

Detecting Urban Informal Settlements in Guangzhou via Sentinel-2 Data and Machine Learning

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Prepared for SYDE 633, Prof. David Clausi

Abstract— Accurate identification of Urban Informal Settlements (UIS) is crucial for effective urban governance, particularly during China's current transition in urban renewal. This study explores a practical framework for UIS detection by integrating Sentinel-2 imagery with machine learning models. Using the core districts of Guangzhou as a study area, we extracted contextual features across varying spatial scales, focusing on the interplay between spectral data and deep structural textures. The results demonstrate that geometric and textural signatures are superior indicators of UIS in complex megacity environments, specifically at the 310 m to 510 m scale. Among the evaluated algorithms, XGBoost achieved the most robust overall performance (OA = 93%), while the MLP model offered exceptional precision (0.97) for positive UIS identification. These findings provide a scalable, cost-effective evidence base for municipal authorities to monitor and evaluate urban planning policies, supporting the shift toward more precise and sustainable urban regeneration strategies.

Index Terms— Urban informal settlements, contextual features, machine learning, Sentinel-2

I. INTRODUCTION

OVER the past decades, the world has been experiencing rapid urbanization. According to the United Nations [1], more than half the world's population lives in urban areas today, and the ratio is projected to rise to 68% by 2050, with close to 90% of the increase happening in Global South countries in Asia and Africa. Rapid urbanization and unprecedented population growth have reshaped the epistemology of urban planning. As posited by [2], although urban informality was once narrowly associated with marginalized squatter settlements, it is now recognized as a generalized mode of metropolitan urbanization. This shift emphasizes developing planning tools and analytical techniques to classify and manage the profound socio-spatial fragmentation and systemic informality arising from accelerated urban transitions. As a primary manifestation of informality, urban informal settlements, encompassing slums, shantytowns, and urban villages, represent poorly planned residential fabrics often defined by high density, degraded living environments, and inadequate public services, all of which compromise public health and urban equity [3]. In the Chinese context, however, this informality is unique because it creates complex "spaces of exception" within the formal urban

administrative areas [4]. Thus, the term urban village has emerged to describe the informal settlement in urban China. Given these complexities, the precise and frequent monitoring of Urban Informal Settlement (UIS) becomes indispensable. It provides the empirical evidence necessary for municipal authorities to move beyond static approaches toward more adaptive, evidence-based urban regeneration and social integration policies.

Traditionally, the monitoring of informal settlements has relied on field surveys and household interviews, which are both time-consuming and labor-intensive [5]. Recent advancements in satellite constellations and high-resolution remote sensing offer a direct, economical, and precise solution for continuous Earth observation [6]. However, despite remote sensing-based UIS detection has evolved over twenty years, a universally applicable methodology has yet to be established [7]. While the recent emergence of integrated Object-Based Image Analysis (OBIA) and machine learning approach has achieved high mapping accuracy, its heavy reliance on high-resolution imagery results in high costs [8]. Similarly, while deep learning methods have gained significant attention recently, their requirement for extensive high-quality training samples affects their widespread application across diverse geographic regions [9]. Therefore, many studies have investigated methods for low-cost, large-scale mapping of UIS, specifically utilizing freely available Sentinel-2 data. For instance, Wurm and colleagues mapped Mumbai's informal settlements using Sentinel-2A [10], as well as research by Maxwell Owusu et al., which utilized Sentinel-2A with machine learning algorithms to achieve strong performance in UIS detection across three cities in Africa [11].

Inspired by these existing studies, this study focuses on exploring a framework for UIS detection in complex megacities by using open-access Sentinel-2 imagery with machine learning algorithms. Specifically, this study seeks to 1) develop an analytical framework that combines contextual features from remote sensing imagery; 2) develop and evaluate machine learning models to distinguish UIS areas in the urban core districts of Guangzhou; 3) determine the morphological characteristics of UIS areas within the complex megacity of Guangzhou; and 4) generate an Urban Informal Settlement Map for the study area to assist urban planners with resource allocation and policy implementation.

II. STUDY AREA AND DATA

A. Study Areas

Guangzhou is located in southern China and serves as the capital city of Guangdong Province. The municipality covers approximately 7,436 km² and had a resident population of about 18.98 million in 2024. Following the Reform and Opening-up policy in the 1980s, Guangzhou experienced rapid urban expansion, and a significant number of villages originally located on the city's periphery were encroached by urban areas, with the land ownership of these villages remaining with rural collectives [12]. This transformation made Guangzhou one of the first megacities in China to witness the emergence of urban informal settlements, or urban villages.

Specifically, this study focuses on the urban core district of Guangzhou (Fig. 1), including Tianhe, Yuexiu, Liwan, Haizhu, Baiyun, and Huangpu districts, for their high degree of urbanization.

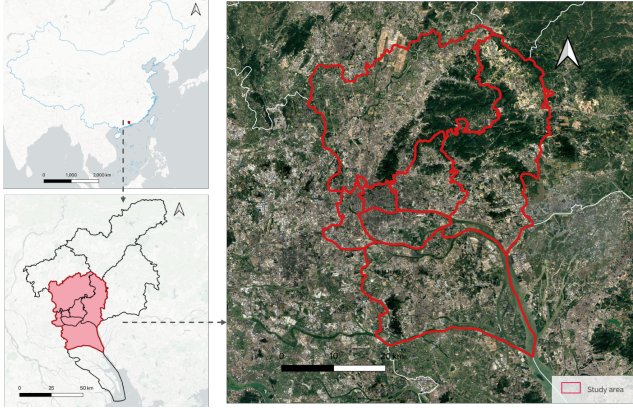


Fig. 1. Study areas

B. Data

Multispectral remote sensing imagery from the European Space Agency's Sentinel-2 sensor, acquired between 15 October 2024 and 15 January 2025, was used in this study. Specifically, four multispectral bands with a spatial resolution of 10 m (blue, green, red, and near-infrared (NIR) bands) were extracted for the study area. The precomputed s2cloudless cloud probability maps (Sentinel-2 Cloud Probability product) were also employed to create cloud free mosaic image. Moreover, land-use data of Guangzhou served as auxiliary data during the sample collection process.

III. METHODS

The study proposed a framework for detecting Urban Informal Settlement (UIS) areas using Sentinel-2 imagery and machine learning models, as illustrated in Fig. 2. The process begins with the preparation of a cloud-free image alongside training samples representing both UIS and non-UIS classes. Then, several contextual features from the imagery at multiple scales. Finally, three machine learning models were employed to detect UIS areas. The performance of each model is evaluated, with the top-performing model ultimately selected to map the spatial distribution of UIS across the study area. In this

study, the image processing was performed using Google Earth Engine (GEE), and the feature extraction and modeling were conducted using Python.

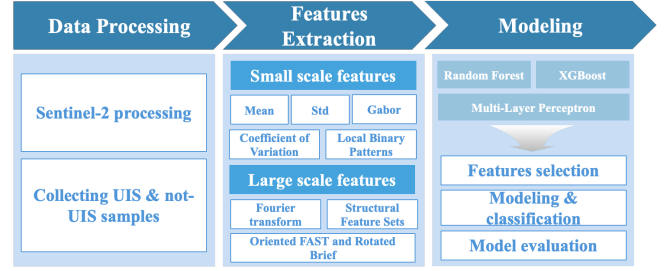


Fig. 2. Methodological framework

A. Data Processing

1) Imagery Processing

For the data preparation stage, this study utilizes Sentinel-2 imagery and the s2cloudless dataset to generate cloud-free composites within GEE. To balance spectral consistency with spatial completeness, a dual-window temporal synthesis strategy was implemented. First, a primary composite was generated for the core study period (Nov 2024 - Dec 2024) using a strict cloud probability threshold (40%) to ensure data quality. Second, to address data gaps caused by cloud cover, a “backup” composite was produced over an extended window (Oct 2024 - Jan 2025) with a relaxed masking threshold (60%). Finally, a cloud-free mosaic was created by filling data voids in the primary collection with observations from the broader temporal backup.

2) Sample Processing

This study focuses on detecting UIS and non-UIS areas, and thus, two categories of samples were selected. The selection of UIS samples was conducted using Google Earth imagery and Baidu Street View, cross-referenced with Guangzhou land-use data. To ensure representativeness, the selection process incorporated different morphological types of UIS areas, including structured, unstructured, and hybrid UIS (Fig. 3):

- Structured UIS refers to areas with relatively orderly layouts and organized spatial arrangements;
- Unstructured UIS is characterized by irregular building patterns, chaotic construction, and narrow, winding alleyways;
- Hybrid UIS typically consists of a mixture of various housing types and is sometimes surrounded by formal residential developments. Non-UIS samples were identified through visual interpretation of Google Earth imagery. Vegetation, water bodies, formal residential areas, commercial and industrial zones, and other built-up areas were included as non-UIS categories.

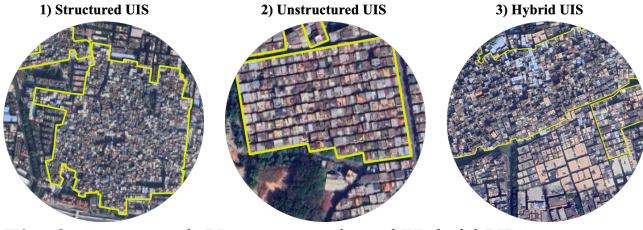


Fig. 3. Structured, Unstructured, and Hybrid UIS

B. Feature Extraction

The contextual features approach characterizes the structural properties of an area by statistically quantifying the spatial arrangements and spectral relationships (such as textures, edges, and pixel groupings) within a defined neighborhood [13]. Contextual features have proven effective in classification tasks, particularly for mapping complex urban structures in high-resolution imagery [13, 14].

Several contextual features were summarized in previous studies. Based on these, this study extracted a set of features to distinguish the UIS areas from non-UIS areas (Table 1).

TABLE I
DESCRIPTION OF FEATURES (TABLE AND DEFINITIONS
EDITED FROM [12, 15])

Name	Description
Mean	The mean brightness of each band, including red, green, blue and NIR
Standard deviation	A measure of the absolute dispersion from the mean
Coefficient of Variation	The ratio of the standard deviation to the mean, providing a dimensionless measure of relative variability
Local Binary Patterns	A micro-texture operator to detect fine-grained primitives, such as edges, spots, and corners
Gabor filters	Utilize a series of sinusoidally modulated Gaussian functions across multiple orientations and scales to extract directional edges from urban morphology.
Fourier transform	Decomposes an image into a spectrum of sinusoidal signals to capture and quantify spatial frequency patterns, effectively distinguishing various urban textures
Structural Feature Sets	A macro-structural descriptor to quantify the spatial extent and regional homogeneity through directional line tracking

Oriented Features from Accelerated Segment Test (FAST) and Rotated Binary Robust Independent Elementary Features (BRIEF)

A computationally efficient detector and descriptor to identify localized salient structures within informal settlements

The feature extraction process is based on calculations within predefined windows, with the resulting values assigned to the central pixel. Following previous studies [16, 17], this study extracts contextual features using multiple window sizes to capture information at varying spatial scales. These features are categorized into small-scale and large-scale features. Specifically, for small-scale metrics such as mean, standard deviation (std), and Coefficient of Variation (CV), window sizes of 3×3 , 5×5 , and 10×10 pixels (corresponding to scales of 30 m, 50 m, and 100 m) were employed. For large-scale features, including Fourier, LSR, ORB, and SFS, window sizes were expanded to 31×31 , 51×51 , and 71×71 pixels (representing 310 m, 510 m, and 710 m, respectively). The blue, green, red, NIR bands, mean brightness and NDVI were used as input, and a total of 141 features were generated at a 10 m spatial resolution.

C. Modeling

1) Sampling

To ensure model generalization, Group K-Fold cross-validation was implemented in the sampling stage. Group K-Fold cross-validation is a sampling technique designed for datasets with grouped dependencies [18]. Group K-fold can avoid group overlap between training and testing sets, reducing data leakage and strengthening model generalizability. In this study, the dataset was first split into an 80% training/validation set and a 20% independent holdout test set. Within the 80% training and validation subset, the Group K-Fold algorithm (with $K=5$) was implemented to partition the data into iterative training and validation folds while strictly maintaining spatial independence.

2) Model Building

Three machine learning models were built for UIS detection, including Random Forest, Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP). ‘RandomizedSearchCV’ was utilized during the modeling process to optimize models’ hyperparameters by performing a randomized search over a specified parameter grid, significantly reducing computational costs compared to a grid search.

3) Accuracy Assessment

To evaluate the accuracy and reliability of the models, a comprehensive set of metrics was used, including overall accuracy, precision, recall, and the F1-score, all derived from confusion matrices. In the context of UIS detection, we prioritized the F1-score for the UIS because it provides a balanced assessment of the model's ability to handle the significant class imbalance. Furthermore,

feature importance was analyzed across the three models: the Random Forest utilized Gini importance to determine feature importance; XGBoost was evaluated based on Average Information Gain; while Permutation Importance was applied to the MLP to identify the key variables.

IV. RESULTS

A. Evaluation of the UIS detection model

1) Random Forest

The Random Forest model achieved an overall accuracy of 88% on the 20% independent holdout test set. For the UIS detection, the F1-score for the UIS class is 0.84, and the recall for the UIS class is 76%. The relatively low recall suggests certain UIS areas were omitted by the model (Fig. 4).

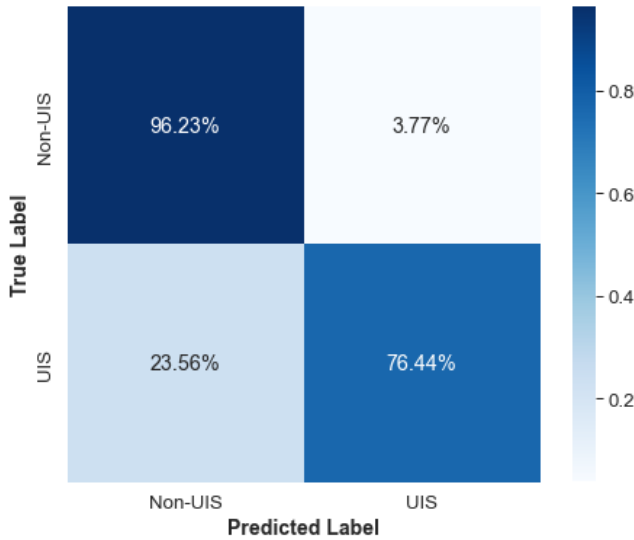


Fig. 4. Confusion Matrix: Random Forest

The result of the feature importance of the Random Forest model (Fig. 5) reveals that: (1) The model is heavily influenced by spectral reflectance. The mean indices of the NIR band are the most dominant, with `nir_mean_k10` and `nir_mean_k5` occupying the top two positions, contributing approximately 0.07 and 0.05 to the relative importance, respectively. This indicates that the unique spectral signature of construction materials and vegetation scarcity are important for mapping UIS areas; and (2) Structural and textural features, like `nir_gabor_a90_k10` and `blue_gabor_a0_k10`, are also essential for distinguishing UIS areas from other urban areas.

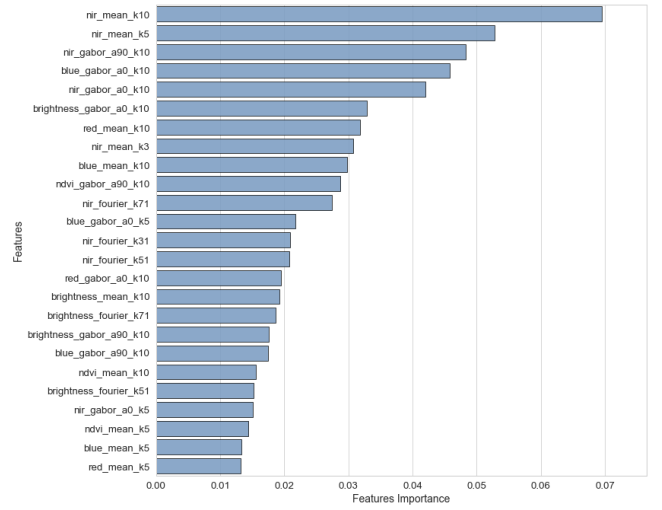


Fig. 5. Random Forest Feature Importance

2) Extreme Gradient Boosting (XGBoost)

The XGBoost model showed an exceptional classification performance with an overall accuracy of 93% on the 20% independent holdout test set. In addition, the model exhibits a high reliability in target class detection, with a UIS precision of 95% and UIS recall of 89%. The resulting F1-score of 0.92 for the UIS class also confirms the model's balanced and robust predictive capability (Fig. 6).

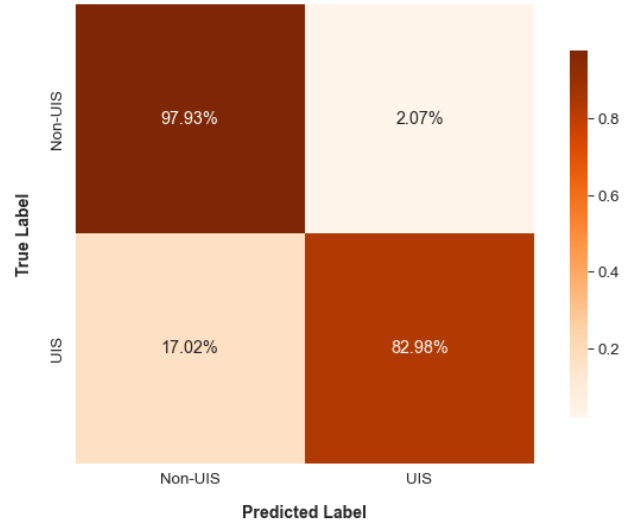


Fig. 6. Confusion Matrix: XGBoost

The result of the feature importance of the XGBoost model (Fig. 7) reveals that structural and spectral features exhibit a significant effect in characterizing complex urban morphology: (1) The most influential feature across iterations is `brightness_gabor_a0_k10`, with a normalized importance of approximately 0.12. This indicates that the edge and orientation of the build-up structure captured by Gabor filters are one of the primary features that the model uses to distinguish UIS areas from non-UIS areas; (2) Spectral signatures from the NIR band, particularly `nir_mean_k10` and `nir_mean_k5`, rank among the top features; and (3)

Multi-scale features play an important role in capturing the heterogeneity of UIS areas across different spatial resolutions. Indices calculated at different scales are proven to be important to the model, such as various NDVI-Gabor combinations.

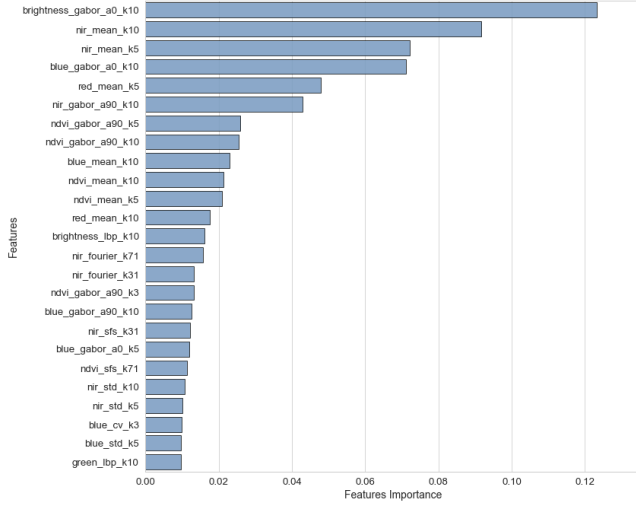


Fig. 7. XGBoost Feature Importance

3) Multi-Layer Perceptron (MLP)

The MLP model achieved an overall accuracy of 92% on the 20% independent holdout test set. Compared to other models, MLP has the highest precision of 97%, while the UIS recall is slightly lower (83%) than that of the XGBoost model (89%). The MLP model can maintain a high F1-score of 0.89 (Fig. 8).

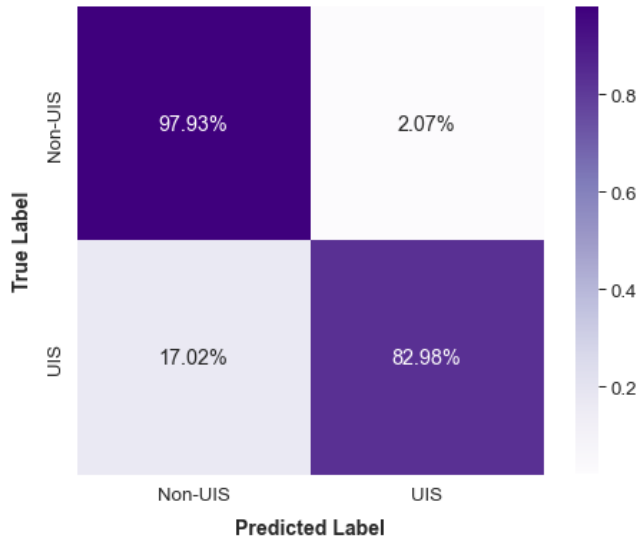


Fig. 8. Confusion Matrix: MLP

The result of the feature importance of the MLP model demonstrates that: (1) The model is exceptionally sensitive to periodic spatial patterns. Fourier transforms related features, specifically `nir_fourier_k31` and `nir_fourier_k51`, occupy the top two positions with normalized importance values of approximately 0.08 and 0.068, respectively. This indicates that the neural

network is good at capturing features associated with high-density, irregular building grains. (2) Beyond frequency, the model also relies heavily on directional textures. Features such as `ndvi_gabor_a90_k10` and `green_gabor_a0_k10` are among the most influential. This suggests that the MLP model effectively integrates the morphological features, such as the orientation of building shadows and narrow alleyways (Fig. 9).

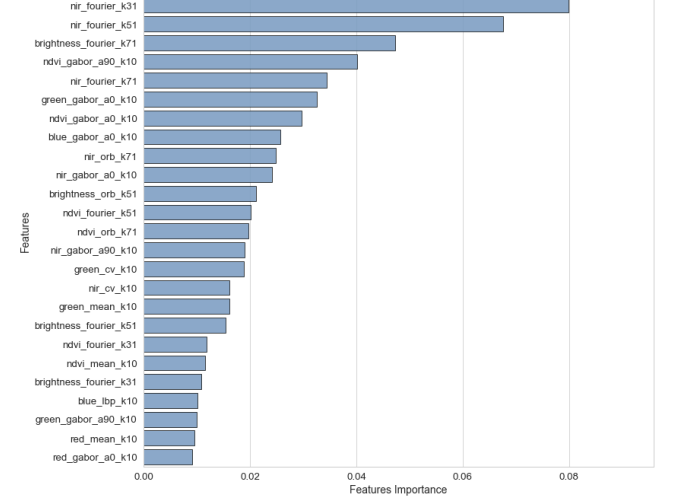


Fig. 9. MLP Feature Importance

4) Model Comparison

In general, three models displayed good performances in UIS-detection, with the overall accuracy around 90% (Table 2). Among the three models, XGBoost reveals the most robust and comprehensive mapping capability, achieving the highest overall accuracy (93%) and the most balanced F1-score (0.92). Its recall of 0.89 also suggests its superior ability to capture various UIS typologies, which significantly reduced "false negatives" compared to the other models. In addition, although the MLP model is slightly lower in overall accuracy (92%) than XGBoost, it achieved a leading precision of 0.97 for the UIS class. This indicates that the neural network is exceptionally reliable in identifications, making it the ideal choice for contexts where avoiding confusion between formal urban areas and informal settlements is the top priority.

TABLE II

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Metric	Random Forest	XGBoost	MLP
Overall Accuracy	88%	93%	92%
UIS Precision	0.93	0.95	0.97
UIS Recall	0.76	0.89	0.83
UIS F1-Score	0.84	0.92	0.89
Non-UIS Recall	96.23%	97.93%	97.93%

Furthermore, the feature importance analysis reveals two main findings: (1) There is a clear difference in classification strategy: while Random Forest relies more

on spectral means features, XGBoost and MLP achieve higher performance by extracting deeper structural signatures. Specifically, XGBoost's reliance on Gabor textures and MLP's reliance on Fourier frequencies demonstrate that the complex spatial arrangement of the built environment is a more important indicator of UIS than spectral features alone. (2) Spatial scale (window size) can influence the model's ability to resolve urban heterogeneities. For textural indicators like Gabor filters and Fourier transforms, medium scales often have a significant contribution to the models. In addition, NDVI and NIR features showed varying importance across different scales.

B. Final Prediction

The best-performing XGBoost model was then applied to predict UIS areas across the study region. The results indicate that the model detected 167.8 km² of UIS, accounting for approximately 5.62% of the total study area (Fig. 10).

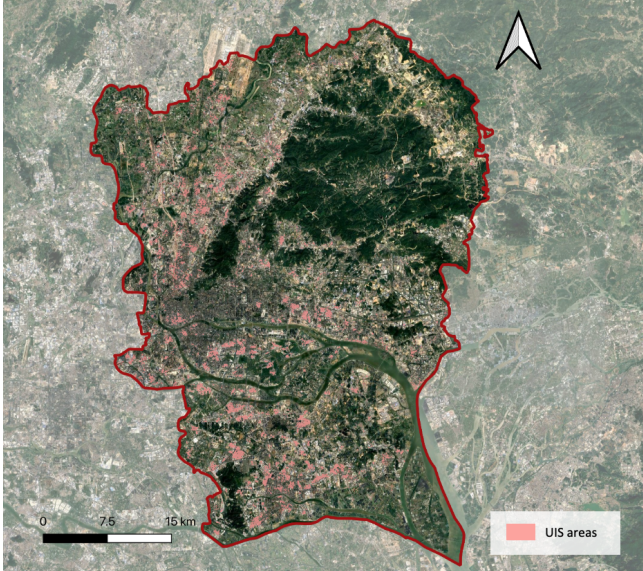


Fig. 10. Results of UIS areas

The quality of the predicted maps was assessed through visual interpretation with the Google Satellite as a reference. Overall, the proposed methodology can effectively identify the majority of large-scale UIS areas, such as Tangxia and Chebei in the Tianhe District and Sanyuanli in the Baiyun District. However, the model shows a tendency toward overprediction in high-density residential areas. The model occasionally confuses traditional old neighborhoods with urban village structures, since the old residential areas have similar morphological characteristics to the structured UIS areas.

Detection of different types of UIS areas was also evaluated. As shown in Fig. 11, the model can effectively identify both structured UIS and unstructured UIS areas. However, in hybrid UIS areas with transitional zones at the periphery, the model may incorrectly classify surrounding formal residential areas as UIS areas.



Fig. 11. Structured, unstructured, and hybrid UIS areas

V. DISCUSSION

In this study, a framework for detecting UIS areas using machine learning models based on contexture features extracted from Sentinel-2 imagery was developed. The high performance across all three models demonstrated that machine learning is highly effective for UIS detection when paired with multi-scale contextual features. Among the evaluated models, the nuances between XGBoost and MLP reveal a critical trade-off for urban planning applications. The high F1-score and recall of XGBoost (0.92 and 0.89, respectively) suggest that it is more adept at capturing the heterogeneity of UIS areas. Conversely, the MLP's exceptional precision (0.97) indicates a more conservative predictive behavior. In practical scenarios, if a municipal authority prioritizes avoiding the socio-political sensitivity of mislabeling formal housing as informal, the MLP would be the preferred model due to its significantly lower false-positive rate.

Another focus of this study lies in characterizing the spatial attributes of UIS in Guangzhou. By analyzing feature importance, it was observed that the superior performance of the XGBoost and MLP algorithms stems from their ability to extract deep structural and textural signatures. The findings indicate that in a complex megacity like Guangzhou, spectral features alone are insufficient indicators of informal settlements. Instead, geometric and textural characteristics (such as narrow street canyons and irregular roof alignments) serve as more robust proxies for identifying UIS.

The results also underscore the importance of medium-scale windows in texture extraction. Features at the 310 m to 510 m scales are sufficiently large to capture the collective arrangement of multiple buildings and alleys, yet small enough to exclude adjacent industrial zones or parklands. Despite these, over-prediction in high-density formal areas and confusion within hybrid UIS zones remain persistent challenges. The model's occasional inability to distinguish between these areas suggests that 'informality' is not merely a physical state but is also deeply tied to socio-economic factors. Consequently, incorporating auxiliary data is essential to further enhance model performance.

There are some limitations to the study. First of all, while this study successfully identifies various UIS types within the study area, the results may be subject to geographic specificity. The model relied on localized training samples and its spatial transferability to new cities remains untested. Future research is required to determine if the methodology maintains its predictive accuracy when applied to cities with different urban morphologies and environmental conditions. Second, the UIS detection models still tend to confuse old residential neighborhoods with UIS. Therefore, in addition to relying on remote sensing imagery, multi-source data can be incorporated

to supplement socioeconomic attributes, such as POI and population data.

VI. CONCLUSION

This study explores a practical framework integrating Sentinel-2 imagery and multi-scale machine learning models to accurately map Urban Informal Settlements (UIS) within a complex megacity environment. The findings demonstrate that in highly heterogeneous cities like Guangzhou, deep structural and textural features, are more robust than spectral indicators alone in distinguishing informal morphologies, specifically at the 310 m to 510 m scale. The ability to characterize UIS areas with temporal and spatial accuracy is important for municipal authorities to implement, monitor, and evaluate urban planning policies. This is particularly vital for Chinese cities currently undergoing a profound transition in urban renewal, where the focus is shifting from wholesale demolition toward precise, sustainable urban governance [17, 18]. By providing a scalable and cost-effective monitoring tool, this research offers a critical evidence base for fostering more inclusive and resilient urban development in the Global South.

GENAI DECLARATION

Before starting the project, I used ChatGPT to explore potential research topics and discussed the feasibility of project ideas. During the project, I used AI tools to identify and troubleshoot coding issues. After completing the report, I used ChatGPT for language and grammar checks. After using this tool, I reviewed and edited the content as needed and take full responsibility for the work.

CONTRIBUTION AND LEARNING

With a background in GIS and urban planning, my prior experience was largely centered on analyzing vector-based spatial data and applying machine learning to structured socioeconomic datasets. However, I had limited exposure to applying machine learning to remote sensing imagery. This project served as a bridge between my existing expertise and the specialized domain of remote sensing.

The study adopts a framework that integrates Sentinel-2 multispectral data with machine learning algorithms. While the high-level methodology draws on established literature for UIS detection, I independently customized the feature engineering pipeline. Several core techniques covered in the curriculum were applied throughout the project: (1) Image Pre-processing: resampling techniques to align the spatial resolution of varying bands to a consistent 10 m grid; (2) Feature Extraction: Image processing operations discussed in class were implemented during the project, specifically focusing on textural analysis.

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