International Cartographic Association
Association Cartographique Internationale

Predicting the Non-agricultural Conversion of Cropland using a Graph Attention Network based Method: the Case Study of Wuhan, China

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Keywords: Cropland non-agriculturalization, Land use, Graph Attention Network

Abstract:

As an important national resource and the foundation of food production, cropland is crucial for ensuring farmers' income and food security. However, amid rapid urbanization and industrialization, developing nations like China confront the significant challenge of cropland non-agriculturalization. Driven by multiple factors, this process involves converting agricultural land to non-agricultural uses and has multiple negative social, economic, and environmental impacts. To effectively manage and reduce the scale of it, widely adopted methods currently include remote sensing, machine learning and deep learning, spatiotemporal analysis, as well as combinations of these methods (Liu M et al., 2022; Lu D et al., 2024). Among them, remote sensing change detection technology can accurately identify the cropland non-agriculturalization patches from dual-phase high-resolution satellite imagery (Zhang H et al., 2024). Interpretable machine learning methods, such as XGBoost and SHAP (Zhang G et al., 2024), are used to identify and analyze the significance of driving factors. Change detection methods based on deep learning are able to be applied to the cropland non-agriculturalization monitoring (Wu Q et al., 2024), but suffer from the reflectance variability and the lack of dataset (Sun Z et al., 2024). Spatiotemporal analysis methods can reveal long-term dynamic changes and factors of the cropland non-agriculturalization (Chen Y et al., 2022), providing more precise and reliable data to support policy formulation for it (Wu X et al., 2024). Although these methods reach a high accuracy in respective fields, they can only detect areas where the cropland non-agriculturalization has already occurred. Correcting this issue is labor-intensive and requires significant material resources for rehabilitation. In addition, current research typically operates within time scales of 5-10 years and lacks a meso-scale approach to bridge the gap between patch-level and county-level scales, which does not meet monitoring and regulation needs. Thus, predicting and preventing high-risk areas is vital. Short-term, meso-scale predictions can offer a better basis for management and policy-making, improving efficiency and reducing costs.

The study proposed a method to predict the cropland non-agriculturalization level by inputting a geographic knowledge graph (GKG) made up of multi-source and multi-scale data into a graph attention network (GAT) model (Veličković P et al., 2017). First, graph modeling. Fixed spatial relationships and dynamically changing attribute features of geographic entities make them naturally suitable for graph-based modeling. This study integrates road networks, river systems, and land-use attributes to partition the study area into nodes. The connections of nodes and their first-order neighbors are taken as adjacent edges to construct the geographic graph structure. Second, feature extraction. There are three components included in the node features: land-use and land-cover (LULC) embedding features generated by random walk and Word2vec model from rasterized LULC data, image features extracted from remote sensing imagery using band value statistics and the gray-level co-occurrence matrix (GLCM), and geo-economic features derived from DEM, maps, and VGI data using RS and GIS processing software. Edge features are obtained by calculating the content similarity between node features. Third, model training. Taking the GKG, which includes the geographic graph structure as well as embedding features, image features, and geo-economic features, as an input for GAT-based model. By integrating attribute-driven and multi-head attention mechanisms, node features' aggregations are achieved in the convolutional layers with weights computed from edge features. After multiple layers of feature updating, the model outputs predictions of cropland non-agriculturalization level for the next year (Figure 1).

Abstracts of the International Cartographic Association, 10, 294, 2025
32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada.
https://doi.org/10.5194/ica-abs-10-294-2025

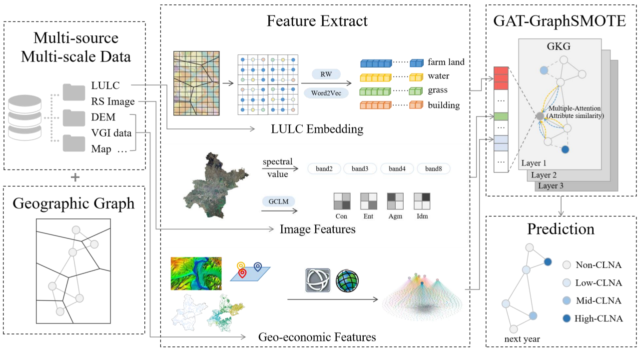

Figure 1. The architecture of the proposed method

The study utilizes the high temporal resolution China Land Cover Dataset (Yang J et al., 2024) to extract annual cropland non-agriculturalization data for suburban areas in Wuhan. By calculating the percentage of the cropland non-agriculturalization area relative to the cultivated land area in the previous year for each node, the cropland non-agriculturalization is categorized into four levels: non, low, mid, and high. A GAT model is used to train,valid and test the data. To balance the number of nodes in different classes, this study introduces the GraphSMOTE mechanism to enhance data during the training phase (Zhao T et al., 2021). Experiments demonstrate that the model effectively captures the features of the GKG, and predicts the cropland non-agriculturalization levels in the four time periods of the 2018-2022. The AUC-ROC reached a maximum of 87% and an average of 80%. Compared to other studies, this method allows for utilizing short-term data to predict the cropland non-agriculturalization levels for the next period, aiding in the delineation of priority areas for future cropland non-agriculturalization monitoring and enabling proactive intervention. Additionally, by constructing the GKG, this method addresses challenges associated with multi-scale and multi-source data integration. The explicit representation of spatiotemporal context enhances the interpretability of the prediction results.

Acknowledgements

This work was supported by the National Natural Science Foundation of China [grant numbers, 42394062].

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https://doi.org/10.5194/ica-abs-10-294-2025