

Article

# A Spatial Decision Support Framework for Winter-Rapeseed Expansion on Stable Winter–Fallow Cropland Using Multi-Source Remote Sensing, Satellite Embedding, and MaxEnt

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## Abstract

Under increasing cropland constraints and pressure to secure oilseed supplies, using winter–fallow cropland for winter rapeseed production can improve annual cropland-use efficiency. Taking the Wanjiang Plain, China, as the study area, this study integrated 10 m winter–fallow cropland maps (2019–2024), 30 m winter rapeseed maps (2000–2022), annual Satellite Embedding features, cropland data, and administrative boundaries. Multi-year occurrence frequency and Getis–Ord  $G_i^*$  statistics characterized temporal persistence and spatial clustering. A MaxEnt model calibrated with 394 occurrence records from long-term high-frequency rapeseed areas and 26 screened embedding dimensions delineated cropland with present-day land-surface characteristics similar to historically persistent rapeseed locations. This layer was progressively intersected with the historical winter–fallow union and stable winter–fallow cropland. Stable winter–fallow cropland covered approximately 4437 km<sup>2</sup>, whereas long-term high-frequency winter rapeseed covered only 568 km<sup>2</sup>, revealing a marked spatial mismatch. Under five-fold spatial cross-validation, the selected linear-feature model with a regularization multiplier of 4 achieved a mean test AUC of  $0.904 \pm 0.015$  and a 10% training-omission rate of  $0.108 \pm 0.022$ . Using the model-specific threshold of 0.3096, the final estimates were 6017 km<sup>2</sup> of potentially suitable cropland, 2943 km<sup>2</sup> of general expansion potential, and 1137 km<sup>2</sup> of candidate spatial priority areas for field verification. The last tier was concentrated mainly in Xuanzhou District, Lujiang County, urban Wuhu, Wuwei City, Nanling County, and He County. The framework provides a cautious spatial-screening basis for optimizing winter–fallow cropland use and guiding subsequent field and feasibility assessments.

**Keywords:** winter–fallow cropland; winter rapeseed; satellite embedding; MaxEnt; multi-source geospatial observations; expansion potential; candidate spatial priority areas



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## 1. Introduction

Ensuring food security and a stable supply of major agricultural products is central to agricultural sustainability [1,2]. With population growth, climate change, cropland constraints, and uncertainties in agricultural trade, increasing output solely through cropland expansion has become increasingly limited [3,4]. Improving the productivity and annual use efficiency of existing cropland is therefore essential for alleviating food and oilseed supply pressures [5–7]. In regions facing limited cropland and pressure on edible vegetable

oil supply, developing underutilized winter cropland can increase the multiple-cropping index, improve annual cropland productivity, and strengthen oilseed supply resilience [8]. Winter-fallow cropland refers to seasonally underutilized cropland that lacks crop cover or effective use after the main-season crop harvest; its utilization exploits the temporal use potential of existing cropland rather than expanding agricultural land. China's 14th Five-Year National Planting Industry Development Plan promotes rapeseed production and rapeseed-rice rotation in winter rapeseed-producing regions of the Yangtze River Basin, providing policy support for winter-rapeseed expansion on winter-fallow cropland.

Winter rapeseed is a major oilseed crop in China and a typical winter crop in the Yangtze River Basin [9–11]. Its growth period is complementary to the winter-fallow period after rice harvest in southern China [12,13]. Under the premise of avoiding substantial competition with rice and other staple crops, rapeseed-rice rotation can improve annual cropland-use efficiency and increase oilseed output [14,15]. Previous studies have shown that winter-fallow cropland in the Yangtze River Basin has considerable potential for winter rapeseed development and can contribute to rapeseed supply [16]. However, crop profitability, rural labor migration, mechanization adaptability, management modes, and cropping-system adjustments have reshaped winter rapeseed cultivation in China over the past two decades, with some traditional production areas experiencing contraction [17]. Identifying suitable expansion areas from widely distributed winter-fallow cropland is therefore important for optimizing winter cropland use and regional agricultural planning [18].

High-resolution and long-term crop spatial datasets provide an important foundation for evaluating winter-fallow cropland utilization and winter-rapeseed expansion potential [19,20]. For winter rapeseed monitoring, MODIS, Landsat, Sentinel-1/2, and Google Earth Engine have been used to map planting areas [21–23], extract phenological characteristics [24–26], and support regional crop mapping [27,28]. Related crop-type mapping studies have also highlighted the roles of time-series imagery, transfer learning, and sample generation [29,30]. CARM30, a 30 m annual rapeseed dataset for China from 2000 to 2022, enables long-term analysis of rapeseed planting patterns [31]. For winter-fallow cropland, studies have identified winter cropland-use status using multi-temporal vegetation indices, cropland cover, and remote-sensing time-series features [32]. Chen et al. developed a 10 m annual winter-fallow cropland dataset for the Wanjiang Plain from 2019 to 2024 using Sentinel-1/2 data and a Random Forest-FR-Net framework [33]. Although these datasets improve the spatial identification of winter rapeseed and winter-fallow cropland, less attention has been paid to their spatial relationship, temporal stability, and expansion priority [34,35].

Winter-rapeseed expansion on winter-fallow cropland requires both stable fallow resources and suitable cultivation environments. Single-year winter-fallow cropland may be influenced by climate variability, market fluctuations, temporary farmer decisions, or classification errors, and may therefore overestimate sustainably usable winter cropland [36]. Conversely, areas with land-surface representations similar to persistent rapeseed locations may already be planted with other winter crops or may not be available for winter use. Delineating expansion areas solely by embedding-based suitability proxy can therefore be inconsistent with actual land-use status. A joint analysis of multi-year winter-fallow stability, historical winter rapeseed cultivation, and embedding-based suitability proxy is needed to distinguish historically fallow and stably fallow cultivation-suitable areas from general areas with land-surface representations similar to persistent rapeseed locations.

Crop suitability evaluation commonly uses climatic, topographic, soil, and hydrological variables to link crop distribution with growing environments. The maximum entropy model (MaxEnt) estimates potential distributions from presence samples and en-

vironmental variables [37], and is suitable when reliable absence samples are difficult to obtain [38,39]. It has been widely used in species distribution modeling and crop suitability assessment [40,41], including potential suitability simulations for maize, rice, wheat, soybean, citrus, and other crops [42,43]. For winter rapeseed, historically stable cultivation areas can provide presence samples for identifying areas with similar environmental conditions. However, traditional environmental variables may not fully capture land cover, vegetation status, moisture background, and farmland landscape patterns within a unified framework.

Artificial-intelligence-driven representations of multi-source geospatial observations provide new environmental features for regional analysis. Satellite Embedding V1, released through Google Earth Engine, provides annual global geospatial embeddings at 10 m resolution, with each pixel represented by a 64-dimensional vector that supports classification, clustering, change detection, and spatial prediction [44]. Embedding features generated from multi-source Earth observation data can provide general-purpose environmental representations for sparse-label mapping and inference. Compared with individual remote-sensing bands or a limited set of environmental indicators, Satellite Embedding can compactly represent multidimensional land-surface differences. This study does not propose a new artificial intelligence model; rather, it explores the use of geospatial embedding features with MaxEnt for agricultural land-use evaluation.

The Wanjiang Plain, located in the lower Yangtze River region, is an important grain and oilseed production region in Anhui Province. It has concentrated cropland, favorable hydrothermal conditions, a strong basis for rapeseed–rice rotation, and the coexistence of winter–fallow cropland and winter rapeseed. Although high-resolution winter–fallow cropland data and long-term winter rapeseed distribution data are available, a comprehensive spatial assessment of winter-rapeseed expansion on winter–fallow cropland remains insufficient. In particular, systematic research is still needed to integrate winter–fallow stability, historical winter rapeseed cultivation, and Satellite Embedding features for progressive identification of candidate expansion areas.

Based on this context, this study integrated winter–fallow cropland data from 2019 to 2024, winter rapeseed data from 2000 to 2022, Satellite Embedding features, and basic geospatial datasets to develop a framework including spatial pattern analysis, temporal stability evaluation, embedding-based suitability proxy modeling, general expansion potential area identification, and delineation of candidate spatial priority areas. The objectives were to: (1) analyze the spatial distribution, occurrence frequency, and local clustering of winter–fallow cropland and winter rapeseed; (2) identify potentially suitable areas for winter rapeseed using MaxEnt with high-frequency historical winter rapeseed samples and Satellite Embedding features; (3) delineate general expansion potential areas by overlaying the suitability map with the historical winter–fallow union, and candidate spatial priority areas by further applying a stable winter–fallow constraint; and (4) compare county-level differences among the three spatial levels to support winter–fallow cropland utilization and winter-rapeseed expansion planning.

## 2. Materials and Methods

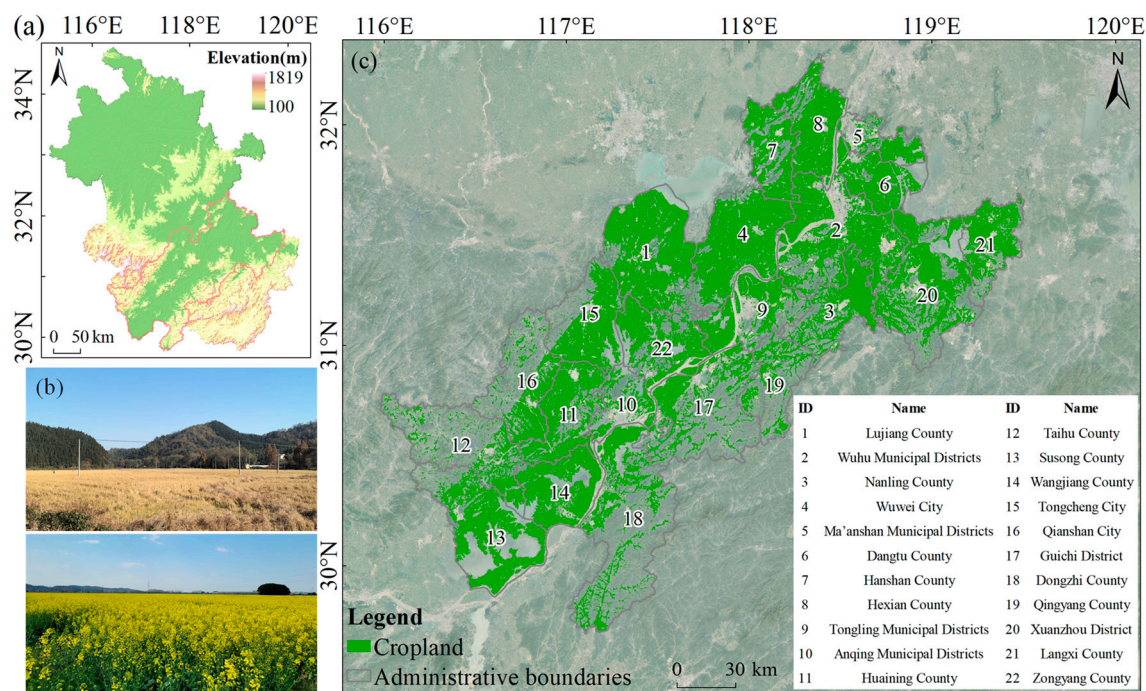
### 2.1. Study Area

The Wanjiang Plain is located along the Yangtze River in Anhui Province, China, and represents an important agricultural production region in the lower Yangtze River. The study area extends approximately from 116° E to 119° E and from 30° N to 32° N, covering Anqing, Chizhou, Tongling, Wuhu, Ma'anshan, Xuancheng, and surrounding counties and districts. Its landforms are dominated by riverine plains, polder plains, valley plains, and

gently sloping low hills. The terrain is generally flat, with dense rivers, lakes, and irrigation and drainage channels, forming a typical lower Yangtze agricultural landscape.

The study area has a subtropical monsoon climate with favorable hydrothermal conditions and synchronous rainfall and heat, making it suitable for rice, rapeseed, wheat, and other crops. Cropland is dominated by paddy fields, with some dryland and mixed paddy–dryland areas. Rice is the main grain crop, while winter rapeseed is an important winter oilseed crop; their complementary growing seasons provide a natural and production basis for rapeseed–rice rotation.

Unless otherwise stated, all map panels in Figures 1 and 3–8 were prepared in the Krasovsky\_1940\_Albers projected coordinate system, with D\_WGS\_1984 as the geographic coordinate system.



**Figure 1.** Overview of the study area. (a) Geographic location and topographic context of the study area in Anhui Province, China; (b) field photographs of typical winter–fallow cropland (**upper**) and winter rapeseed fields (**lower**); (c) spatial distribution of cropland across county-level administrative units in the study area. Green areas represent cropland, gray lines denote county-level administrative boundaries.

The Wanjiang Plain has multiple agricultural functions, including grain production, oilseed crop cultivation, and cropland protection. Recent changes in labor structure, crop profitability, and farming management have led to spatial differences in winter cropland use. The region therefore provides a typical case for examining winter–fallow cropland utilization and winter-rapeseed expansion planning in southern rice-based agricultural systems.

## 2.2. Data Sources and Preprocessing

### 2.2.1. Data Sources

This study used winter–fallow cropland maps, winter rapeseed maps, Satellite Embedding features, cropland data, and administrative boundaries. The winter–fallow cropland and winter rapeseed datasets were derived from published annual spatial products. Instead of repeating remote-sensing classification, this study used these datasets to analyze temporal stability, spatial clustering, suitability, and expansion priorities. Their temporal coverage, resolution, sources, and uses are summarized in Table 1.

Table 1. Data sources and uses.

| Data Type                   | Period                                        | Original Spatial Resolution | Unified Analytical Resolution | Data Source                                                                                             | Main Use                                                                                                 |
|-----------------------------|-----------------------------------------------|-----------------------------|-------------------------------|---------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| Winter–fallow cropland maps | 2019–2024                                     | 10 m                        | 30 m                          | Chen et al.                                                                                             | Spatial pattern analysis, occurrence frequency calculation, and stable winter–fallow cropland extraction |
| Winter rapeseed maps        | 2000–2022                                     | 30 m                        | 30 m                          | CARM30 dataset                                                                                          | Spatiotemporal pattern analysis, high-probability presence sample extraction, and MaxEnt modeling        |
| Satellite Embedding data    | 2024 (2020 and 2022 for sensitivity analysis) | 10 m                        | 30 m                          | Google Earth Engine Satellite Embedding V1                                                              | Satellite Embedding predictor input for MaxEnt modeling                                                  |
| Administrative boundaries   | 2024                                          | Vector                      | —                             | Standard Map Service System                                                                             | Study area clipping, county-level statistics, and mapping                                                |
| Cropland data               | 2020                                          | Multi-source                | 30 m                          | China 2020 land-use remote-sensing monitoring data; ESA WorldCover 2021 v200 (auxiliary exclusion only) | Primary cropland-domain definition and auxiliary removal of obvious non-cropland pixels                  |

Winter–fallow cropland data were obtained from the 10 m annual dataset for the Wanjiang Plain from 2019 to 2024 developed by Chen et al. [33]. Generated from Sentinel-1/2 imagery and a Random Forest–FR-Net framework, the dataset was used to analyze annual distribution, occurrence frequency, local clustering, and stable winter–fallow cropland. The annual winter–fallow cropland maps were obtained from our previously published and independently peer-reviewed mapping study [33], rather than being newly classified in the present study. In that study, the annual maps for 2019–2024 were evaluated using reference samples, with F1 scores ranging from 85.70% to 89.30% and overall accuracies ranging from 84.02% to 88.36%. The mean F1 score and overall accuracy across the six years were 87.21% and 85.64%, respectively. These published accuracy statistics provide the quality basis for using the annual maps as secondary input data in the present analysis.

Winter rapeseed data were obtained from CARM30, a 30 m annual rapeseed dataset for China from 2000 to 2022 [31]. Because rapeseed cultivation in the Wanjiang Plain is dominated by winter rapeseed, CARM30 rapeseed pixels within the study area were used for occurrence frequency analysis, spatial clustering, and presence sample extraction for MaxEnt.

Satellite Embedding data were obtained from the annual Satellite Embedding V1 product released through Google Earth Engine [19,44]. The product represents each pixel with a 64-dimensional embedding vector that captures integrated land-surface information, including land cover, vegetation growth, moisture conditions, and farmland landscape patterns. The 2024 embedding was used to represent the recent land-surface state and served as candidate Satellite Embedding predictors for MaxEnt. Because Satellite Embedding V1 is an externally developed, versioned product delivered through Google Earth Engine, exact reconstruction depends on continued access to the same annual assets and product definition; this dependency is considered explicitly in Section 4.5.

The 64 bands of the Satellite Embedding product (A00–A63) are coordinates in a learned multidimensional latent space rather than conventional spectral or environmental variables with predefined physical units. Each dimension may jointly encode information from multiple Earth observation sources, temporal trajectories, land-surface characteristics, and spatial context. Consequently, the individual embedding dimensions cannot be assigned unique meteorological, soil, topographic, or land-cover meanings. In this study, the selected dimensions were treated jointly as data-driven geospatial predictors, and their individual contributions were interpreted only in terms of predictive importance.

Satellite Embedding V1 was generated independently of the occurrence records used in this study, and none of the 394 winter-rapeseed occurrence records participated in the construction or training of the embedding product. Therefore, there was no direct transfer of the response labels into the predictor-generation process. Nevertheless, because the annual embedding summarizes multi-sensor Earth-observation information, it may indirectly encode vegetation phenology, crop cover, moisture conditions, and agricultural management. Accordingly, the MaxEnt output was interpreted as present-day land-surface representational similarity to historically persistent winter-rapeseed locations, rather than as a mechanistic estimate of intrinsic agronomic suitability.

Cropland data were used to constrain agricultural production space and interpret distribution differences. China's 2020 land-use remote-sensing monitoring dataset was used as the primary cropland mask. ESA WorldCover 10 m v200 was used only as an auxiliary exclusion layer for boundary refinement: pixels classified as cropland in the China 2020 dataset but identified as obvious built-up land, permanent water, or tree cover in WorldCover were removed, whereas WorldCover-only cropland pixels were not added [45]. The 2021 WorldCover product was therefore used for spatial boundary checking rather than temporal updating. The resulting categorical mask was aligned to the 30 m analytical grid using nearest-neighbor resampling.

#### 2.2.2. Data Preprocessing

To ensure spatial consistency, all datasets underwent coordinate transformation, study-area clipping [46,47], resolution harmonization, pixel alignment, and format conversion [48,49]. All rasters were transformed to the Krasovsky\_1940\_Albers projected coordinate system (geographic coordinate system: D\_WGS\_1984) and aligned to the original 2024 Satellite Embedding–MaxEnt reference grid, including its 30 m cell size, spatial extent, grid origin, and valid analytical domain.

All raster datasets were transformed to the same Krasovsky\_1940\_Albers projected coordinate system (geographic coordinate system: D\_WGS\_1984) and ultimately aligned to the original 2024 Satellite Embedding–MaxEnt grid, including its 30 m cell size, spatial extent, and grid origin. The annual 10 m winter–fallow maps were converted to 30 m using majority aggregation, whereby the class occupying the largest proportion of each target cell was retained; the aligned annual binary maps were then summed to obtain the 2019–2024 occurrence frequency. The CARM30 winter-rapeseed maps were already at 30 m, and nearest-neighbor resampling was used only when projection or grid-origin alignment was required before calculating the 2000–2022 frequency. The categorical cropland mask and the resulting frequency rasters were also aligned using nearest-neighbor resampling. Satellite Embedding bands were exported directly from Google Earth Engine at a scale of 30 m following the select–mosaic–clip–export workflow, without bilinear interpolation or a user-defined mean-aggregation operation. The 2020 and 2022 embedding rasters were subsequently aligned to the original 2024 grid using nearest-neighbor resampling. MaxEnt predictions were generated directly on this common grid and were not resampled

after prediction. Annual winter–fallow cropland and winter rapeseed rasters were then converted into binary data, with target pixels assigned 1 and other pixels assigned 0.

(1) Calculation of winter–fallow cropland occurrence frequency

$$P_i^{WF} = \frac{\sum_{t=1}^n W_{i,t}}{n} \times 100 \quad (1)$$

where  $P_i^{WF}$  is the winter–fallow occurrence frequency of pixel  $i$ ;  $W_{i,t}$  indicates whether pixel  $i$  was identified as winter–fallow cropland in year  $t$ , with 1 for yes and 0 otherwise; and  $n = 6$ . The six-year frequency classes were 16.67%, 33.33%, 50.00%, 66.67%, 83.33%, and 100%. Pixels identified as winter–fallow cropland in at least five years ( $\geq 83.33\%$ ) were defined as stable winter–fallow cropland, reducing the influence of occasional fallow events and classification errors.

(2) Calculation of winter-rapeseed occurrence frequency

Based on the 23 annual winter rapeseed maps from 2000 to 2022, the occurrence frequency of winter rapeseed for each pixel was calculated as follows:

$$P_i^{WR} = \frac{\sum_{t=1}^m R_{i,t}}{m} \times 100 \quad (2)$$

where the winter-rapeseed occurrence frequency of pixel  $i$  was calculated from the 23 annual maps for 2000–2022. Frequency was classified as absent (0), low ( $>0$ –16.67%), medium–low ( $>16.67$ –33.33%), medium ( $>33.33$ –50.00%), medium–high ( $>50.00$ –66.67%), high ( $>66.67$ –83.33%), and very high ( $>83.33$ –100%). For occurrence-sample generation, long-term high-frequency cultivation was operationally defined as more than 66.67% of the 23 years, which corresponds to at least 16 years ( $16/23 = 69.57\%$ ).

(3) Processing of Satellite Embedding features

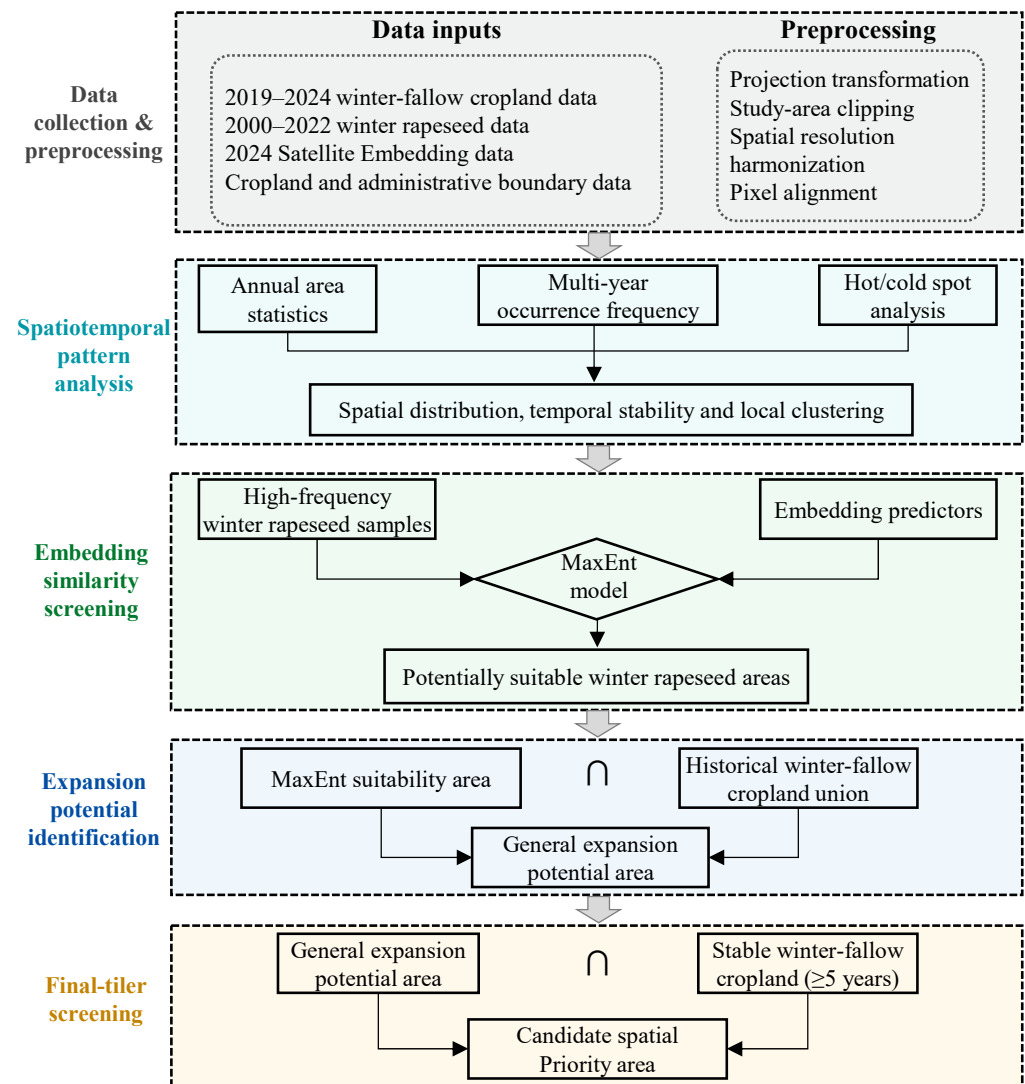
The 64 annual Satellite Embedding dimensions were exported and aligned as candidate predictors. Their screening, robustness assessment, and treatment as latent rather than directly physical variables are described in Section 2.3.4.

## 2.3. Methods

### 2.3.1. Research Framework

This study developed a framework consisting of data preprocessing, spatiotemporal pattern analysis, embedding-based suitability proxy modeling, general expansion potential area identification, and delineation of candidate spatial priority areas (Figure 2). After projection, clipping, resolution harmonization, and pixel alignment, occurrence frequency and Getis–Ord  $G_i^*$  hot spot analysis were used to reveal the spatial distribution, temporal stability, and local clustering of winter–fallow cropland and winter rapeseed. High-frequency historical winter rapeseed areas provided presence samples, and screened Satellite Embedding features were used in MaxEnt to identify potentially suitable areas within cropland. The suitability map was then overlaid with the historical winter–fallow union to identify general expansion potential areas and further overlaid with stable winter–fallow cropland to delineate candidate spatial priority areas.

The framework progressively overlays an embedding-based suitability proxy, historical winter–fallow occurrence, and multi-year winter–fallow stability. This hierarchy distinguishes three levels: potentially suitable areas, general expansion potential areas, and candidate spatial priority areas.



**Figure 2.** Research framework and workflow.

Spatial preprocessing, raster alignment, overlay analysis, area calculation, and map production were performed using ArcGIS 10.8 (Esri, Redlands, CA, USA). Satellite Embedding data were accessed and exported through Google Earth Engine [19]. Random Forest feature screening, MaxEnt v3.4.4 modeling [37–39], cross-validation, and statistical summaries were implemented in R (R Foundation for Statistical Computing, Vienna, Austria).

### 2.3.2. Spatial Distribution and Area Statistics

To describe annual and county-level differences, areas of winter–fallow cropland and winter rapeseed were calculated from annual binary rasters for the whole study area and for each county-level administrative unit. The winter–fallow cropland area of county  $k$  in year  $t$  was calculated as follows:

$$A_{k,t}^{WF} = \sum_{i=1}^{N_k} W_{i,t} \times a \quad (3)$$

where  $A_{k,t}^{WF}$  denotes the winter–fallow cropland area of county  $k$  in year  $t$ ;  $W_{i,t}$  indicates whether pixel  $i$  was winter–fallow cropland in year  $t$ , with a value of 1 if yes and 0 otherwise;

$a$  represents the area of a single raster pixel; and  $N_k$  denotes the total number of raster pixels in county  $k$ . The winter rapeseed area of county  $k$  in year  $t$  was calculated as follows:

$$A_{k,t}^{WR} = \sum_{i=1}^{N_k} R_{i,t} \times a \quad (4)$$

where  $A_{k,t}^{WR}$  denotes the winter rapeseed area of county  $k$  in year  $t$ ;  $R_{i,t}$  indicates whether pixel  $i$  was winter rapeseed in year  $t$ , with a value of 1 if yes and 0 otherwise. The remaining symbols are the same as those in Equation (3).

Annual total areas, county-level statistics, and multi-year overlays were used to compare winter–fallow cropland and winter rapeseed distributions. Because no formal trend significance test was conducted, initial–final year differences were interpreted descriptively rather than as statistically significant long-term trends.

### 2.3.3. Temporal Stability and Spatial Hot Spot Analysis

Temporal stability was characterized using multi-year occurrence frequency. Winter–fallow cropland stability was calculated from the six annual maps for 2019–2024, while winter rapeseed stability was calculated from 23 annual maps for 2000–2022. Higher frequency indicates stronger persistence of the corresponding land-use state.

Local clustering of winter–fallow cropland and winter rapeseed was analyzed using the Getis–Ord  $G_i^*$  statistic [50,51]. A 5 km  $\times$  5 km regular grid was constructed, and winter–fallow cropland and winter rapeseed areas were calculated for each grid cell. A spatial weight matrix based on grid relationships was then used to calculate local  $G_i^*$  values:

$$G_i^* = \frac{\sum_{j=1}^n w_{ij}x_j - \bar{x}\sum_{j=1}^n w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^n w_{ij}^2 - \left(\sum_{j=1}^n w_{ij}\right)^2}{n-1}}} \quad (5)$$

where  $G_i^*$  is the local spatial clustering statistic for unit  $i$ ;  $x_j$  is the winter–fallow cropland or winter rapeseed area in unit  $j$ ;  $w_{ij}$  is the spatial weight;  $n$  is the number of spatial units;  $\bar{x}$  and  $S$  are the mean and standard deviation of the attribute values. Cell-level winter fallow field (WFF) and winter rapeseed (WR) values were summarized using the original 5 km  $\times$  5 km regular grid. This spatial support was selected as a compromise between retaining sub-county spatial detail and providing stable cell-level area summaries: each grid cell integrates approximately 250,000 source pixels at 10 m resolution or 27,778 pixels at 30 m resolution, while retaining 1672 analytical units across the study area. Getis–Ord  $G_i^*$  statistics were calculated using a fixed-distance-band conceptualization of spatial relationships, Euclidean distances between grid-cell centroids, and row-standardized binary weights. Under the baseline 5 km band, the focal cell and its orthogonally adjacent cells entered the local statistic for an interior grid cell.

To assess sensitivity to the spatial-neighborhood definition while holding the aggregation support constant, the analysis was repeated using 7.5 and 10 km distance bands. The 7.5 km band additionally incorporated first-order diagonal neighbors, whereas the 10 km band represented a broader neighborhood. This design isolated distance-band sensitivity without conflating it with changes in grid support. Multiple-testing sensitivity was evaluated by applying the Benjamini–Hochberg false-discovery-rate correction separately to each dataset and distance-band combination. Both unadjusted and FDR-adjusted classifications were compared using rank correlations of  $G_i^*$  z-scores, seven-class agreement, Jaccard overlap, and retention of baseline hotspot cells. Hot spots and cold spots were classified at 99%, 95%, and 90% confidence levels.

Winter–fallow hot spots indicate spatially concentrated winter cropland idleness, while winter rapeseed hot spots indicate persistent cultivation cores. Comparing the two helps reveal spatial matches and mismatches between fallow resources and historical planting bases.

#### 2.3.4. Feature Screening and Robustness Analysis

Before MaxEnt modeling, the 64 Satellite Embedding dimensions were screened using a Random Forest classifier fitted to the 394 persistent winter-rapeseed occurrence records and 10,000 randomly sampled background locations within the valid predictor domain. The classifier contained 500 trees, and predictor importance was quantified using MeanDecreaseAccuracy and MeanDecreaseGini. Dimensions with a MeanDecreaseGini value greater than the across-dimension mean (11.8518) were retained. This procedure selected 26 dimensions: A02, A03, A04, A05, A07, A08, A10, A14, A17, A20, A24, A27, A28, A30, A35, A36, A38, A40, A42, A43, A44, A49, A50, A58, A60, and A63. This screening preceded MaxEnt modeling and did not use MaxEnt contribution or permutation-importance estimates.

We additionally evaluated whether model performance depended on this particular screening rule. Four feature representations were compared using the same occurrence records, 10,000 fixed background locations, MaxEnt settings, random 10-fold assignments, and 50 km spatial 5-fold assignments: (1) all 64 embedding dimensions; (2) the original 26 RF-selected dimensions; (3) fold-specific nested RF selection; and (4) fold-specific principal component analysis retaining at least 95% of the variance. In the nested RF analysis, class-balanced bootstrap samples were used and feature selection was performed exclusively within each training fold. PCA was fitted to the training-background environmental data within each fold, without using test-fold records. Model performance was assessed using test ROC–AUC, precision–recall AUC, the true skill statistic calculated from a training-derived threshold, and the Brier score. An absolute test ROC–AUC difference of less than 0.02 was regarded as practically small for this sensitivity assessment.

#### 2.3.5. High-Probability Sample Extraction and MaxEnt Suitability Modeling for Winter Rapeseed

MaxEnt estimates relative environmental suitability from presence records and background environments when reliable absence data are unavailable [37–39]. Candidate occurrence records were generated within pixels cultivated with winter rapeseed in at least 16 of the 23 years. Boundary, duplicate, and obviously abnormal records were removed, followed by a verified minimum-distance filter of 5 km, yielding 394 occurrence records. Their realized nearest-neighbor distance was at least 5.000 km (median = 5.520 km; interquartile range = 5.160–6.353 km). Because local de-clustering cannot eliminate all spatial dependence, five-fold spatial cross-validation used approximately  $50 \times 50$  km blocks, assigning presence and background records in the same held-out blocks to the same fold [52].

MaxEnt v3.4.4 was run from R using the 26 screened Satellite Embedding predictors, 394 occurrence records, and 10,000 fixed background locations sampled within cropland and the valid predictor domain. Logistic output was used throughout. Random partitions supported matched sensitivity analyses, whereas spatially blocked folds were used for model-complexity selection and conservative performance assessment [53]. The occurrence coordinates, background coordinates, and spatial-fold assignments were generated once and held fixed across candidate configurations; the retained assignment tables permit the same records and folds to be reused during reconstruction.

Model evaluation included test ROC–AUC, the 10% training-omission rate (OR10), the training–testing AUC difference, and model complexity. For temporal comparisons, the true

skill statistic (TSS) was also calculated using thresholds derived from the corresponding training data.

MaxEnt model complexity was optimized using spatially structured five-fold cross-validation. The occurrence and background samples were assigned to approximately 50 km spatial blocks to reduce the spatial dependence between training and testing data. We evaluated 30 combinations comprising five feature-class settings (L, LQ, LQH, LQHP, and LQHPT) and six regularization multipliers (0.5, 1, 1.5, 2, 3, and 4), resulting in 150 model fits. Each candidate setting was evaluated using spatial test AUC, the 10% training omission rate on spatially withheld samples (OR10), the difference between training and testing AUC, and the number of active parameters.

Model selection followed a predefined parsimony rule. Candidate models within one standard error of the minimum spatial OR10 were retained; among these, settings within 0.01 of the highest eligible spatial test AUC were compared, and the model with the fewest active parameters was selected. A higher regularization multiplier was used only as a final tie-breaker. This procedure selected linear features with a regularization multiplier of 4 (L/RM4). The final model used 26 predictors, 394 occurrence records, 10,000 background locations, a maximum of 500 iterations, a convergence threshold of  $1 \times 10^{-5}$ , and logistic output.

After model-complexity selection, L/RM4 was refitted using ten fixed random 80:20 occurrence partitions, with the same 10,000 background locations retained in every replicate. Each fitted model generated a logistic prediction over the full common analytical domain, and the final continuous suitability-proxy surface was obtained as the cell-wise arithmetic mean of the ten replicate prediction surfaces. The saved replicate-assignment vectors define the partitions directly and were reused across model comparisons. For each replicate, the logistic threshold maximized training sensitivity plus background specificity, where background specificity is the proportion of background locations predicted below the threshold rather than specificity against survey-confirmed absences. The unrounded mean of the ten replicate-specific thresholds was 0.3096 and was applied to the mean continuous surface to generate the final binary map. The original cutoff of 0.25 was retained only for provenance and diagnostic comparison. Final suitable cropland was intersected with winter–fallow cropland occurring in at least one of six years to define general expansion potential and with winter–fallow cropland occurring in at least five years to define candidate spatial priority areas for field verification (Table S6).

Recurrence-threshold sensitivity was evaluated separately from final-model selection. To isolate the effect of the winter–fallow definition, the audited original 2024 GUI binary suitability map and its 0.25 cutoff were held fixed while comparing winter fallow in at least four years (T4), at least five years (T5), and all six years (T6). Total area, Jaccard overlap with T5, county-level rank correlations, top-five and top-ten overlap, and maximum rank change were calculated. These diagnostic areas are not substitutes for the final L/RM4 estimates reported in Section 3.6 (Table S5).

The integer implementation of the long-term rapeseed-frequency criterion was also audited. More than 66.67% of the 23 study years correspond to cultivation in at least 16 years ( $16/23 = 69.57\%$ ). Adjacent thresholds of 15/23 and 17/23 years were examined, and 394 occurrence records were retained after 5 km filtering under the main 16/23-year criterion (Table S5).

Because the annual winter–fallow maps had already undergone a dedicated accuracy assessment in the source study [33], we did not repeat the remote-sensing classification or accuracy assessment in the present study. Instead, we evaluated the robustness of the downstream candidate-area delineation to plausible changes in annual recurrence by comparing winter–fallow thresholds of  $\geq 4/6$ ,  $\geq 5/6$ , and  $6/6$  years. This analysis does not

constitute full probabilistic pixel-level error propagation, but it provides a direct assessment of whether moderate changes in the recurrence criterion alter the estimated candidate area and county-level prioritization.

### 2.3.6. Temporal Sensitivity and Spatially Structured Validation

To assess whether the use of a single-year Satellite Embedding affected the suitability estimates, we conducted a matched temporal sensitivity analysis using the 2020, 2022, and 2024 annual Google Satellite Embedding V1 datasets. For each year, the same 26 embedding dimensions (A02, A03, A04, A05, A07, A08, A10, A14, A17, A20, A24, A27, A28, A30, A35, A36, A38, A40, A42, A43, A44, A49, A50, A58, A60, and A63) were aligned to the original 2024 30 m Krasovsky\_1940\_Albers grid (geographic coordinate system: D\_WGS\_1984). The analysis was restricted to the common valid domain of the three annual predictor stacks, which contained 41,364,253 cells; only 12 edge cells (0.0108 km<sup>2</sup>) were excluded from the original reference domain. All 394 presence records and the same 10,000 background points were retained in every annual model.

MaxEnt 3.4.4 was run in R using automatic feature selection, a regularization multiplier of 1, a convergence threshold of  $1 \times 10^{-5}$ , a maximum of 500 iterations, default prevalence of 0.5, and logistic output. The same ten repeated 80:20 random presence partitions were applied across the three years. An additional five-fold spatial validation used 50 km blocks and withheld presence and background records jointly. Test ROC–AUC and TSS were calculated independently, and annual ensemble predictions were obtained by averaging the ten random-partition predictions. This matched configuration was used only for temporal sensitivity and was distinct from the tuned L/RM4 configuration used for final 2024 mapping.

Temporal consistency was evaluated using Pearson's and Spearman's correlations and the mean absolute and root mean square differences between continuous prediction maps. For a common binary diagnostic, all three matched annual ensembles were classified with the fixed 0.25 cutoff used by the original configuration and compared using Jaccard and Sørensen–Dice indices. Temporal stability of variable importance was evaluated using rank correlations and overlap among the five most influential dimensions (Table S3).

### 2.3.7. Identification of General Potential Areas for Winter–Rapeseed Expansion on Winter–Fallow Cropland

The MaxEnt-based potentially suitable areas represent cropland with present-day land-surface representations similar to historical high-frequency winter rapeseed areas, but they do not indicate whether the land is fallow in winter. Thus, potential suitability alone does not equal available winter–fallow expansion space.

To identify expansion space with a winter–fallow resource basis, pixels identified as winter–fallow cropland in at least one year during 2019–2024 were extracted as the historical winter–fallow union and overlaid with the MaxEnt suitability map. The general expansion potential area was calculated as follows:

$$P_i = S_i \times F_i \quad (6)$$

where  $P_i$  indicates whether pixel  $i$  belongs to the general expansion potential area;  $S_i$  indicates whether pixel  $i$  is located within the MaxEnt-based potential suitability area, with a value of 1 if yes and 0 otherwise; and  $F_i$  indicates whether pixel  $i$  was identified as winter–fallow cropland at least once during 2019–2024, with a value of 1 if yes and 0 otherwise.

The general expansion potential area satisfies both the embedding-based suitability proxy and at least one historical winter–fallow occurrence. Compared with the MaxEnt-

based suitability area, it excludes suitable cropland without winter–fallow status during the study period and is closer to the practical resource base for expansion.

### 2.3.8. Delineation of Candidate Spatial Priority Areas Constrained by Stable Winter–Fallow Cropland

Because the general expansion potential area may include fields fallow only in individual years, it still has uncertainty in sustained availability. To improve stability, the MaxEnt-based suitability area was overlaid with stable winter–fallow cropland identified as fallow in at least five years during 2019–2024, thereby delineating candidate spatial priority areas:

$$Q_i = S_i \times F_i^{stable} \quad (7)$$

where  $Q_i$  indicates whether pixel  $i$  belongs to the candidate spatial priority areas;  $S_i$  indicates whether pixel  $i$  is within the MaxEnt-based potentially suitable area; and  $F_i^{stable}$  indicates whether pixel  $i$  is stable winter–fallow cropland, with 1 for yes and 0 otherwise.

Candidate spatial priority areas satisfy both the embedding-based suitability proxy and multi-year stable winter–fallow status, highlighting winter cropland resources with more reliable long-term availability. They should be interpreted as preliminary candidate areas, not final implementable expansion areas, because field contiguity, irrigation and drainage, mechanization, profitability, and farmer willingness were not included.

Three nested spatial-screening levels were defined. First, potentially suitable areas were cropland cells exceeding the final MaxEnt threshold and were interpreted as areas with present-day land-surface representations similar to historically persistent winter-rapeseed locations. Second, general expansion-potential areas were obtained by intersecting the potentially suitable areas with cropland that had been winter–fallow at least once during 2019–2024. Third, candidate spatial priority areas for field verification were restricted to potentially suitable cropland that had been winter–fallow in at least five of the six years. These categories represent progressively constrained spatial-screening results rather than directly available land for winter-rapeseed expansion.

## 3. Results

### 3.1. Feature-Selection Sensitivity and Robustness

The Random Forest screening retained 26 of the 64 Satellite Embedding dimensions, reducing predictor dimensionality by 59.4%. Their identities, screening scores, and subsequent MaxEnt importance values are reported in Table S2.

Model discrimination was largely insensitive to feature representation (Table S1). Under random 10-fold cross-validation, mean test ROC–AUC ranged from 0.906 to 0.912; under 50 km spatial five-fold validation, it ranged from 0.901 to 0.905. Relative to the retained 26-dimensional model, all paired mean ROC–AUC differences were below 0.005 and therefore well within the prespecified practical tolerance of 0.02.

The nested RF procedure retained an average of  $19.1 \pm 1.2$  dimensions under random validation and  $18.8 \pm 1.6$  dimensions under spatial validation. Fourteen dimensions were selected in every random and spatial training fold, of which 11 were included in the original 26-dimensional set. PCA consistently required 26 components to explain at least 95% of the training-background variance. The original 26-dimensional model produced slightly higher TSS values than the full-dimensional and PCA models, whereas nested RF produced the highest mean TSS. The full-dimensional and PCA models showed lower Brier scores, indicating a modest calibration advantage. Overall, the results demonstrate that predictive discrimination and spatial transferability were robust to alternative feature representations, although the membership of individual RF-selected dimensions varied among resamples. The original 26-dimensional set was therefore retained for the main analysis

because it substantially reduced dimensionality while preserving practically equivalent predictive performance.

### 3.2. Temporal Sensitivity and Spatial Robustness

Model performance remained high across the three annual Satellite Embedding datasets (Tables 2 and S3). Under ten repeated 80:20 random partitions, test ROC–AUC was  $0.9240 \pm 0.0084$ ,  $0.9255 \pm 0.0124$ , and  $0.9080 \pm 0.0177$  for 2020, 2022, and 2024, respectively. The corresponding five-fold 50 km spatial estimates were  $0.9208 \pm 0.0074$ ,  $0.9181 \pm 0.0091$ , and  $0.9052 \pm 0.0068$ . Spatial blocking reduced ROC–AUC by only 0.0028–0.0074 and TSS by 0.0000–0.0190, supporting the robustness of broad discrimination while providing a more conservative assessment.

**Table 2.** Model performance under repeated random and spatially blocked validation using annual Satellite Embedding datasets.

| Year | Repeated Random<br>80:20 ROC–AUC | Spatial 5-Fold<br>ROC–AUC | Repeated Random<br>80:20 TSS | Spatial 5-Fold TSS    |
|------|----------------------------------|---------------------------|------------------------------|-----------------------|
| 2020 | $(0.9240 \pm 0.0084)$            | $(0.9208 \pm 0.0074)$     | $(0.6781 \pm 0.0321)$        | $(0.6590 \pm 0.0247)$ |
| 2022 | $(0.9255 \pm 0.0124)$            | $(0.9181 \pm 0.0091)$     | $(0.6737 \pm 0.0715)$        | $(0.6597 \pm 0.0347)$ |
| 2024 | $(0.9080 \pm 0.0177)$            | $(0.9052 \pm 0.0068)$     | $(0.6433 \pm 0.0562)$        | $(0.6433 \pm 0.0221)$ |

Note: Values are means  $\pm$  standard deviations across partitions or folds. Random validation used ten repeated 80:20 presence partitions; spatial validation used five approximately 50 km folds and withheld presence and background records jointly. TSS used a threshold derived from the corresponding training data.

The annual predictor representations also exhibited substantial temporal consistency at the fixed set of 394 presence and 10,000 background locations. Averaged across the 26 embedding dimensions, the band-wise Pearson’s correlations were 0.858 for 2020–2022, 0.846 for 2022–2024, and 0.801 for 2020–2024. This gradual decline with increasing temporal separation indicates that the embedding features preserved their broad spatial structure while still capturing year-specific land-surface variation.

The continuous suitability predictions showed a similarly consistent regional ranking. Pairwise Spearman’s correlations were 0.906 for 2020–2022, 0.885 for 2022–2024, and 0.852 for 2020–2024. The corresponding Pearson’s correlations were 0.779, 0.734, and 0.670, while the mean absolute differences were 0.050, 0.062, and 0.069, respectively. Thus, temporal separation produced a gradual increase in prediction differences, but the broad spatial ordering of suitability remained stable.

Binary classifications based on the common diagnostic cutoff of 0.25 were more sensitive than the continuous rankings. Sørensen–Dice coefficients were 0.609, 0.573, and 0.511 for 2020–2022, 2022–2024, and 2020–2024, respectively; the corresponding Jaccard indices were 0.438, 0.401, and 0.343. These values describe temporal sensitivity under the matched original configuration and are not the threshold used for the final tuned 2024 map.

Variable-importance rankings contained a temporally stable core but also showed some reordering among years. Spearman’s correlations for percent contribution ranged from 0.599 to 0.800, with four of the five leading dimensions shared by each pair of years. For permutation importance, rank correlations ranged from 0.538 to 0.701, and three of the five leading dimensions were shared between each pair. In particular, A05 and A07 consistently occurred among the five most influential dimensions. Overall, the temporal sensitivity analysis demonstrates that model discrimination, broad suitability rankings, and the principal contributing embedding dimensions were relatively robust, whereas exact threshold-based classification boundaries exhibited greater annual sensitivity.

### 3.3. Spatial Distribution Patterns of Winter–Fallow Cropland and Winter Rapeseed

Using winter–fallow cropland maps from 2019 to 2024 and winter rapeseed maps from 2000 to 2022, this study compared winter cropland-use status and winter rapeseed cultivation patterns in the Wanjiang Plain. Both showed clear spatial heterogeneity, but differed in distribution extent, spatial continuity, and county-level patterns. Winter–fallow cropland was widely distributed across multiple counties, whereas winter rapeseed showed stronger local clustering and temporal contraction.

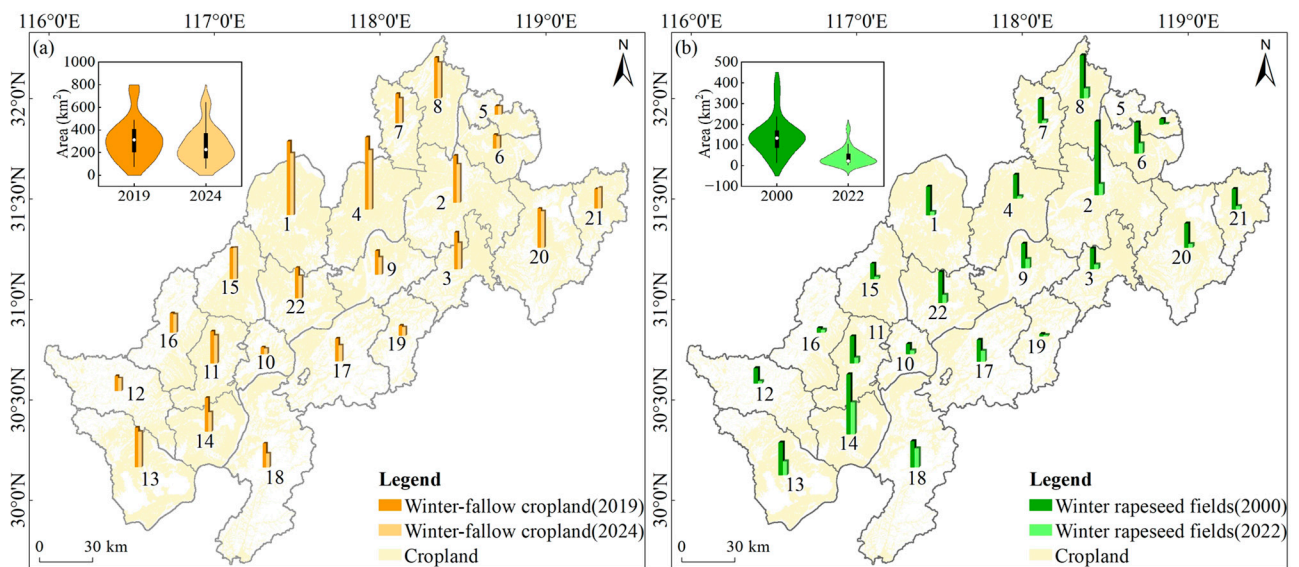
As shown in Figure 3a, winter–fallow cropland was widely distributed across the Wanjiang Plain in both 2019 and 2024, mainly concentrated in plains along the Yangtze River, polder plains, and counties with relatively concentrated cropland. Its spatial pattern can be characterized as “riverine distribution, contiguous plains, and mosaic-like patches in hilly areas”. In the areas along both sides of the Yangtze River, river–lake polder areas, and relatively flat agricultural regions, winter–fallow cropland patches were relatively concentrated and spatially continuous. In contrast, in the gently sloping low-hill areas in the southwestern and southeastern parts of the study area, winter–fallow cropland was mostly distributed as scattered patches. The county-level area statistics in Figure 3a further indicate substantial differences in winter–fallow cropland area among counties in 2019, and a similar county-level differentiation pattern remained in 2024. Compared with 2019, the total area of winter–fallow cropland decreased in 2024, but several counties still retained relatively large winter–fallow areas, indicating that winter cropland idleness in the Wanjiang Plain was not merely an occasional single-year phenomenon but showed a certain degree of spatial persistence.

The spatial pattern of winter rapeseed cultivation differed markedly from that of winter–fallow cropland. As shown in Figure 3b, winter rapeseed was relatively widely distributed in the study area in 2000, forming concentrated cultivation patches in plains along the Yangtze River, polder areas, and some traditional agricultural counties. By 2022, the distribution extent of winter rapeseed had contracted substantially, and its spatial pattern had become more localized and fragmented, with some previously contiguous planting areas shrinking. County-level area statistics also show that winter rapeseed areas in most counties were smaller in 2022 than in 2000, while differences among counties remained evident. It should be noted that Figure 3 mainly reflects spatial differences between two representative years, namely 2000 and 2022; long-term cultivation stability still needs to be assessed using multi-year occurrence frequency from 2000 to 2022.

The comparison indicates both overlap and mismatch between winter–fallow cropland and winter rapeseed. Some riverine and polder counties had abundant fallow resources and retained a basis for winter rapeseed cultivation, while other counties had large winter–fallow areas but limited existing rapeseed planting. Thus, neither single-year winter–fallow area nor existing rapeseed distribution alone is sufficient for locating expansion priorities; multi-year fallow stability, historical cultivation, and embedding-based suitability proxy must be considered together.

### 3.4. Temporal Stability and Spatial Clustering Characteristics of Winter–Fallow Cropland

To identify winter–fallow resources with sustained utilization potential, multi-year occurrence frequency was calculated from six annual winter–fallow maps, and Getis–Ord  $G_i^*$  was used to identify local clusters of high and low winter–fallow area.



**Figure 3.** Spatial distribution patterns of winter-fallow cropland and winter rapeseed in the Wanjiang Plain. (a) Spatial distribution and county-level area differences in winter-fallow cropland in 2019 and 2024; (b) spatial distribution and county-level area differences in winter rapeseed in 2000 and 2022. The light-yellow background represents cropland, while the orange and green bar symbols indicate county-level area distributions of winter-fallow cropland and winter rapeseed in different years, respectively. The inset violin plots show the differences in county-level area distributions between the corresponding years.

As shown in Figure 4a, winter-fallow cropland of different frequency levels was distributed across the Wanjiang Plain, but high-frequency winter-fallow cropland accounted for a relatively large proportion. The areas identified as winter-fallow cropland in five and six of the six years accounted for 20.8% and 28.5% of the historical winter-fallow cropland union, respectively. Together, they accounted for 49.3% of the historical winter-fallow cropland union during 2019–2024, with an area of approximately 4437 km<sup>2</sup>. This indicates that nearly half of the historical winter-fallow cropland in the study area remained fallow in winter for at least five of the six years, showing strong temporal persistence. In contrast, low-frequency winter-fallow cropland identified in only one or two years accounted for 10.6% and 10.9%, respectively, with a combined proportion of 21.5%, suggesting that occasional or short-term fallow fields accounted for a relatively limited proportion. Medium-frequency winter-fallow cropland, identified in three or four years, accounted for 13.0% and 16.2%, respectively, reflecting a certain degree of fluctuation in winter cropland-use status.

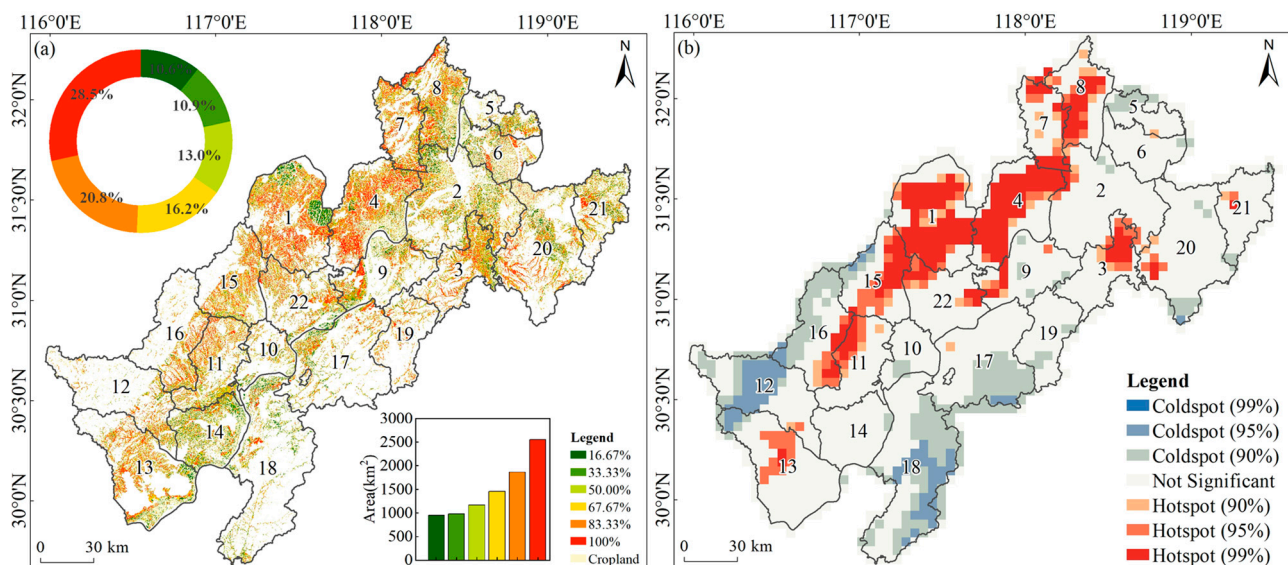
Spatially, stable winter-fallow cropland with an occurrence frequency of no less than 83.33% was mainly distributed in plains along the Yangtze River, polder plains, and some gently sloping agricultural areas, generally appearing as point-like, belt-like, and locally patchy patterns. In Lujiang County, Wuwei City, He County, Hanshan County, and some riverine areas of Anqing, high-frequency winter-fallow patches were relatively concentrated and spatially continuous. In contrast, in the hilly areas of the southwestern and southeastern parts of the study area, high-frequency winter-fallow cropland mostly appeared as scattered and mosaic-like patches due to fragmented cropland distribution. This pattern suggests that winter-fallow stability has clear county-level differences and is associated with regional terrain conditions, cropland concentration, and farmland spatial patterns.

Figure 4b further reveals the local spatial clustering pattern of winter-fallow cropland. Significant hot spots were mainly distributed in the central-northern part of the study area and along parts of the Yangtze River. A relatively continuous high-value cluster was formed in the Lujiang–Wuwei–He County–Hanshan area, while local hot spot patches were

also found in Tongcheng City, Huaining County, Wangjiang County, and Susong County. These areas not only had relatively large winter–fallow cropland areas but also showed significant high-value clustering among neighboring spatial units, indicating strong spatial continuity of winter cropland idleness. They therefore represent resource-concentrated areas that require particular attention in subsequent identification of winter-rapeseed expansion potential.

The original ArcGIS 5 km Gi\* outputs were reproduced to numerical precision. The maximum absolute differences in Gi\* z-scores were  $1.60 \times 10^{-7}$  for WFF and  $2.95 \times 10^{-7}$  for WR, and the numbers of neighbors and seven-class Gi\* assignments matched exactly. Across the 7.5 and 10 km alternatives, rank correlations of the Gi\* z-scores with the 5 km baseline ranged from 0.930 to 0.981. For the unadjusted results, hotspot Jaccard indices ranged from 0.729 to 0.839, and 96.7–98.8% of the baseline hotspot cells remained hotspots under the alternative distance bands.

After Benjamini–Hochberg correction, hotspot Jaccard indices ranged from 0.514 to 0.755, while 98.2–99.5% of the baseline FDR-significant hotspot cells were retained. The comparatively lower Jaccard values mainly reflected an expansion of significant hotspot areas under broader distance bands rather than the disappearance of the baseline hotspot cores. At the baseline 5 km distance, FDR correction reduced the number of significant cells from 576 to 186 for WFF and from 169 to 113 for WR. WFF cold spots were more sensitive in spatial extent, with raw cold-spot Jaccard indices of 0.532–0.586, and no WFF cold spot remained significant at the 5 km baseline after FDR correction. No WR cold spots were detected under any tested configuration. Overall, the principal hotspot pattern was stable, although peripheral significance classes and the extent of WFF cold spots depended more strongly on neighborhood definition and multiple-testing adjustment (Table S4).



**Figure 4.** Multi-year occurrence frequency and spatial hot spot distribution of winter–fallow cropland. (a) Spatial distribution of winter–fallow cropland occurrence frequency during 2019–2024. The inset doughnut chart shows the area proportions of different occurrence-frequency classes, and the inset bar chart shows the corresponding winter–fallow cropland area for each frequency class. (b) Spatial distribution of winter–fallow cropland hot and cold spots identified using the Getis–Ord Gi\* statistic. Cold spots and hot spots represent low-value and high-value spatial clusters of winter–fallow cropland area, respectively, classified at the 90%, 95%, and 99% confidence levels. The mapped 90%, 95%, and 99% classes are the unadjusted probabilities from the baseline 5 km distance-band analysis; the corresponding Benjamini–Hochberg FDR-adjusted sensitivity results are reported in Table S4.

Significant cold spots were mainly distributed along the mountainous and hilly margins of the southwestern study area and in some areas with fragmented cropland, such as Taihu County, Qianshan City, southern Dongzhi County, and local parts of the eastern study area. These cold spot areas had relatively small winter–fallow cropland areas, and low-value spatial units were significantly clustered, indicating limited winter–fallow cropland resources. The remaining parts of the study area were dominated by non-significant areas, indicating that winter–fallow cropland area and neighboring distributions did not form stable high-value or low-value clusters. Overall, winter–fallow cropland in the Wanjiang Plain showed strong temporal stability and local spatial clustering. Stable winter–fallow cropland and significant hot spots jointly indicate areas where winter cropland remained underutilized for multiple consecutive years and was spatially concentrated, providing a relatively stable land resource basis for identifying winter-rapeseed expansion potential areas and candidate spatial priority areas.

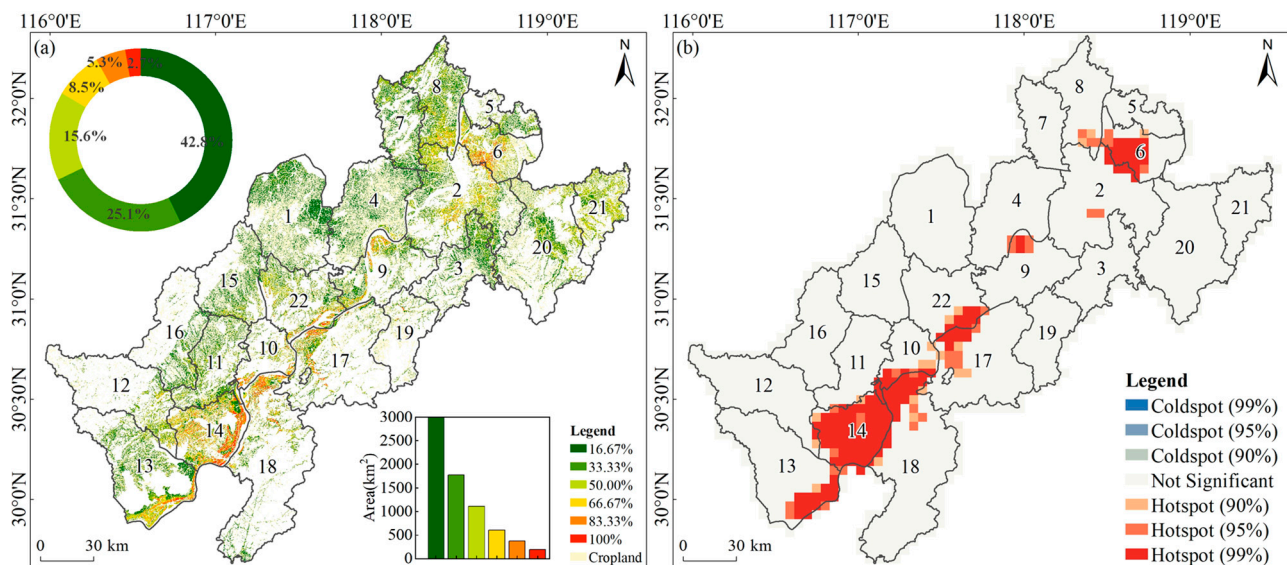
### 3.5. Temporal Stability and Spatial Clustering Characteristics of Winter Rapeseed

Using 23 annual winter rapeseed maps from 2000 to 2022, this study analyzed occurrence frequency and local clustering. Winter rapeseed was dominated by low- and medium–low-frequency occurrences, while long-term high-frequency cultivation was limited, indicating strong interannual variability and spatial localization.

As shown in Figure 5a, the historical winter rapeseed distribution was mainly concentrated in the low-frequency and medium–low-frequency classes. The low-frequency cultivation area, with an occurrence frequency of no more than 16.67%, accounted for 42.8%, while the medium–low-frequency cultivation area, with an occurrence frequency of 16.67–33.33%, accounted for 25.1%. Together, these two classes accounted for 67.9% of the historical winter rapeseed distribution, with an area of approximately 4807 km<sup>2</sup>. This indicates that most historical winter rapeseed areas in the study region were planted only in a small number of years, without clear long-term continuous cultivation characteristics. Medium-frequency areas with occurrence frequencies of 33.33–50.00% accounted for 15.6%, and medium–high-frequency areas with occurrence frequencies of 50.00–66.67% accounted for 8.5%, indicating that some areas had a certain basis for winter rapeseed cultivation but limited temporal continuity.

The combined high- and very-high-frequency classes (>66.67%; operationally at least 16 of 23 years) covered approximately 568 km<sup>2</sup>, or 8.0% of the historical winter rapeseed distribution. These pixels represent empirically persistent cultivation locations shaped jointly by land-surface conditions, cropping history, management, and socioeconomic influences; they were used as occurrence-sample sources rather than interpreted as a purely biophysical niche.

Spatially, low-frequency winter rapeseed patches were widely distributed in the study area but showed weak spatial continuity and were mostly scattered and mosaic-like. Medium–high-frequency and stable cultivation areas were clearly concentrated in a few riverine agricultural regions and traditional winter rapeseed-growing areas, especially in local areas near Wangjiang County, Dongzhi County, Guichi District, urban Tongling, Fanchang District, and urban Ma’anshan. These areas generally exhibited belt-like clustering along the Yangtze River and adjacent plain agricultural regions, indicating that some areas along the Yangtze River still retained a relatively strong historical basis for winter rapeseed cultivation.



**Figure 5.** Multi-year occurrence frequency and spatial hot spot distribution of winter rapeseed. (a) Spatial distribution of winter-rapeseed occurrence frequency during 2000–2022. The inset doughnut chart shows the area proportions of different occurrence-frequency classes, and the inset bar chart shows the corresponding winter rapeseed area for each frequency class. (b) Spatial distribution of winter rapeseed hot and cold spots identified using the Getis–Ord Gi\* statistic. Cold spots and hot spots represent low-value and high-value spatial clusters of winter rapeseed area, respectively, classified at the 90%, 95%, and 99% confidence levels. The mapped 90%, 95%, and 99% classes are the unadjusted probabilities from the baseline 5 km distance-band analysis; the corresponding Benjamini–Hochberg FDR-adjusted sensitivity results are reported in Table S4.

The Getis–Ord Gi\* results in Figure 5b further indicate that significant winter rapeseed hot spots were mainly concentrated in the Wangjiang–Dongzhi–Guichi–Tongling–Fanchang riverine belt, as well as in local areas of Dangtu County and urban Ma’anshan. These areas had high winter rapeseed areas and formed significant high-value clusters among neighboring spatial units, reflecting a concentrated historical cultivation basis and spatial persistence. Compared with the hot spot pattern of winter–fallow cropland, winter rapeseed hot spots were much smaller in extent and more spatially concentrated, indicating strong localization of the long-term high-frequency winter rapeseed core areas.

Significant cold spots of winter rapeseed were relatively limited in extent, and most of the study area was classified as non-significant. This indicates that insufficient winter rapeseed cultivation in the Wanjiang Plain was mainly reflected in low-frequency, scattered, and discontinuous distributions, rather than in large continuous low-value clusters. Therefore, existing winter rapeseed hot spots can represent core areas with a relatively strong historical cultivation basis, but the potential expansion space for winter rapeseed should not be limited to existing hot spot areas. Instead, it should be comprehensively identified by integrating winter–fallow cropland resources, winter–fallow stability, and embedding-based suitability proxy.

Combining Figures 4 and 5, the Wanjiang Plain exhibited an overall pattern of relatively abundant stable winter–fallow cropland but limited long-term high-frequency winter rapeseed cultivation areas. High-frequency winter–fallow areas and hot spots mainly represent resource-concentrated areas where winter cropland has remained underutilized for multiple years, whereas high-frequency winter rapeseed areas and hot spots reflect core areas where existing planting activities have been relatively persistent. The two types of areas overlapped only in some riverine agricultural regions, while spatial mismatches occurred in other areas. These findings further indicate that winter-rapeseed expansion on

winter–fallow cropland should not be extrapolated solely from existing winter rapeseed hot spots. Instead, potentially suitable areas, general expansion potential areas, and candidate spatial priority areas should be identified step by step by integrating suitability modeling, historical winter–fallow distribution, and stable winter–fallow constraints.

### 3.6. Identification of Potentially Suitable Areas for Winter Rapeseed Based on MaxEnt and Satellite Embedding

Based on 394 occurrence records extracted from long-term high-frequency winter rapeseed areas, the 26 screened Satellite Embedding dimensions were used in MaxEnt to delineate potentially suitable cropland. Higher logistic values indicate greater present-day land-surface similarity to the historical reference locations, not direct agronomic feasibility.

The selected L/RM4 configuration achieved a mean spatial test AUC of  $0.9036 \pm 0.0147$ , an OR10 of  $0.1081 \pm 0.0222$ , and a mean training–testing AUC difference of 0.0075. The final binary map used the model-specific ensemble threshold of 0.309605913 (0.3096).

The matched annual sensitivity models produced spatial-validation estimates close to their repeated-random estimates (Table S3), whereas the tuned L/RM4 model governed the final 2024 map. Keeping these roles separate prevents temporal sensitivity results obtained under the matched original configuration from being interpreted as final-model parameter selection.

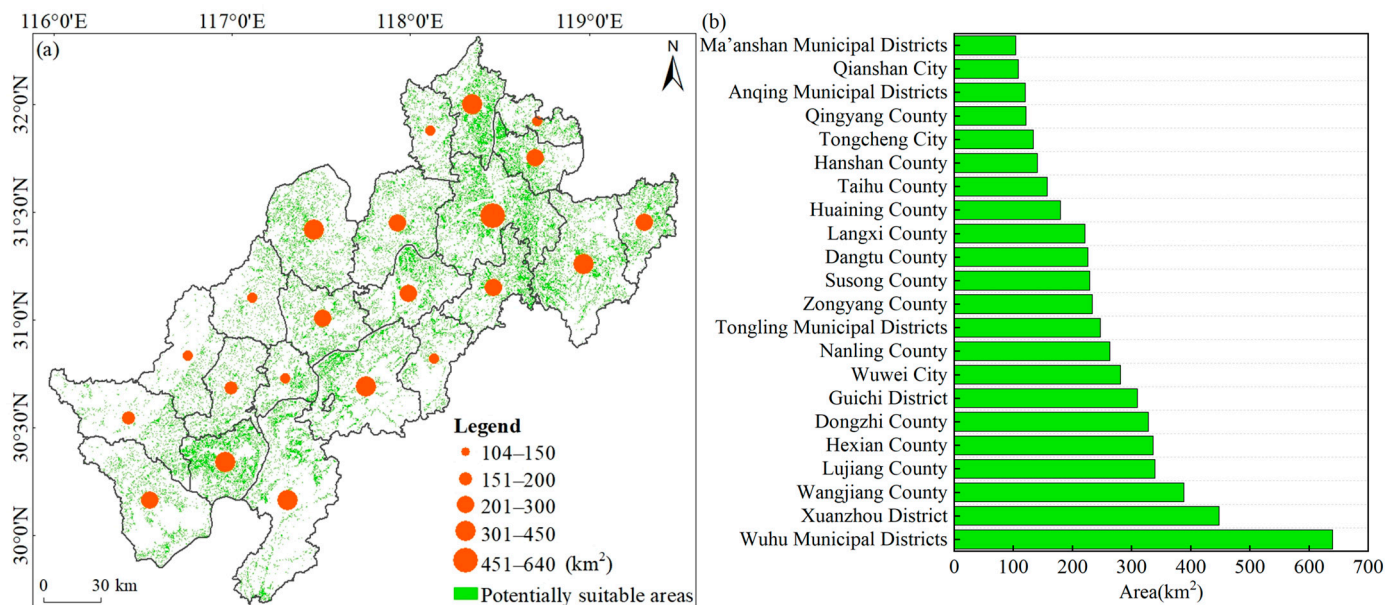
Across 30 candidate configurations, the selected L/RM4 model retained 26 active parameters and achieved a spatial test AUC of  $0.904 \pm 0.015$ , OR10 of  $0.108 \pm 0.022$ , and a train–test AUC difference of 0.007. The default LQHPT/RM1 configuration had similar discrimination ( $0.901 \pm 0.009$ ) but higher omission ( $0.180 \pm 0.018$ ), a larger train–test gap (0.039), and an average of 155.6 active parameters. Thus, tuning substantially reduced complexity and apparent overfitting.

The continuous predictions of the selected and original models remained strongly correlated (Pearson’s  $r = 0.926$ ; Spearman’s  $\rho = 0.960$ ), indicating that the principal spatial suitability pattern was broadly preserved. Nevertheless, applying the original fixed threshold of 0.25 to the selected model increased the estimated suitable and downstream screened areas. This result demonstrates that the mapped area is sensitive not only to model complexity but also to the threshold transferred between model settings. The final binary threshold for the selected model was therefore determined separately from its replicate-specific threshold distribution.

The threshold audit confirmed that the original cutoff of 0.25 was obtained by rounding the mean of the ten original GUI replicate-specific thresholds (mean = 0.254430, SD = 0.024115; range = 0.209500–0.290700) to two decimal places. For the tuned L/RM = 4 model, the replicate-specific thresholds averaged 0.309606 (SD = 0.026697; range = 0.279752–0.354313; coefficient of variation = 8.62%). Applying this model-specific threshold, rather than carrying forward the original cutoff of 0.25, reduced the tuned-model estimates of suitable cropland, general expansion potential, and candidate spatial priority areas by 26.95%, 26.92%, and 32.86%, respectively. The final estimates comprised 6016.66 km<sup>2</sup> of suitable cropland, 2943.30 km<sup>2</sup> of general expansion potential, and 1137.21 km<sup>2</sup> of candidate spatial priority areas. Relative to the original GUI-model estimates, these final values differed by +8.26%, +2.46%, and +9.52%, respectively, indicating that the principal area-based conclusions remained stable after jointly accounting for model complexity and threshold recalibration. Detailed threshold and area results are provided in Table S6.

As shown in Figure 6a, the potentially suitable areas for winter rapeseed were widely distributed across the Wanjiang Plain, mainly in plains along the Yangtze River, polder plains, valley plains, and some gently sloping agricultural areas. The overall pattern can be characterized as “riverine clustering, contiguous plains, and mosaic-like patches in

hilly areas". In the flat areas along the Yangtze River and around lakes, where cropland is relatively concentrated, potentially suitable patches showed strong spatial continuity. In contrast, in hilly areas with greater terrain variation and more fragmented cropland, potentially suitable patches were more scattered or mosaic-like. This spatial pattern is broadly consistent with the regional characteristics of favorable hydrothermal conditions, high cropland concentration, and a strong traditional agricultural basis in the Wanjiang Plain.



**Figure 6.** Distribution and county-level statistics of potentially suitable areas for winter rapeseed based on MaxEnt and Satellite Embedding. (a) Spatial distribution of potentially suitable areas for winter rapeseed cultivation and county-level area classes. Green areas indicate potentially suitable areas for winter rapeseed, and orange circles represent county-level area classes of potentially suitable areas. (b) County-level area statistics of potentially suitable areas for winter rapeseed. The horizontal bar chart shows differences in potentially suitable area among counties, indicating the uneven county-level distribution of winter rapeseed suitability.

The final potentially suitable cropland covered 6017 km<sup>2</sup>. This area represents recent integrated land-surface characteristics similar to those of long-term high-frequency winter-rapeseed locations; it does not indicate winter-fallow availability, yield, or practical plantability. It was therefore used only as the embedding-based similarity layer for subsequent winter-fallow overlays.

At the county level, the area of potential suitability varied substantially. Figure 6b shows that urban Wuhu had the largest potentially suitable area, exceeding 600 km<sup>2</sup>. Xuanzhou District, Wangjiang County, Lujiang County, He County, Dongzhi County, Guichi District, and Wuwei City also had relatively large potentially suitable areas, forming the main distribution zones of modeled land-surface similarity in the study area. These counties have relatively concentrated cropland resources and land-surface representations similar to those of historical high-frequency winter rapeseed cultivation areas, making them an important basis for subsequent identification of winter-rapeseed expansion potential on winter-fallow cropland. In contrast, urban Ma'anshan, Qianshan City, urban Anqing, Qingyang County, Tongcheng City, and Hanshan County had relatively small potentially suitable areas, indicating either a limited modeled-similarity area or more dispersed patches.

The MaxEnt–Satellite Embedding analysis delineated a regional land-surface-similarity layer for the progressive screening framework. Because this extent remained broader than

the winter–fallow resource base, the historical winter–fallow union and stable winter–fallow mask were applied sequentially rather than treating modeled similarity as immediately available expansion land.

In the recurrence-threshold diagnostic, the original audited GUI suitability map and 0.25 cutoff were held fixed to isolate the effect of the winter–fallow criterion. Candidate area was 1528.95 km<sup>2</sup> under T4, 1038.35 km<sup>2</sup> under T5, and 536.62 km<sup>2</sup> under T6. These values are sensitivity diagnostics; the final tuned-model T5 estimate is 1137.21 km<sup>2</sup> (Tables S5 and S6).

Despite these changes in area, the county-level spatial prioritization remained highly stable. Relative to T5, Spearman's rank correlations were 0.977 for T4 and 0.979 for T6, while the corresponding Kendall coefficients were 0.896 and 0.913. The top-ten county overlap was 90% under both alternative thresholds, and the maximum county-rank change was three positions. Xuanzhou District, Lujiang County, Wuhu Municipal Districts, and Wuwei City remained within the four highest-ranked administrative units under all three scenarios. These results indicate that the principal geographical pattern of prioritization was robust, although the estimated amount of candidate land was threshold-dependent.

The rapeseed-frequency audit confirmed that the operational threshold was at least 16 of 23 years. It yielded 567.98 km<sup>2</sup>, closely reproducing the approximately 568 km<sup>2</sup> reported in the main analysis; adjacent thresholds of 15/23 and 17/23 years produced 686.40 and 462.54 km<sup>2</sup>, respectively (Table S5).

### 3.7. Spatial Distribution and County-Level Patterns of General Expansion Potential Areas

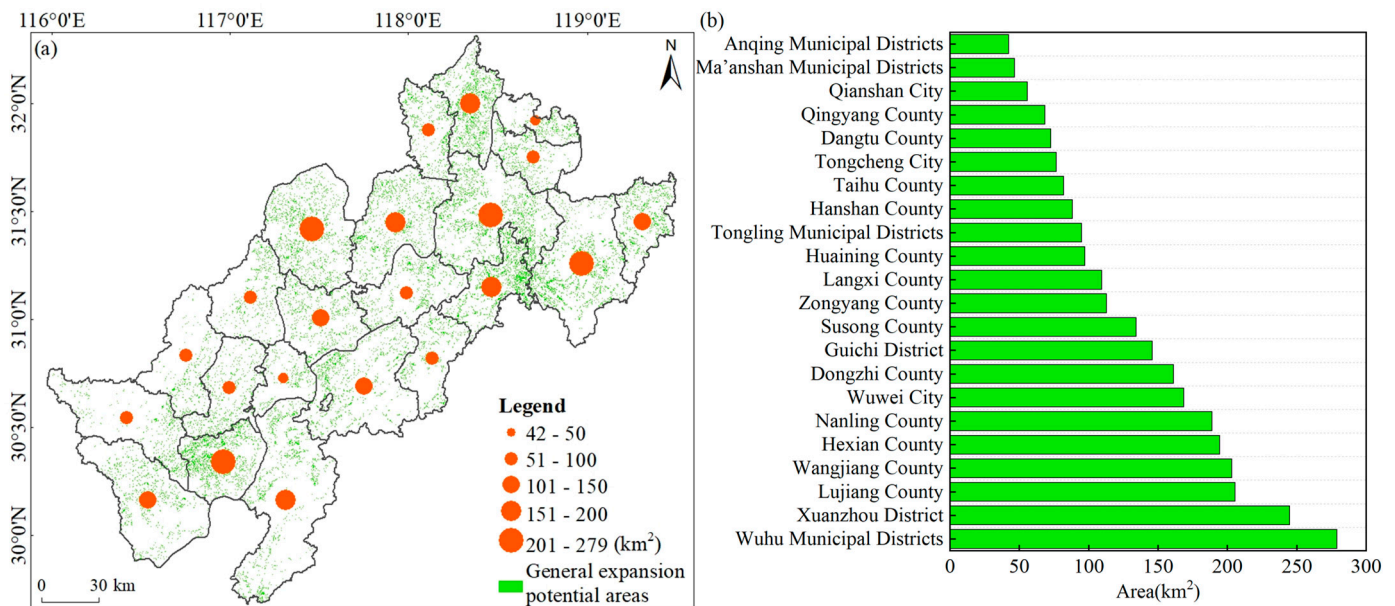
The MaxEnt-based potential suitability area reflects an embedding-based suitability proxy, but not whether cropland is actually fallow in winter. To screen expansion space with winter–fallow resources, this study overlaid potentially suitable areas with cropland identified as winter–fallow at least once during 2019–2024, thereby identifying general expansion-potential areas.

The general expansion-potential area covered 2943 km<sup>2</sup>, equivalent to 48.92% of the 6017 km<sup>2</sup> potentially suitable area. The winter–fallow-union overlay therefore removed approximately 3073 km<sup>2</sup> (51.08%) of modeled suitable cropland that had not been identified as winter fallow during 2019–2024. This substantial reduction shows why embedding-based similarity alone should not be interpreted as available winter–fallow expansion space.

As shown in Figure 7a, the general expansion potential areas were mainly distributed in plains along the Yangtze River, polder plains, valley plains, and some gently sloping cropland areas. The overall pattern was similar to that of the MaxEnt-based potential suitability area, but the spatial extent was substantially reduced and the patches became more concentrated. In riverine plains and polder agricultural areas, general potential patches were relatively continuous, indicating that these areas had both high modeled land-surface similarity and a winter–fallow cropland resource basis. In contrast, in areas with greater topographic variation or more fragmented cropland, general potential areas were mostly distributed as scattered patches with relatively weak spatial continuity.

County-level statistics further indicate marked differences in general expansion potential among counties. Figure 7b shows that urban Wuhu, Xuanzhou District, Lujiang County, Wangjiang County, He County, Nanling County, and Wuwei City had relatively large general expansion potential areas and formed the main concentration zones for winter-rape seed expansion on winter–fallow cropland in the Wanjiang Plain. Among them, urban Wuhu had the largest general potential area, indicating a high degree of overlap between winter rapeseed suitability and historical winter–fallow cropland resources. In contrast, urban Anqing, urban Ma'anshan, Qianshan City, Qingyang County, and Dangtu County had relatively small general potential areas, suggesting a lower degree of overlap between

winter–fallow resources and winter rapeseed suitability, or relatively limited potential patch sizes.



**Figure 7.** Distribution and county-level statistics of general expansion potential areas for winter rapeseed on winter–fallow cropland. (a) Spatial distribution of general expansion potential areas and county-level area classes. Green areas indicate cropland that satisfies both potential suitability for winter rapeseed and winter–fallow occurrence at least once during 2019–2024, while orange circles represent county-level area classes of general expansion potential areas. (b) County-level area statistics of general expansion potential areas. The horizontal bar chart shows differences in general expansion potential areas among counties, reflecting the county-level overlap between winter–fallow cropland resources and potentially suitable areas for winter rapeseed.

The transition from potentially suitable areas to general expansion potential areas shows that the embedding-based suitability proxy cannot be directly converted into winter–fallow cropland expansion potential. The general expansion potential area emphasizes the spatial attribute of being both historically fallow and located within the land-surface-similarity layer, and represents an important intermediate layer connecting model-based spatial screening with the practical resource basis of winter–fallow cropland. This area can serve as a preliminary screening result for winter-rapeseed expansion, but it may still contain fields that were fallow only in individual years, and its sustained use potential and expansion stability remain uncertain. Therefore, multi-year stable winter–fallow constraints need to be further introduced to identify more stable candidate spatial priority areas from the general potential areas.

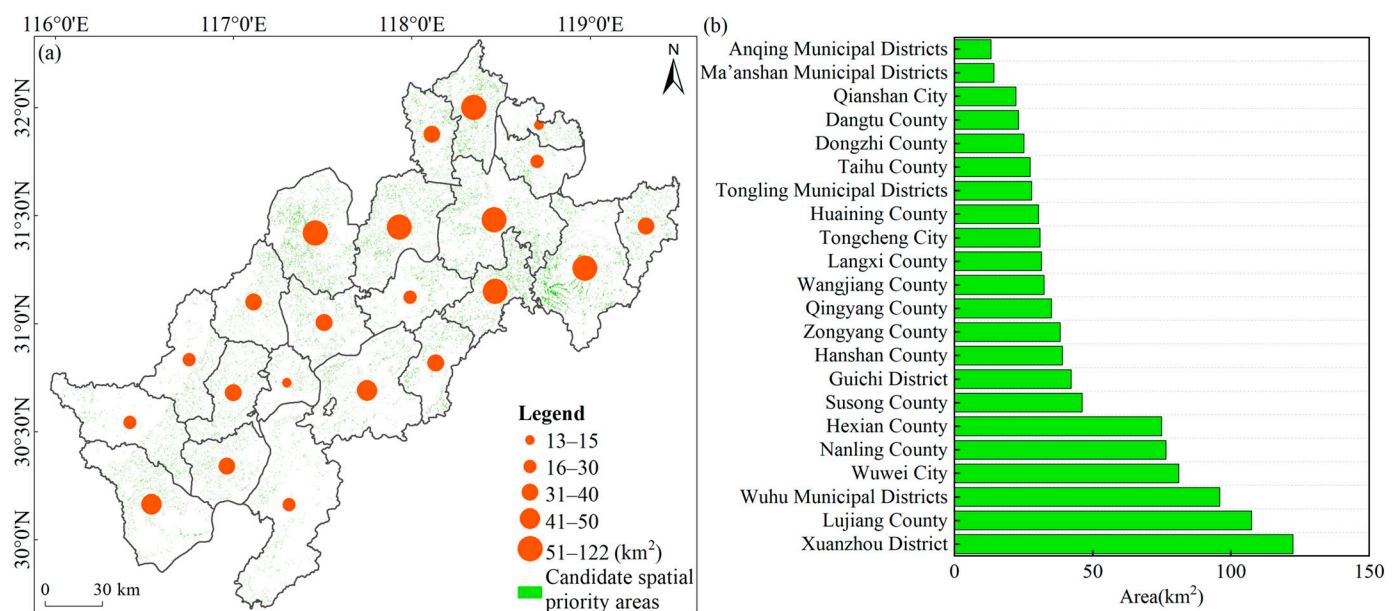
### 3.8. Spatial Distribution and County-Level Patterns of Candidate Spatial Priority Areas

The general expansion potential area may include cropland that was fallow only in a few years, leaving uncertainty in sustained availability. To reduce the influence of occasional fallow events, the MaxEnt-based suitability area was further overlaid with stable winter–fallow cropland identified as fallow in at least five years during 2019–2024 to delineate candidate spatial priority areas.

The candidate spatial priority areas covered 1137 km<sup>2</sup>, equivalent to 18.90% of potentially suitable cropland and 38.64% of the general expansion-potential area. Applying the stable winter–fallow constraint removed approximately 1806 km<sup>2</sup>, a further reduction of 61.36%. The resulting area is a scenario-dependent spatial shortlist for field verification rather than an inventory of immediately plantable land.

As shown in Figure 8a, the candidate spatial priority areas were mainly distributed in plains along the Yangtze River, polder plains, valley plains, and some gently sloping agricultural areas. Their overall spatial pattern was more concentrated than that of the general expansion potential areas. Compared with the general expansion potential areas shown in Figure 7, some scattered patches, low-frequency winter-fallow areas, and patches with poor spatial continuity were removed under the stability constraint. The retained candidate spatial priority areas therefore had stronger winter-fallow persistence and clearer spatial screening value. This indicates that stable winter-fallow constraints can effectively reduce the potential expansion range and improve the stability and reliability of candidate areas for winter-rapeseed expansion planning in the Wanjiang Plain.

County-level statistics show that the candidate spatial priority areas were mainly concentrated in Xuanzhou District, Lujiang County, urban Wuhu, Wuwei City, Nanling County, and He County. Among them, Xuanzhou District had the largest candidate spatial priority areas, followed by Lujiang County and urban Wuhu. These counties not only had extensive modeled land-surface similarity but also showed a high degree of overlap between modeled-similarity areas and multi-year stable winter-fallow cropland. This indicates that they have both a winter-fallow resource basis and relatively stable potential for winter cropland-use conversion, making them key areas for field verification, demonstration area screening, and spatial planning optimization for winter-rapeseed expansion in the Wanjiang Plain.



**Figure 8.** Distribution and county-level statistics of candidate spatial priority areas for winter-rapeseed expansion constrained by stable winter-fallow cropland. (a) Spatial distribution of candidate spatial priority areas and county-level area classes. Green areas indicate cropland that satisfies both potential suitability for winter rapeseed and stable winter-fallow status, defined as being fallow in at least five years during 2019–2024, while orange circles represent county-level area classes of candidate spatial priority areas. (b) County-level area statistics of candidate spatial priority areas. The horizontal bar chart shows differences in candidate spatial priority areas among counties, reflecting the county-level overlap between stable winter-fallow cropland and potentially suitable areas for winter rapeseed.

In contrast, urban Anqing, urban Ma'anshan, and Qianshan City had relatively small candidate spatial priority areas. This suggests that although these areas may contain some potentially suitable space for winter rapeseed, their overlap with stable winter-fallow

cropland is relatively low, or their candidate patches are small and spatially discontinuous. Therefore, from the MaxEnt-based potential suitability area to the general expansion potential area and then to the candidate spatial priority areas, both county rankings and spatial distributions changed to some extent. This further demonstrates that winter-rapeseed expansion planning should not rely solely on embedding-based suitability proxy or single-year winter-fallow identification, but should comprehensively consider modeled land-surface similarity, historical winter-fallow occurrence, and winter-fallow stability.

Candidate spatial priority areas constitute the strictest screening tier, combining embedding-based similarity with winter fallow in at least five of six years. They can support county-level field surveys and demonstration-site screening, but practical feasibility still requires assessment of field contiguity, irrigation and drainage, mechanization, profitability, and farmer willingness.

## 4. Discussion

### 4.1. Spatial Mismatch Between Stable Winter-Fallow Cropland and Insufficient Continuous Winter Rapeseed Cultivation

Stable winter-fallow cropland covered approximately 4437 km<sup>2</sup> during 2019–2024, or 49.3% of the historical winter-fallow union, whereas long-term high-frequency winter rapeseed covered only 568 km<sup>2</sup> (8.0% of its historical distribution). This mismatch is consistent with evidence that seasonal cropland use reflects not only land-surface conditions but also profitability, labor, fragmentation, mechanization, irrigation and drainage, and farmers' willingness to cultivate [54–59]. Because these socioeconomic factors were not measured directly here, they are treated as plausible contextual mechanisms rather than causal findings.

Winter-fallow cropland is not newly created cropland, but underutilized existing cropland during winter. Expanding winter rapeseed on such land therefore exploits temporal cropland-use potential rather than extending agricultural land boundaries. In rice-based regions such as the Wanjiang Plain, the complementary growing seasons of rice and winter rapeseed provide an opportunity to increase the multiple-cropping index without substantially occupying staple grain production space.

Winter-fallow and winter rapeseed hot spots overlapped only in some riverine agricultural areas. In Lujiang, Wuwei, He County, Hanshan, and parts of the Anqing riverine zone, stable winter-fallow cropland was concentrated, but continuous rapeseed cultivation was weak, indicating that fallow resources do not automatically become winter rapeseed production space [59,60].

Long-term high-frequency winter rapeseed cultivation, defined operationally as at least 16 of 23 years, represents a realized land-use pattern jointly shaped by environmental conditions, cropping history, management, and operator decisions. Previous studies show that rapeseed production and planting willingness can respond to labor availability, mechanization, production costs, prices, operational scale, subsidies, and agricultural insurance [9,61,62].

These studies provide plausible context but do not directly explain the Wanjiang Plain pattern. Because spatially and temporally matched household, market, and farm-management data were unavailable, the historical high-frequency pixels were used only as empirical reference locations. The MaxEnt output is therefore interpreted as present-day land-surface similarity rather than a causal explanation of cultivation persistence.

### 4.2. Stable Winter-Fallow Constraints Improve the Specificity of Expansion Space Identification

This study distinguished three spatial levels. The MaxEnt-based potentially suitable area represents cropland whose present-day land-surface representation is similar

to historical high-frequency winter rapeseed areas. The general expansion potential area adds a historical winter–fallow occurrence condition, representing cropland that was both within the modeled-similarity layer and fallow at least once during 2019–2024. The candidate spatial priority tier further applies a stable winter–fallow constraint, requiring both embedding-based suitability proxy and fallow status in at least five years.

The progressive screening reduced 6017 km<sup>2</sup> of potentially suitable cropland to 2943 km<sup>2</sup> of general expansion potential (48.92%) and then to 1137 km<sup>2</sup> of candidate spatial priority areas (38.64% of the general tier and 18.90% of the suitability tier). The final stable-fallow constraint removed approximately 1806 km<sup>2</sup>, or 61.36% of the general tier, demonstrating that modeled similarity, historical fallow occurrence, and persistent fallow status do not fully overlap.

County-level rankings also changed after applying the stability constraint. Urban Wuhu, Wangjiang, Lujiang, and He County had large general expansion potential areas, while candidate spatial priority areas became concentrated in Xuanzhou, Lujiang, urban Wuhu, Wuwei, Nanling, and He County. This indicates a higher overlap between the embedding-based suitability proxy and multi-year stable winter–fallow cropland in the latter group, making them stronger candidates for field verification and demonstration planning.

Candidate spatial priority areas are not final implementable expansion areas. They mainly reflect embedding-based suitability proxy and temporal fallow stability, while field contiguity, irrigation and drainage infrastructure, mechanization, profitability, farming operators, and farmer willingness remain to be evaluated.

#### 4.3. Role and Interpretation of Satellite Embedding–MaxEnt Spatial Screening

The feature-set sensitivity analysis indicates that the mapped suitability pattern was not contingent on a single variable-screening rule. The full 64-dimensional representation, the original RF-selected feature set, fold-specific RF selection, and PCA-based reduction produced closely comparable ROC–AUC values under both random and spatial cross-validation. Moreover, the original 26-dimensional model showed a smaller train–test AUC gap than the full-dimensional model, consistent with a reduction in model complexity and potential overfitting.

Nevertheless, the exact membership of the RF-selected dimensions was not completely stable across resamples. The nested analysis identified a persistent core of 14 dimensions, but several dimensions outside the original set were also repeatedly selected. The retained 26 dimensions should therefore be regarded as a parsimonious predictive representation rather than a uniquely optimal subset. In addition, Satellite Embedding dimensions are latent coordinates that jointly encode multi-sensor and temporal information; individual dimensions do not have fixed one-to-one physical interpretations. Consequently, their importance values indicate predictive relevance within the embedding space rather than causal effects of specific climatic, soil, or topographic factors. Future work combining foundation-model-derived representations with explicit environmental covariates and independent occurrence datasets would be valuable for strengthening mechanistic interpretation.

Satellite Embedding provides a compact learned representation of recent land-surface conditions. However, the present analysis evaluates only an embedding-only configuration; it does not include conventional-predictor-only or combined-input baselines and therefore provides no evidence that the embedding is equivalent or superior to climatic, soil, terrain, hydrological, or accessibility predictors. Its role in this study is limited to a data-driven land-surface-similarity screen, and the latent dimensions are not interpreted as individual environmental drivers.

Combining historical high-frequency occurrence records with annual Satellite Embedding identifies cropland whose recent land-surface representation resembles empirically persistent cultivation locations. This output is useful as the first screening tier, provided that it is not interpreted as temporally invariant agronomic suitability.

The embedding dimensions are latent coordinates without unique physical meanings. Their importance values therefore indicate predictive relevance within the learned representation rather than causal effects of specific meteorological, soil, or topographic factors. Future representation-probing studies could examine their associations with purpose-specific conventional variables without assigning one-to-one physical labels.

Although the 394 occurrence labels were not used to construct Satellite Embedding V1, indirect target-related signals from vegetation phenology, crop cover, moisture, or management cannot be excluded. Similar broad patterns across the 2020, 2022, and 2024 embeddings, 50 km spatial validation, and alternative feature representations reduce dependence on a single year, partition, or screening rule, but do not establish a purely biophysical interpretation.

A three-way benchmark comprising conventional-predictor-only, embedding-only, and combined-input models remains necessary to quantify the incremental information contributed by the embedding. A valid comparison would require temporally matched climatic data, harmonized soil, terrain, and hydrological predictors, identical occurrence and background records, the same spatial folds, separate complexity tuning for each predictor set, and preferably independent field validation. Because such a like-for-like benchmark was not available in the present analysis, this absence is treated as a limitation, and no comparative performance claim is made for Satellite Embedding.

The winter–fallow recurrence audit showed that absolute candidate area depends on the persistence criterion, whereas county rankings and top-ranked overlap remained stable. The final 1137 km<sup>2</sup> estimate is therefore interpreted as the T5 planning scenario from the tuned model, not as an invariant land inventory.

#### 4.4. Implications for Winter-Rapeseed Expansion Planning and Annual Cropland Use

The results provide spatial guidance for winter-rapeseed expansion in the Wanjiang Plain. Xuanzhou, Lujiang, urban Wuhu, Wuwei, Nanling, and He County had relatively large candidate spatial priority areas, indicating a large overlap between modeled land-surface similarity and stable winter–fallow resources. These counties can be prioritized for field verification and demonstration site screening, with attention to field contiguity, irrigation and drainage conditions, road accessibility, and mechanized operations.

Susong, Guichi, Hanshan, Zongyang, Qingyang, Wangjiang, Langxi, Tongcheng, and Huaining had medium candidate spatial priority areas and may be treated as secondary regions for field verification and feasibility assessment. Their feasibility could be improved through high-standard farmland construction, agricultural socialized services, mechanized rapeseed sowing and harvesting, and moderately scaled farming.

Urban Anqing, urban Ma’anshan, Qianshan, Dangtu, Dongzhi, Taihu, and urban Tongling had relatively small candidate spatial priority areas and should not be treated as first-choice zones for large-scale expansion. Winter rapeseed in these areas may be considered for localized verification and, where feasible, small-scale demonstrations, winter cropland cover, landscape improvement, or ecological functions.

From a sustainable agriculture perspective, expanding winter rapeseed on winter–fallow cropland can reduce bare cropland, enhance annual use intensity, increase oilseed output under a stable rice-based system, and potentially improve farmland landscapes and pollinator resources [63–65]. However, expansion may also increase water and fertilizer inputs, waterlogging risks, mechanization costs, and labor demand. Expansion planning

should therefore balance stable fallow resources, embedding-based suitability proxy, and production conditions rather than simply pursuing larger areas.

#### 4.5. Uncertainties and Future Research Directions

The temporal sensitivity analysis qualifies rather than invalidates the 2024-based result. Discrimination and broad spatial rankings were similar across the 2020, 2022, and 2024 embeddings, but threshold-defined boundaries were less stable. The final map should therefore be interpreted as similarity between historically persistent rapeseed locations and land-surface conditions represented by the 2024 embedding, not as temporally invariant or causally determined agronomic suitability.

Because temporally matched occurrence observations were unavailable, the comparison evaluates sensitivity to the year of the predictor representation rather than true temporal transferability or actual changes in rapeseed suitability. The direction of sensitivity can be identified—the 2024 representation produced a more expansive prediction—but its bias relative to unknown ground truth cannot be determined. The exact area estimates should therefore be treated as scenario-dependent, while the more persistent spatial patterns provide stronger evidence for regional prioritization and subsequent field verification.

The uncertainty of the input remote-sensing products should nevertheless be considered when interpreting the results. Commission errors in an annual winter–fallow map may artificially increase the estimated recurrence frequency, whereas omission errors may cause genuinely persistent winter–fallow cropland to be assigned to a lower-frequency class. The requirement of winter fallow in at least five of the six years reduces sensitivity to isolated single-year errors; for example, one annual omission does not exclude cropland that is otherwise consistently classified as winter fallow. However, spatially systematic classification errors may persist across years and cannot be assumed to cancel through temporal aggregation.

The final tuned-model estimate of 1137 km<sup>2</sup> remains conditional on the model-specific threshold and the five-of-six-year winter–fallow criterion. The separate recurrence audit showed substantial variation in absolute extent but stable county prioritization. Field verification is therefore required before site-specific use; full probability propagation would additionally require annual per-pixel classification uncertainty, which is unavailable from the published input maps.

The high retention of baseline hotspot cells indicates that the principal WFF and WR hotspot cores were not artifacts of the selected 5 km distance band. Nevertheless, broader distance bands increased the spatial extent of significant clusters, and WFF cold spots were more sensitive to both neighborhood definition and FDR correction. Consequently, interpretation should emphasize recurrent hotspot cores rather than exact confidence-class boundaries or isolated peripheral cells. Because grid resolution was held constant to isolate the effect of spatial-neighborhood distance, the analysis does not fully eliminate the modifiable areal unit problem associated with alternative aggregation resolutions. Multiresolution grid analyses may therefore provide a useful extension in future regional applications.

The threshold analysis demonstrates that model-complexity tuning and binary classification should be evaluated jointly. Directly transferring the original cutoff of 0.25 to the tuned model would have substantially expanded all three mapped area classes, whereas recalibration using replicate-specific thresholds corrected this inflation. After applying the model-specific threshold, the differences from the original GUI estimates remained below 10%, supporting the robustness of the regional-scale area and prioritization conclusions. Nevertheless, thresholding necessarily simplifies a continuous suitability gradient, and the resulting areas remain conditional on the selected MaxEnt configuration, cropland mask, and winter–fallow cropland products. Accordingly, the identified candidate spatial priority

areas should be interpreted as a regional screening result for subsequent field verification and planning assessment, rather than as direct evidence of field-level plantability or immediate implementation feasibility.

Although this study developed an integrated framework for identifying winter-rapeseed expansion potential on winter-fallow cropland, several uncertainties remain.

First, winter-fallow cropland and winter rapeseed data were derived from remote-sensing products, so classification errors may propagate into occurrence frequency, hot spot analysis, suitability modeling, and priority area identification. Multi-year frequency, high-frequency sample extraction, and stable fallow constraints reduced single-year errors, but field surveys, UAV imagery, or county-level statistics should be used to validate key candidate areas.

Second, exact reconstruction depends on the third-party Satellite Embedding V1 product and continued access to the same product version and annual Google Earth Engine assets. Changes in the embedding-generation procedure, band definitions, preprocessing, versioning, or service availability could prevent exact replication of the predictor stack. Moreover, the final screening result is anchored to the 2024 land-surface representation. The 2020, 2022, and 2024 sensitivity analysis measures dependence on predictor year, but it neither reconstructs conditions throughout 2000–2022 nor tests temporal transferability against year-matched occurrence observations. Future applications should archive exported predictor stacks and product metadata and should use temporally matched occurrence data when available.

Third, MaxEnt represents statistical relationships between presence samples and background environments. Its outputs indicate potential suitability, not yield level or management feasibility. Future studies should integrate irrigation and drainage, road accessibility, field contiguity, profitability, mechanized services, and farmer willingness to build a more comprehensive feasibility assessment.

Finally, the analysis did not quantify socioeconomic and farm-management determinants of winter rapeseed persistence. Labor availability, production costs, mechanized services, market prices, subsidies, land fragmentation, and operator preferences may determine whether cropland that is similar in the modeled land-surface representation and stably fallow can actually be converted to rapeseed production. Because spatiotemporally matched farm-level data were unavailable, these factors were not incorporated retrospectively using unmatched contemporary county statistics. Future work should combine household surveys, agricultural production records, field geometry, mechanized-service accessibility, and cost-benefit information with the spatial shortlist developed here.

The candidate spatial priority areas should be interpreted as a spatial shortlist for further investigation rather than land that is immediately available for winter-rapeseed expansion. Practical implementation additionally depends on field contiguity, irrigation and drainage conditions, mechanization accessibility, expected profitability, farmer willingness, and local policy constraints, which were not explicitly incorporated into the present framework. Field surveys and socioeconomic feasibility assessments are therefore required before implementation decisions are made.

## 5. Conclusions

This study developed a progressive spatial screening framework that integrates multi-temporal winter fallow field maps, historical winter-rapeseed occurrence, Satellite Embedding features, and MaxEnt modeling to identify candidate spatial priority areas for winter-rapeseed expansion. Rather than directly equating modeled suitability with expansion potential, the framework distinguishes among land-surface representational similarity, the availability of winter-fallow cropland, and the temporal stability of such land. This

distinction provides a more cautious and operational interpretation of crop-suitability modeling results.

The results reveal a pronounced spatial mismatch between stable winter fallow fields and historically persistent winter rapeseed cultivation in the Wanjiang Plain. This indicates that the continued underuse of winter cropland cannot be attributed solely to differences in the modeled land-surface representation. The actual utilization of winter-fallow fields within the modeled similarity layer is also likely to depend on land fragmentation, irrigation and drainage conditions, access to mechanization, production profitability, labor availability, and farmers' willingness to cultivate. Incorporating the temporal stability of winter fallow fields therefore helps narrow broad suitability predictions into a more targeted spatial basis for subsequent field investigation and agricultural planning.

The identified candidate spatial priority areas should be interpreted as preliminary spatial shortlists rather than direct recommendations for winter rapeseed planting. Their practical feasibility requires field verification and further assessment of land contiguity, infrastructure, mechanized farming conditions, economic returns, and farmer participation. Future research should integrate independent field observations and socioeconomic information, compare conventional-predictor-only, embedding-only, and combined-input models under a common validation design, and evaluate the temporal and regional transferability of the framework.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi15090411/s1>, Table S1: sensitivity of MaxEnt performance to alternative Satellite Embedding feature representations; Table S2: Random Forest screening scores and MaxEnt importance of the 26 retained Satellite Embedding dimensions; Table S3: comparison of repeated-random and spatially blocked validation for the annual MaxEnt sensitivity models; Table S4: sensitivity of Getis-Ord  $G_i^*$  results to distance-band selection and false-discovery-rate adjustment; Table S5: sensitivity to alternative winter-fallow and rapeseed recurrence thresholds; Table S6: provenance of the MaxEnt logistic threshold and area estimates under the original and tuned model configurations.

**Author Contributions:** Conceptualization, Yinlan Huang and Shi Chen; methodology, Jingqiao Fang; software, Tianshuo Xie; validation, Shi Chen; formal analysis, Yinlan Huang; investigation, Tianshuo Xie; resources, Yinlan Huang; data curation, Shi Chen and Jingqiao Fang; writing—original draft preparation, Shi Chen; writing—review and editing, Yinlan Huang and Shi Chen; visualization, Jingqiao Fang and Tianshuo Xie; supervision, Shi Chen; project administration, Yinlan Huang; funding acquisition, Shi Chen. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** The publicly available source datasets used in this study are identified in Section 2.2.1. The Supplementary Materials provide the numerical results of feature screening, model validation, temporal and spatial sensitivity analyses, recurrence-threshold sensitivity, and MaxEnt threshold provenance (Tables S1–S6). To support reconstruction of the analysis, the machine-readable 394 occurrence locations, 10,000 background locations, saved spatial-fold and replicate assignments, and the R scripts used for feature screening, MaxEnt tuning, cross-validation, ensemble averaging, threshold calculation, and area extraction are available from the corresponding author upon reasonable request. Full copies of the third-party source rasters are not redistributed because the authors do not own those products and because of their large file sizes; users should obtain the same product versions from the providers cited in Section 2.2.1. Processed spatial outputs are available from the corresponding author subject to the applicable provider terms.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

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