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Remote Sensing Identification and Spatiotemporal Evolution of Cultivated Land Non-Agriculturalization in Qixian County Based on Google Earth Engine

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Abstract: Cultivated land non-agriculturalization is an important manifestation of county-level land use transition. Timely identification of its spatial distribution and phased evolution is essential for farmland protection and rational land resource allocation. Taking Qixian County in Henan Province, China, as the study area, this paper used Sentinel-2 imagery from 2020, 2023, and 2025 on the Google Earth Engine platform. Percentile compositing was employed to generate multi-temporal feature images, and a random forest classifier was used to extract land use information. A unified cultivated land mask for 2020 was then used as a constraint, and post-classification comparison was applied to identify the conversion of cultivated land to non-agricultural uses. The spatiotemporal evolution of non-agriculturalization was analyzed in terms of area, transition type, and spatial distribution. The results show that the overall accuracy of land use classification in the three periods was higher than 83%, and the Kappa coefficient was above 0.77. The areas of cultivated land non-agriculturalization in 2020–2023, 2023–2025, and 2020–2025 were 54.5241 km², 10.3185 km², and 40.6306 km², respectively. Conversion to water dominated in 2020–2023, whereas conversion to orchard/woodland became dominant later. Spatially, non-agriculturalization was concentrated around the county seat, township centers, and transport corridors.

Keywords: Cultivated land non-agriculturalization, Google Earth Engine, Random forest, Remote sensing, Spatiotemporal evolution.

1. Introduction

With the continuous advancement of urbanization and adjustment of agricultural structure, county-level cultivated land use patterns are undergoing remarkable changes, and cultivated land non-agriculturalization has become an important topic in land use change research [1,2]. Qixian County, located in northern Henan Province, is a typical agricultural county in the plain area. In recent years, infrastructure construction, urban expansion, and agricultural restructuring have markedly affected cultivated land use, making the area representative for county-scale studies. Previous studies have mainly focused on the overall scale and driving factors of cultivated land non-agriculturalization, whereas phased changes and spatial differentiation at the county scale remain insufficiently explored. Therefore, based on the Google Earth Engine platform and multi-temporal Sentinel-2 imagery, this study identifies cultivated land non-agriculturalization in Qixian County and analyzes its spatiotemporal evolution characteristics [3].

2. Study Area and Data Sources

2.1. Study Area

Qixian County is located in Hebi City, Henan Province, in the transitional zone from the piedmont hills of the Taihang Mountains to the plain. The overall terrain is higher in the west and lower in the east. The western part is dominated by hills and low mountains, whereas the eastern part consists mainly of plains suitable for agriculture. Owing to the significant differences in natural topography and human activities, the county exhibits strong spatial heterogeneity in cultivated land use, construction expansion, and land transition.

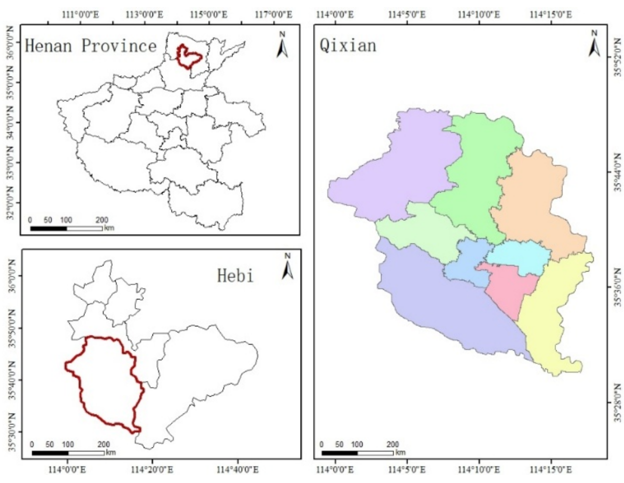

Figure 1. Location of the study area in Qixian County.

2.2. Data Sources

The main datasets used in this study include: (1) Sentinel-2 remote sensing images from 2020, 2023, and 2025 for land use classification; (2) the Third National Land Survey data and ESA WorldCover data [4] for auxiliary sample selection and result verification; and (3) high-resolution Google Earth historical imagery for visual interpretation and accuracy assessment. To reduce the effects of cloud contamination and seasonal differences, images from the growing season of each year were selected and processed on the Google Earth Engine platform using cloud masking and percentile compositing, thereby improving the stability and comparability of the classification results.

3. Methods

3.1. Remote Sensing Image Preprocessing

Sentinel-2 imagery for the three periods was acquired and processed on the Google Earth Engine platform. Cloud- and shadow-affected pixels were removed using a cloud-masking procedure. Percentile compositing was then applied to generate stable multi-temporal composite images, reducing the influence of abnormal observations in single-date imagery. Spectral bands and spectral indices were further combined to construct feature sets for subsequent classification.

3.2. Land Use Classification

According to the actual land use conditions in Qixian County, five classes were defined: cultivated land, orchard/woodland, construction land, water, and other land. A random forest classifier was used to classify the imagery of each period, and training samples and validation samples were employed to obtain the final land use maps [3,5]. Because of its strong nonlinear fitting capacity and robustness to noisy features, the random forest method is suitable for multi-source and multi-feature remote sensing classification.

3.3. Identification and Spatiotemporal Analysis of Cultivated Land Non-Agriculturalization

Using a unified cultivated land mask of the base year as a spatial constraint, post-classification comparison was adopted to identify the conversion of cultivated land to non-agricultural uses in different periods [6]. Three periods, namely 2020–2023, 2023–2025, and 2020–2025, were examined. The evolution characteristics were analyzed from the perspectives of area scale, transition type, and spatial distribution.

4. Results and Analysis

4.1. Land Use Classification Results and Accuracy Assessment

The land use classification results show a clear spatial pattern in Qixian County. Orchard/woodland and other land are mainly distributed in the western hilly area, cultivated land is concentrated in the eastern plain, and construction land is clustered around the county seat and township centers. The accuracy assessment indicates that the overall accuracy of all three classifications exceeded 83%, and the Kappa coefficient was higher than 0.77, demonstrating that the results are sufficiently reliable for identifying cultivated land non-agriculturalization.

Table 1. Classification accuracy in 2020, 2023, and 2025.

Year	OA/%	Kappa
2020	83.12	0.771
2023	96.80	0.956
2025	92.86	0.885

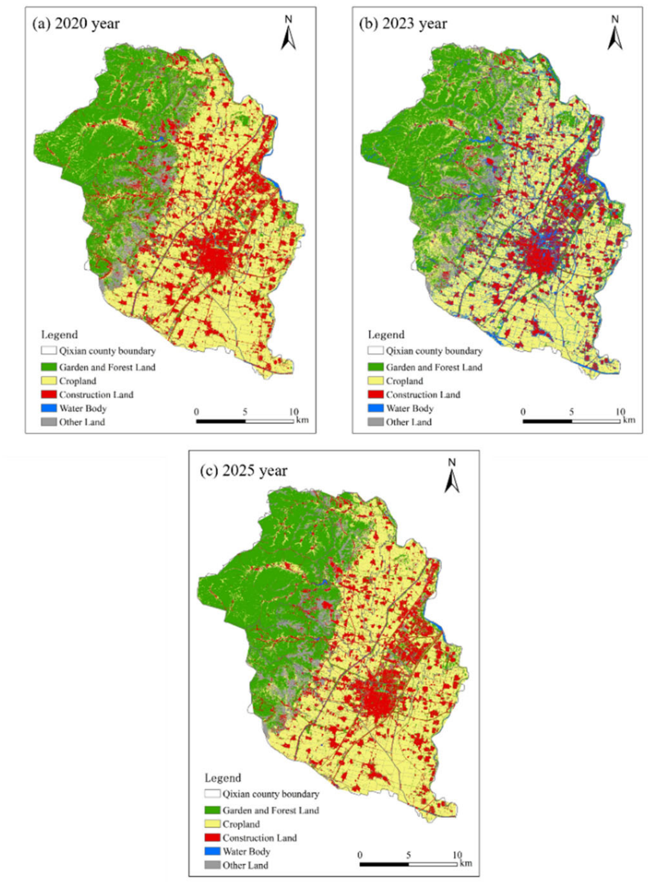

Figure 2. Land use classification results in 2020, 2023, and 2025.

4.2. Scale and Type Characteristics of Cultivated Land Non-Agriculturalization

Table 2. Area and major transition types of cultivated land non-agriculturalization in different periods.

Period	Transition type	Area/km²	Share/%
2020–2023	Cultivated land to orchard/woodland	14.9251	27.37
	Cultivated land to construction land	5.1161	9.38
	Cultivated land to water	25.0056	45.86
	Cultivated land to other land	9.4773	17.38
	Total	54.5241	100.00
2023–2025	Cultivated land to orchard/woodland	6.5416	63.40
	Cultivated land to construction land	0.8493	8.23
	Cultivated land to water	0.0015	0.01
	Cultivated land to other land	2.9261	28.36
	Total	10.3185	100.00
2020–2025	Cultivated land to orchard/woodland	16.6985	41.09
	Cultivated land to construction land	9.0794	22.35
	Cultivated land to water	0.0522	0.13
	Cultivated land to other land	14.8005	36.43
	Total	40.6306	100.00

The identified results indicate that cultivated land non-agriculturalization in Qixian County showed clear stage-based variation during the study period. The area of cultivated land converted to non-agricultural uses was 54.5241 km² in 2020–2023, 10.3185 km² in 2023–2025, and 40.6306 km² in 2020–2025. These results suggest that the earlier stage experienced the most intense conversion, whereas the later stage was notably weaker.

Transition types also differed across periods. In 2020–2023, cultivated land conversion to water was dominant, reflecting the effects of water-related engineering, pond expansion, or aquaculture-related land use change. In contrast, in 2023–2025 and over the whole period of 2020–2025, conversion from cultivated land to orchard/woodland accounted for the largest share, indicating that agricultural restructuring and adjustments in planting patterns played an important role.

4.3. Spatiotemporal Evolution of Cultivated Land Non-Agriculturalization

Spatially, cultivated land non-agriculturalization in Qixian County was mainly concentrated in the central and eastern plain areas, especially around the county seat, township centers, and areas with favorable transport conditions, whereas the western hilly region exhibited much less change. The distribution was relatively extensive in 2020–2023, shrank considerably in 2023–2025, and over 2020–2025 showed an aggregated pattern around urbanized areas and transport corridors.

These results indicate a strong spatial selectivity in cultivated land non-agriculturalization. On the one hand, natural topographic conditions impose a basic constraint on land transition, and the eastern plains, where cultivated land is concentrated and land use intensity is high, are more prone to conversion. On the other hand, areas surrounding the county seat and townships are more strongly affected by population concentration, infrastructure development, and land development activities, making them high-incidence zones of cultivated land transition.

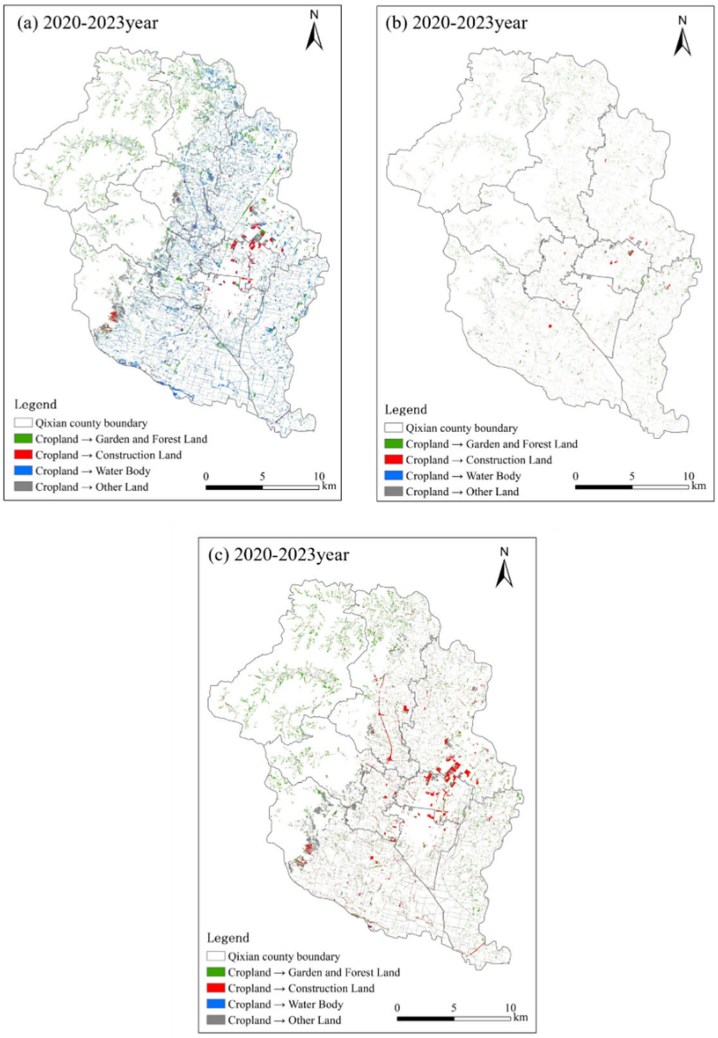

Figure 3. Spatial distribution of cultivated land non-agriculturalization in different periods.

5. Conclusion

Based on the Google Earth Engine platform and Sentinel-2 imagery from 2020, 2023, and 2025, this study identified cultivated land non-agriculturalization in Qixian County and analyzed its spatiotemporal evolution. The results show that the land use classification framework based on Google Earth Engine and the random forest method is suitable for county-level studies, with overall classification accuracy above 83% in all three periods. The areas of cultivated land non-agriculturalization in 2020–2023, 2023–2025, and 2020–2025 were 54.5241 km², 10.3185 km², and 40.6306 km², respectively, indicating a strong early-stage change followed by a later decline. Transition types also displayed obvious temporal differences, shifting from cultivated land-to-water conversion in the earlier period to cultivated land-to-orchard/woodland conversion in the later period. Spatially, the process was mainly concentrated around the county seat, township centers, and transport-accessible areas. Overall, cultivated land non-agriculturalization in Qixian County exhibits clear stage characteristics and spatial heterogeneity, and the results can provide a reference for county-level farmland protection and land use management.

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