangdong-Hong Kong-Macao Greater Bay Area in China." *Environmental Impact Assessment Review* 104 (7): 107333. https://doi.org/10.1016/j.eiar.2023.107333.

Wang, J., and T. Chen. 2022. "A Multi-Scenario Land Expansion Simulation Method from Ecosystem Services Perspective of Coastal Urban Agglomeration: A Case Study of GHM-GBA, China." *Land* 11 (11): 1934. https://doi.org/10.3390/land11111934.

Wang, J., J. Zhang, N. Xiong, B. Liang, Z. Wang, and E. Cressey. 2022. "Spatial and Temporal Variation, Simulation and Prediction of Land Use in Ecological Conservation Area of Western Beijing." *Remote Sensing* 14 (6): 1452. https://doi.org/10.3390/rs14061452.

Wang, Q., Q. Guan, Y. Sun, Q. Du, X. Xiao, H. Luo, J. Zhang, and J. Mi. 2023. "Simulation of Future Land Use/Cover Change (LUCC) in Typical Watersheds of Arid Regions Under Multiple Scenarios." *Journal of Environmental Management* 335 (6): 117543. https://doi.org/10.1016/j.jenvman.2023.117543.

Wang, Q., D. Liu, F. Gao, X. Zheng, and Y. Shang. 2023. "A Partitioned and Heterogeneous Land-Use Simulation Model by Integrating CA and Markov Model." *Land* 12 (2): 409. https://doi.org/10.3390/land12020409.

Wang, W., T. Wu, Y. Li, H. Zheng, and Z. Ouyang. 2021. "Matching Ecosystem Services Supply and Demand Through Land Use Optimization: A Study of the Guangdong-Hong Kong-Macao Megacity." *International Journal of Environmental Research and Public Health* 18 (5): 2324. https://doi.org/10.3390/ijerph18052324.

Wang, X., P. Cong, Y. Jin, X. Jia, J. Wang, and Y. Han. 2021. "Assessing the Effects of Land Cover Land Use Change on Precipitation Dynamics in Guangdong–Hong Kong–Macao Greater Bay Area from 2001 to 2019." *Remote Sensing* 13 (6): 1135. https://doi.org/10.3390/rs13061135.

Wang, Y., C. Liu, Y. Wang, Y. Liu, and T. Liu. 2024. "Climate Risk Assessment and Adaption Ability in China's Coastal Urban Agglomerations - A Case Study of Guangdong-Hong Kong-Macao Greater Bay Area." *Journal of Cleaner Production* 452 (2): 142036. https://doi.org/10.1016/j.jclepro.2024.142036.

Wang, Y., J. Shen, W. Yan, and C. Chen. 2019. "Backcasting Approach with Multi-Scenario Simulation for Assessing Effects of Land Use Policy Using GeoSOS-FLUS Software." *MethodsX* 6 (1): 1384–1397. https://doi.org/10.1016/j.mex.2019.05.007.

Wu, Y., J. Wang, and A. Gou. 2024. "Research on the Evolution Characteristics, Driving Mechanisms and Multi-Scenario Simulation of Habitat Quality in the Guangdong-Hong Kong-Macao Greater Bay Based on Multi-Model Coupling." *Science of the Total Environment* 924 (1): 171263. https://doi.org/10.1016/j.scitotenv.2024.171263.

Yang, D., W. Luan, Y. Li, Z. Zhang, and C. Tian. 2023. "Multi-Scenario Simulation of Land Use and Land Cover Based on Shared Socioeconomic Pathways: The Case of Coastal Special Economic Zones in China." *Journal of Environmental Management* 335 (6): 117536. https://doi.org/10.1016/j.jenvman.2023.117536.

Yang, J., and X. Huang. 2021. "The 30m Annual Land Cover Dataset and Its Dynamics in China from 1990 to 2019." *Earth System Science Data* 13 (8): 3907–3925. https://doi.org/10.5194/essd-13-3907-2021.

Yu, Z., M. Zhao, Y. Gao, T. Wang, Z. Zhao, and S. Wang. 2023. "Multiscenario Simulation and Prediction of Land Use in Huaibei City Based on CLUE-S and PLUS Models." *Applied Sciences* 13 (12): 7142. https://doi.org/10.3390/app13127142.

Yue, S., G. Ji, W. Chen, J. Huang, Y. Guo, and M. Cheng. 2023. "Spatial and Temporal Variability Characteristics of Future Carbon Stocks in Anhui Province Under Different SSP Scenarios Based on PLUS and InVEST Models." *Land* 12 (9): 1668. https://doi.org/10.3390/land12091668.

Zhang, Y., M.-P. Kwan, and J. Yang. 2023. "A User-Friendly Assessment of Six Commonly Used Urban Growth Models." *Computers, Environment and Urban Systems* 104 (12): 102004. https://doi.org/10.1016/j.compenvurbsys.2023.102004.

Zhao, X., P. Wang, S. Gao, M. Yasir, and Q. U. Islam. 2023. "Combining LSTM and PLUS Models to Predict Future Urban Land Use and Land Cover Change: A Case in Dongying City, China." *Remote Sensing* 15 (9): 2370. https://doi.org/10.3390/rs15092370.

Zhong, Y., X. Zhang, Y. Yang, and M. Xue. 2023. "Optimization and Simulation of Mountain City Land Use Based on MOP-Plus Model: A Case Study of Caijia Cluster, Chongqing." *ISPRS International Journal of Geo-Information* 12 (11): 451. https://doi.org/10.3390/ijgi12110451.

Zhu, K., Y. Cheng, W. Zang, Q. Zhou, Y. El Archi, H. Mousazadeh, M. Kabil, K. Csobán, and L. D. Dávid. 2023. "Multiscenario Simulation of Land-Use Change in Hubei Province, China Based on the Markov-FLUS Model." *Land* 12 (4): 744. https://doi.org/10.3390/land12040744.