Mixed-use classification of buildings based on multi-source spatiotemporal big data

Keywords: spatiotemporal big data; graph neural network; building scale land use classification; mixed-use buildings

1. Introduction

Due to the rapid development of cities and widespread urban renewal projects, especially in megacities, a single land use model can no longer meet the growing and diverse needs of people (He et al., 2021). Therefore, mixed land use has gradually become an ideal choice to maintain urban livability (Nabil & Eldayem, 2015; Ma et al., 2024). In Japan, national and local governments have adopted the "compact city" strategy, integrating residential, medical, commercial and other functions within a limited single area, i.e. mixed-use development of land (Ministry of Land, Infrastructure, Transport and Tourism, 2015), in order to provide services to different groups with different needs (Abdullahi et al., 2015). Although mixed-use of land can reduce commuting distance and promote community vitality (Stevenson et al., 2016; Yue et al., 2017; Ma et al., 2024), it can also bring some problems to urban development, such as combining commercial and residential areas, which may cause noise pollution and traffic congestion (Sperry et al., 2012; Kwon & Choi, 2014). Therefore, identifying the composition and spatial distribution of mixed-use of land is an important foundation for evaluating existing planning and design, as well as planning future urban development strategies.

The mixed-use development of land is carried out at multiple scales, sorted by degree of refinement as follows: mixed-use zoning at the community level, large-scale commercial complexes at the block level, and multifunctional buildings (Cao & Chatman, 2015). As an important component of urban space, urban buildings have multiple functions such as residence, work, and commerce (Xue et al., 2024). In contemporary urban planning, the spatial distribution of mixed-use at the building scale is of great significance in understanding urban spatial patterns (Zhou et al., 2023), landscape design, and constructing urban digital twins (Xia et al., 2022), and is an essential tool for urban planners (He et al., 2021). However, collecting land use information at the building scale over a large spatial area requires extensive field investigations and typically consumes a significant amount of resources (Liu et al., 2018). Therefore, the mapping of mixed-use of land at the building scale has attracted widespread attention from scholars. This makes it imperative to design models that can automate the generation of accurate and up-to-date mixed-use of building maps.

Remote sensing images can provide high-resolution and high coverage spectral features of land cover, and are therefore widely used in land cover and land use classification tasks (He et al., 2025). For example, Tong et al. (2020) used 150 labelled remote sensing images to classify land cover. Gong et al. (2020) used random forest algorithm and point of interest (POI), nighttime light, and other remote sensing data to classify land use in cities across China. Typically, land use classification is conducted at the parcel scale. Using road network to segment satellite images into parcels and then using spectral or spatial features within the parcels for land use classification (Guzder-Williams et al., 2023; Xiong et al., 2024). However, land use classification at the parcel scale may lead to omissions or misclassifications, for example, some kindergartens and community clinics may be located within residential parcel, while parcel based classification may simply classify them as residential parcel. Therefore, parcel scale land use classification often lack the granularity needed to distinguish human activity at the building scale.

Remote sensing images mainly focus on observing the spectral features of land. Although data such as nighttime light have provided strong support for measuring socioeconomic factors in recent years, their capability to perceive human activities remains relatively limited (Zheng et al., 2023). However, the function of buildings is closely related to human activities (Pei et al., 2014; Chen et al., 2017). For example, Kang et al. (2018) generated building classification maps based on Google Street View data and verified the effectiveness of street view data in land use classification tasks. Wu et al. (2020) evaluated the mixed-use of land using sub-pixel decomposition techniques and social media check-in data. Zhou et al. (2023) used POI data to classify building functions, improving classification accuracy. Obviously, human activity data can compensate for the limitations of remote sensing and provide strong support for land use classification tasks.

The geometric features of buildings are important in identifying building class (Wang et al., 2021). For example, industrial buildings occupy a larger area than residential buildings, and commercial buildings in the Central Business District are often higher than industrial buildings. To consider the geometric features of building in the task of building functional classification, researchers have proposed a shape based indicator system, including aspect ratio, area, compactness, etc. (Xu et al., 2022; Kong et al., 2024). These methods are implemented only on two-dimensional building footprints and typically involve manual selection and construction of features, which are susceptible to subjectivity and difficult to capture the overall geometric features of buildings. In addition, they rarely consider the spatial contextual information of buildings. However, incorporating such spatial context is crucial for building function classification. For instance, residential buildings tend to cluster together, whereas industrial buildings are usually located away from residential areas.

Although considerable efforts have been made in developing various land use classification models, several issues remain unresolved to date:

1) Current land use classification studies primarily use pixels, grids, objects, or parcels as the basic units, with relatively limited attention given to building scale land use classification. Moreover, in the compact cities, mixed-use of building is common; however, existing studies often assign a single class to a building based solely on its dominant function, ignoring the phenomenon of mixed-use at the building scale.

2）In current land use classification studies, the human activity data commonly used—such as POI, nighttime light image, street view, and social media data—are typically static and lack sufficient spatial and temporal resolution. As a result, they can only capture limited aspects of human activity and are insufficient to support the fine-grained land use classification required for identifying mixed-use at the building scale.

3) Existing land use classification studies, when considering building geometric features, typically construct two-dimensional features based only on building footprints. Moreover, they often require the manual construction of a large feature set, which is prone to subjectivity.

To address the above limitations, this study incorporates spectral, geometric, and human activity features of buildings, as well as their functional correlations with neighboring buildings. A Graph Neural Network model, GraphSAGE, is employed to model the relationships between buildings, and TimesNet is used to integrate the temporal features of human activity. In addition, this study proposes a method for automatically extracting geometric features from 3D building models. The main contributions of this research are as follows:

1) This study performs land use classification of mixed-use functions at the building scale, thereby improving both the spatial and attribute granularity of land use classification. It enriches the semantic information of building attributes and provides a more fine-grained representation of urban space, enabling a more comprehensive understanding of building functional.

2) By integrating spectral, geometric, and spatiotemporal human activity features of buildings and modeling inter-building relationships using GraphSAGE, the performance of land use classification is significantly enhanced.

3) A novel method based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is proposed to automatically extract geometric features from 3D building model.

2. Study Area and Data

Tokyo, as the political, economic, and cultural center of Japan, covers an area of 2,194 square kilometers and is home to approximately 14 million people and around 2.5 million buildings. As shown in Figure 1, this study focuses on the 23 wards of Tokyo, which constitute the city's core. These wards are characterized by a high density of buildings and a densely populated urban environment. Moreover, due to Japan's adoption of a “compact city” development strategy, the buildings in the 23 wards exhibit significant mixed-use characteristics. Therefore, this area provides an ideal scenario for research on mixed-use land use classification at building scale.

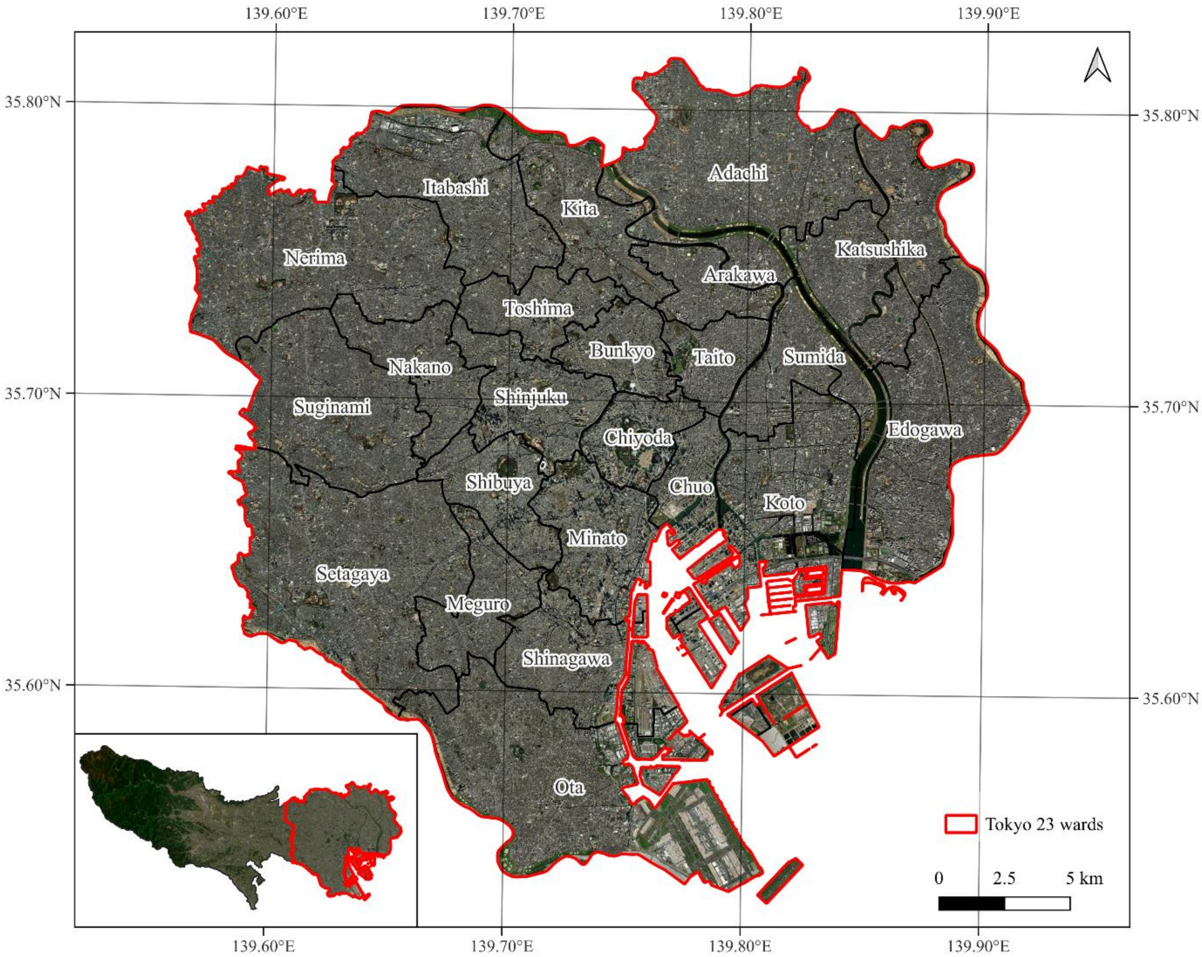


Fig. 1. Study area

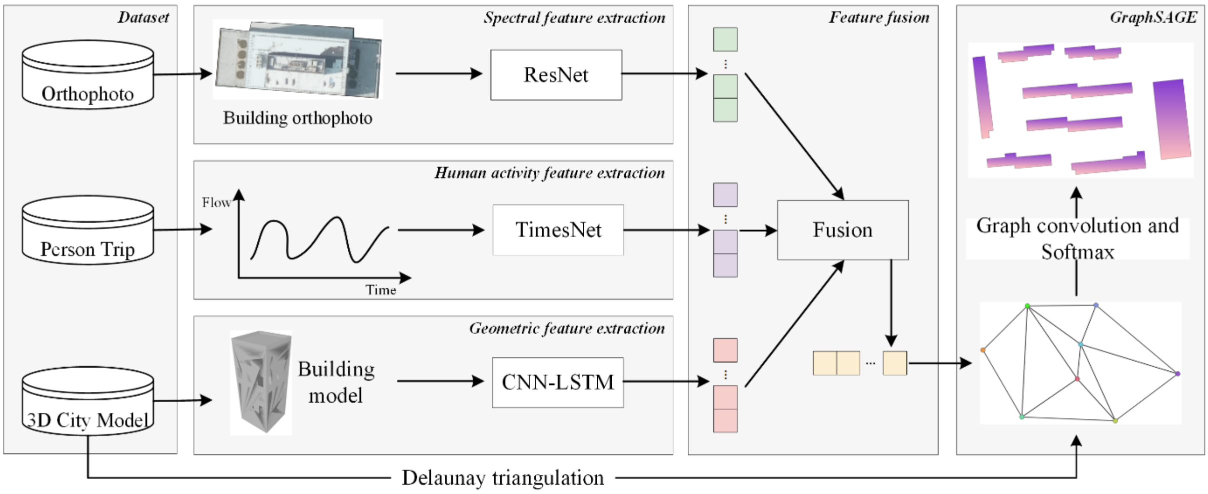
The datasets used in this study are summarized in Table 1. High-resolution orthophotos (0.2 m) provide detailed spectral information about buildings. The 3D City Model offers geometric information and is also used for orthophoto clipping. The Person Trip dataset is employed to extract human activity features of buildings; it contains detailed daily mobility information for individuals, including departure time, origin and destination locations, transportation modes, and trip purposes. POI data are used to train the land use classification model. This dataset includes 39 primary categories and 2,209 secondary categories, offering rich class diversity suitable for constructing a mixed-use land use classification model.

Table 1. Data used in this study.

Data	Source	Format
Orthophoto	Geospatial Information Authority of Japan	Raster (0.2m)
3D City Model	PLATEAU by MLIT	Vector
Person Trip	People Flow Project	Vector
POI	Telepoint Pack DB by ZENRIN	Vector

3. Methodology

This study conducts land use classification at the building scale, aiming to identify mixed-use buildings. As illustrated in Figure 2, the proposed method integrates spectral, spatiotemporal human activity, and 3D geometric features of buildings. The fused feature vectors are then used as nodes of GraphSAGE to construct a graph neural network.



4. Research Plan and Expected Results

	1st ~ 2nd months	3rd ~ 4th months	5th ~ 6th months	7th ~ 8th months	9th ~ 10th months	11th ~ 12th months
Data collection and preprocessing						
Trip data cleaning and transformation						
Feature extraction from 3D models						
Construction and training of GraphSAGE						
Accuracy evaluation and result analysis						
Finalizing report and academic publication						

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