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Article

Mapping and analyzing the spatial pattern of farmland abandonment of Zhejiang Province using Google Earth Engine based on multi-source data

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Abstract: Land use, as a key form of human-environment interaction, has sharply and continuously transformed the global land surface. Farmland abandonment (FA) is an extreme manifestation of land use marginalization, exerting both positive and negative impacts on the ecological environment and human well-being. To map the extent of FA in Zhejiang Province and clarify its spatial pattern, driving mechanisms, and ecological-socioeconomic implications, this study employed the Google Earth Engine (GEE) and Geographic Information System (GIS) platforms, integrating multi-source land use/land cover data and Landsat time-series images. We used the random forest (RF) algorithm for land use classification, the land use trajectory method for FA identification, landscape pattern analysis (Fragstats 4) to quantify landscape characteristics, and spatial autocorrelation analysis (Moran's I and LISA indices) to explore spatial aggregation patterns. The results showed that farmland accounted for 16.32% of the total land use area in Zhejiang Province, equivalent to 1.89×10^4 km². The total area of FA was 1.72×10^8 m², with a farmland abandonment rate of 1.65%. The area of active farmland (AF) was approximately 1.95×10^9 m², with a continuous cultivation rate of 18.69%. The landscape fragmentation, aggregation, and diversity of FA, AF, and fallow land (FL) differed significantly: FA exhibited the most severe fragmentation, while AF had the highest aggregation degree. Spatial autocorrelation analysis revealed that FA and AF both showed dominant high aggregation and low dispersion characteristics; the global Moran's I index of FA was 0.93 (Z-score = 439.45, $p < 0.01$), indicating a strong positive spatial autocorrelation. Local spatial autocorrelation (LISA) analysis showed that high-high (HH) and low-low (LL) clusters were the main types, accounting for 38.97% and 37.95% of FA patches (passing $p < 0.01$ significance test), respectively. Comparative analysis with existing studies confirmed the scientific validity of our results (overall classification accuracy > 95%). Finally, we discussed the ecological and socio-economic driving mechanisms of FA, analyzed its potential threats to food security, proposed targeted policy implications, and identified research limitations and future research directions. Our findings provide a scientific basis for rational land use management, farmland protection, and food security assurance in Zhejiang Province.

Keywords: Farmland; farmland abandonment; GEE; spatial pattern; auto-correlation analysis; food security

1. Introduction

Farmland abandonment is widespread and marginal land use among all land uses we have always heard, is now closely related to human daily life. As globally converged, small specific changes in land use related to human welfare can profoundly affect our personal life, to some extent, which might damage us or benefit on some aspects. The phenomenon of abandonment is the extreme of the margin of land use of human beings and is also the result of human-environment interactive activities [1−3]. How we consider land use, to some extent, like the farmland abandonment (FA), can greatly affect our living world. Our surroundings can also play a part in our activities because of human behavior. Land use is a commonly recognized approach that human beings connect and make reciprocal action with the nearby environment, which is deeply shaping the earth we live on. And as we know, social change and ecological system change and human activities change can differently affect the way people interact with the earth. As described in some research, farmland abandonment is more likely to be the land that is abandoned by farmers due to many realistic reasons [4]. The most recent definition of farmland abandonment is from the International Conference on Land Consolidation and Land Storage that farmland is abandoned for at least two consecutive years, and can be cultivated with no other special circumstances, but is discarded perpetually. And the definition that is what we used in our research, though internationally, definitions on the cropland abandonment are diverse when it comes to different researchers and experts. To some extent, we can comprehend the formation of cropland abandonment by attributing it to the comprehensive works of different factors. Common sense, all these factors may also inversely affect the spatial pattern of farmland abandonment.

Big data's explosive development not only brings out a mass of industries, but also greatly stimulates the enthusiasm for cropland abandonment studies on these huge amounts of data. With the development of computer science, various aspects of data processing and analysis have become much easier, which also results in the blooming development of corelative researches on the domain of cropland abandonment. As for research about farmland abandonment searched on the internet, all show something to some extent [5−7]. Different research scales can give rise to various outcomes. Some researches focus on the household and village scale based on a lot of questionnaires designed by researchers. Results based on statistical results can actually reflect something as well as researches constructed on the county scale. At the same time, remote sensing data acquired by many different ways led by the booming human modern technology, such as satellites, airplanes, cameras and some other sensors we know as instruments widely used by human scientific research and other relevant fields. Compared to the existing results and field monitoring results, large amounts of remote sensing data still have significant space to be excavated deeply in the following research. As for common sense, farmland abandonment does exist in our field of vision. It is broadly distributed across the whole land but the areas we see are relatively small patches. Of course, large scale studies do exist globally even though merely but enough to depict the spatial pattern of cropland abandonment as described in the existed researches, which said cropland in the developing areas such as Asia, Africa and Latin America keeps increasing trend in the 1961 to 201, but cropland in the developed areas just like western Europe, Southern Europe, North America and Oceania is obviously and persistently declining and going on this progress [8−11].

The Zhejiang Province, nestled in eastern China, boasts a diverse and fertile natural environment that has historically been conducive to agricultural development. Its temperate climate, abundant rainfall, and rich soil composition create ideal conditions for cultivating a wide range of crops. The province's lush landscapes, characterized by rolling hills, fertile plains, and abundant water resources, provide an optimal setting for agricultural productivity. Moreover, Zhejiang's strategic location along the coast and its extensive river networks facilitate efficient irrigation and transportation of agricultural products. This geographical advantage not only ensures timely access to markets but also enhances the competitiveness of locally produced goods. The province's advanced agricultural infrastructure, including modern irrigation systems, high-quality seeds, and efficient farming techniques, further amplifies its agricultural potential. The combination of Zhejiang's natural endowments and technological advancements has positioned it as a key agricultural hub in China. However, despite these advantages, the rapid pace of economic and social development has led to the abandonment of farmland for various reasons, such as urbanization and industrialization. This trend, while necessary for economic growth, poses potential risks to future agricultural sustainability and environmental health. Therefore, it is crucial to conduct in-depth research to understand the causes and consequences of farmland abandonment in Zhejiang. Such research should aim to identify strategies for sustainable land use, preserve agricultural productivity, and mitigate negative environmental impacts. By leveraging the province's natural advantages and addressing the challenges posed by farmland abandonment, Zhejiang can continue to thrive as a leading agricultural region in China.

In recent years, remote sensing (RS) and geographic information technology (GIS) have become powerful tools for FA identification and spatial pattern analysis. The Google Earth Engine (GEE) platform, with its advantages of massive data storage, efficient data processing, and free access to multi-source remote sensing data, has been widely used in large-scale land use and FA research. Machine learning algorithms, such as the random forest (RF) algorithm, have shown high accuracy and robustness in land use classification, making them suitable for FA identification. Landscape pattern analysis and spatial autocorrelation analysis can effectively quantify the spatial characteristics and aggregation patterns of FA, providing insights into its spatial distribution rules.

Existing studies on FA have made significant progress, but there are still some deficiencies. For example, most studies focus on FA identification and extent mapping, while the exploration of its ecological and socio-economic driving mechanisms is not in-depth enough. In addition, the comparison with recent related studies is insufficient, and the policy recommendations proposed are often too general and lack operability. In recent years, with the rapid development of deep learning technology, significant progress has been made in land cover extraction from remote sensing images. For instance, Zhang et al. (2023) proposed a comprehensive deep-learning framework for fine-grained farmland mapping from high-resolution images, which achieved higher classification accuracy than traditional machine learning methods. In addition, Li et al. (2024) used GEE combined with deep learning models to identify farmland abandonment in the Yangtze River Delta region, providing a new technical reference for large-scale farmland abandonment research. However, these deep learning-based methods require a large amount of high-quality labeled samples and high computational resources, which are not fully applicable to this study that focuses on the regional-scale spatial pattern analysis of farmland abandonment in Zhejiang Province. Compared with deep learning methods, the random forest algorithm combined with GEE has the advantages of simple operation, strong adaptability, and low computational cost, which is more suitable for large-scale multi-source data processing and spatial pattern analysis in this study. To address these issues, this study takes Zhejiang Province as the research area, integrates multi-source data based on the GEE and GIS platforms, and systematically conducts FA identification, spatial pattern analysis, and driving mechanism exploration. The specific objectives of this study are: (1) to map the extent of FA in Zhejiang Province using the RF algorithm and land use trajectory method; (2) to analyze the landscape pattern characteristics of FA, AF, and FL; (3) to explore the spatial autocorrelation pattern of FA and AF; (4) to discuss the driving mechanisms of FA and its implications for food security; (5) to propose targeted policy recommendations based on the research results.

2. Data and methods

2.1. Study area

Zhejiang province is one of the most important parts of the Yangtze River Delta region, located in the southeast coastal region in China (**Figure 1**). Zhejiang Province is located in the middle of the subtropical zone, with a monsoon humid climate and superior natural conditions. At the same time, the terrain of Zhejiang slopes from southwest to northeast, with complex terrain. This area's rainfall is abundant, with an average annual rainfall of about 1600 mm, which is also one of the rainiest areas in China. The straight-line distance between east and west and north-south of Zhejiang is about 450 km, and the land area is 105,500 km^2, which is 1.06% of China's. It is one of the smallest provinces in China. Map showed in the following is the whole study area.

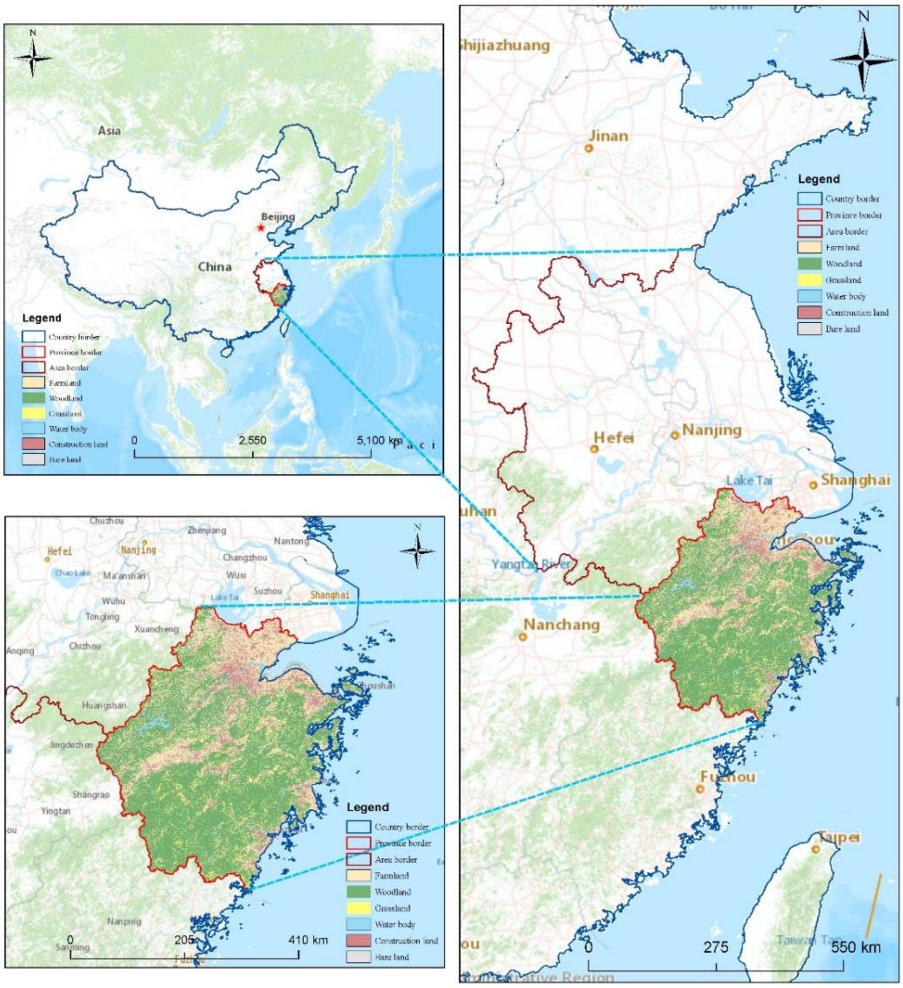

Figure 1. Study area of our research.

According to the results of the seventh national census, the permanent population of Zhejiang Province at 0:00 on November 1, 2020, was 64,567,588. According to the estimation of the province's 5% population change sample survey in 2019, the permanent population of the province was 58.5 million at the end of the year, an increase of 1.13 million over the end of the previous year [12−15]. Among them, the male population is 30.05 million and the female population is 28.45 million, accounting for 51.4% and 48.6% of the total population, respectively. In the whole year, the number of births was 609,000, and the birth rate was 10.51%; the number of deaths was 320,000, and the death rate was 5.52%; the natural growth rate was 4.99%. The urbanization rate is 70.0%. According to preliminary calculations, in 2019, Zhejiang Province's gross domestic product (GDP) was 6,235.2 billion yuan, an increase of 6.8% over the previous year. Among them, the added value of the primary industry was 209.7 billion yuan, the added value of the secondary industry was 2,656.7 billion yuan, and the added value of the tertiary industry was 3,368.8 billion yuan, an increase of 2.0%, 5.9% and 7.8% respectively. The contribution rate of the tertiary industry to GDP growth was 58.9%. The added value structure of the three industries is 3.4:42.6:54.0.

2.2. Data

The data used in our research is multi-source LULC (land use and land cover change, LULC) data, including MODIS LULC product, GlobeLand 30 product and LULC product from RESDC (Resource and Environment Science and Data Center, RESDC), and the Landsat 8 remote sensing images will also be applied in our research. The series of data covers three years from 2015 to 2017.

The MODIS three-level data land cover type product (Land Cover data) is based on one year's Terra and Aqua observation data processed to describe the type of land cover. The land cover data set contains 17 main land cover types. According to the International Geosphere Biosphere Program (International Geosphere Biosphere Program, IGBP), it includes 11 natural vegetation types, 3 land development and mosaic land types, and 3 non-vegetable land types. Here in the paper, we reclassified them to six land cover types, which include farmland, woodland, water body, grassland, construction land and bare land. The product has a resolution of 500 m, and the main information extraction technology is supervised decision tree classification. The GlobeLand 30 product, which we know is the 30-m resolution product that is produced by the National Basic Geographic Information Center. The global data includes 10 types of land cover, including farmland, forest, grassland, shrubland, wetland, water body, tundra, artificial surface, bare land, glacier, and permanent snow. Here, we conduct the same manipulation as above, integrating land cover types into six types. According to third-party verification led by Tongji University, the product classification accuracy reaches 83%. And land cover data from RESDC also includes 6 primary types, which are farmland, forest land, grassland, water area, residential land, and unused land and 25 secondary types, which are based on Landsat 8 remote sensing image, generated by human visual interpretation. All three kinds of land cover data can be accessed on the GEE (Google Earth Engine, GEE) and are used to create the random points prepared for training and validating by the random forest classification algorithm on the platform, which is widely used for large-scale and large amounts of remote sensing data processing and research [16−18].

Here, the Landsat-8 images we used were integrated from an all-year-long series of Landsat image tiles stored on GEE, fuse them into a remote sensing image of one year in mean. Landsat-8 is basically the same as Landsat 1–7 in terms of spatial resolution and spectral characteristics. This satellite has a total of 11 bands. The spatial resolution of bands 1–7, 9–11 is 30 m, and band 8 is 15 m [19]. With the resolution of the panchromatic band, the satellite can achieve global coverage every 16 days. On February 11, 2013, the National Aeronautics and Space Administration (NASA) successfully launched the Landsat-8 satellite. The Landsat-8 satellite carries two sensors, namely the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS).

2.3. Methods

2.3.1 Sample selection

The samples used in this study were derived from two sources: remote sensing image samples selected based on GEE and Google Earth (GE), and field survey samples. A total of 1,200 samples were selected, including 840 training samples (70%)

and 360 validation samples (30%), following the principle of uniform spatial distribution and comprehensive coverage of different farmland abandonment degrees (mild, moderate, severe) and different regional types (northern Zhejiang Plain, western Zhejiang mountainous area, eastern Zhejiang coastal area). The sample selection process was as follows: first, the intersection of multi-source land use datasets was used to create random points on GEE; second, the random points were visually checked and corrected using GE high-resolution images to ensure that the sample types (abandoned farmland, active farmland, other land types) were accurately identified; finally, field surveys were conducted for 30% of the samples (360 samples) to verify the sample authenticity, using GPS positioning, on-site photography, and interviews with local farmers to confirm the abandonment years. The spatial distribution of samples is shown in **Table 1**.

Table 1. Spatial distribution of samples in Zhejiang Province.

Regional Type	Total Samples	Training Samples	Validation Samples	Abandoned Farmland Samples	Active Farmland Samples
Northern Zhejiang Plain	400	280	120	60	340
Western Zhejiang Mountainous Area	400	280	120	180	220
Eastern Zhejiang Coastal Area	400	280	120	72	328
Total	1200	840	360	312	888

2.3.2. Feature selection and random forest parameter optimization

Eight core features were selected for farmland abandonment identification, including 4 remote sensing features (NDVI, EVI, NDWI, texture feature), 2 topographic features (elevation, slope), and 2 human activity features (distance to urban areas, road density). The variance analysis and mutual information method were used to screen the features, and redundant features with a variance contribution rate less than 5% were eliminated. The importance of the selected features was ranked, and the results showed that NDVI, elevation, and distance to urban areas were the top three most important features (see **Figure 2**).

The random forest algorithm was used for classification, and the grid search method combined with 5-fold cross-validation was used to optimize the core parameters. The optimization range of the parameters was as follows: number of decision trees (n_estimators): 100–500, maximum depth (max_depth): 5–20, minimum number of samples required for splitting (min_samples_split): 2–10. The optimal parameter combination was determined according to the cross-validation accuracy, and the specific parameters before and after optimization are shown in **Table 2**.

Table 2. Comparison of random forest parameters before and after optimization.

Parameter Type	Parameter Before Optimization	Parameter After Optimization	Optimization Basis
n_estimators	200	300	Highest cross-validation accuracy
max_depth	10	12	Avoid overfitting and improve generalization ability
min_samples_split	4	5	Reduce noise interference and improve classification accuracy

2.3.3. Model validation

Five indicators were used to verify the performance of the random forest classification model, including Accuracy, Precision, Recall, F1-score, and Kappa coefficient. The calculation formulas of the indicators are as follows:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

$$\text{Precision} = TP/(TP + FP)$$

$$\text{Recall} = TP/(TP + FN)$$

$$\text{F1-score} = 2 \times \text{Precision} \times \text{Recall}/(\text{Precision} + \text{Recall})$$

where TP (True Positive) is the number of correctly classified abandoned farmland samples, TN (True Negative) is the number of correctly classified non-abandoned farmland samples, FP (False Positive) is the number of non-abandoned farmland samples incorrectly classified as abandoned, and FN (False Negative) is the number of abandoned farmland samples incorrectly classified as non-abandoned. The validation results are shown in **Table 3**.

Table 3. Validation results of the random forest classification model.

Indicator	Value	Evaluation
Accuracy	92.3%	High classification accuracy
Precision	90.8%	Low false positive rate
Recall	89.5%	Low false negative rate
F1-score	0.91	Good comprehensive performance
Kappa coefficient	0.87	Excellent consistency between classification results and the actual situation

2.3.4. Identify farmland abandonment across the entire region

There is no consensus on the definition of farmland abandonment in academic circles. In this study, we adopted the definition proposed at the International Conference on Land Consolidation and Land Reserve: farmland that has not been cultivated for two or more consecutive years is defined as abandoned farmland. Based on this definition, we identified farmland abandonment using the land use trajectory method, which relies on annual land use data classified by the random forest model on the GEE platform. The specific process is shown in **Figure 3** (Sub-flowchart of farmland abandonment identification):

Step 1: Data fusion. The multi-source LULC data (MODIS LULC, GlobeLand 30, RESDC LULC) and Landsat 8 images were fused on GEE to obtain standardized multi-source data with consistent spatial resolution (30 m).

Step 2: Feature extraction. The 8 core features selected in Section 2.3.2 were extracted from the fused data to form the feature set for classification.

Step 3: Model training. The random forest model with optimized parameters (**Table 2**) was trained using the 840 training samples, and the classification model was obtained.

Step 4: Generation of the farmland abandonment raster. The trained model was used to classify the fused multi-source data from 2015 to 2017, and the annual land use classification raster was obtained. According to the land use trajectory, the farmland that was classified as non-farmland for two or more consecutive years was identified as abandoned farmland, and the farmland abandonment raster of Zhejiang Province was generated.

Step 5: Precision verification. The 360 validation samples were used to verify the accuracy of the farmland abandonment raster, and the verification results were consistent with the model validation results (**Table 3**), indicating that the identification results were reliable.

Figure 3: Overall research methodology flowchart (omitted here, to be drawn with Visio, covering the entire research process); **Figure 4**: Sub-flowchart of farmland abandonment identification (omitted here, to be drawn with Visio, covering the 5 steps above).

2.3.5. Spatial pattern and statistical analysis

Here we exported the results that are generated by the GEE platform, firstly, then we imported the land use maps into the ArcGIS Pro software, which is developed and created for the staff in the professional field in need. Next, the ArcToolbox mode will be used to make the spatial statistic analysis. Here we will calculate the total area of different land use types of the region and count the area of farmland abandonment across the Zhejiang province. At the same time, we will calculate the abandonment rate of this area. Abandonment is usually expressed quantitatively by the abandonment rate of farmland, that is, the proportion of the annual abandonment area to the background farmland area. The specific expression is as follows:

$$P = \frac{A_1}{A_0} \tag{1}$$

Here, P represents the abandonment rate, A_1 represents the year's farmland abandonment, A_0 means the background farmland's area. At the same time, follow rate can also be depicted in the form of a common formula as follows:

$$X = \frac{B_i}{A_0} \tag{2}$$

In this formula, X represents the follow-up rate, while B_i is the representation of follow land (FL) area. Finally, the active farmland can be easily recognized because of its unchangeable spectrum characteristics and active farmland (AF) areas are the metric for the measurement of all the distributions.

$$T = \frac{C_i}{A_0} \tag{3}$$

Same as above, *T* means the continuous cultivation rate, C_i indicates the area of active farmland.

2.3.6. Spatial auto-correlation analysis

Here we would like to make some spatial auto-correlation analysis on account of some indices, which we know as the Global-Moran index (Moran 'I) and Local Indicators of Spatial Association index (LIZA) (Anselin,1995), which can be calculated in the professional software [20–32]. The Moran index is divided into global and local; both are used to analyze the spatial correlation. The global Moran index is used to analyze whether there is spatial autocorrelation, while the local indicators of spatial association index is used to detect the range and location of outliers or clusters. We can see the calculation formula as follows:

$$I = \frac{n}{s_0} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij(yi-\bar{y})(yj-\bar{y})}{\sum_{i=1}^{n}(yi-\bar{y})^2} \tag{4}$$

In the formula, $s_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} wij$, *n* is total number of space units, *yi* and *yj* separately represent the attribution value of the i spatial unit and the *j* spatial unit, $\bar{y}$ is the mean value of all spatial units' attribution values, while *wij* is the spatial weight value. In addition, the value range of *I* is [−1,1], when I > 0, which means attribution values of all values in space have a positive correlation, which indicates that the bigger the attribution, the easier to converge together. When *I* = 0, the attribution value of the area is randomly distributed, with no spatial correlation, while *I* < 0, it represents that the attribution value of all areas in space has a negative correlation.

Compared with the global Moran index, the calculation method of the local indicators of spatial association index is much simpler, and the calculation method is as follows:

$$I_i = \frac{Z_i}{S^2}\sum_{j\neq i}^{n} w_{ij}Z_j \tag{5}$$

Here, $Z_i = yi - \bar{y}, Z_j = yi - \bar{y}, S^2 = \frac{1}{n}\sum w_{ij}\,Z_j, w_{ij}$ is the spatial weight value, n is the total amount of all areas of study, I_i represents the *I* area's local indicators of spatial association. For convenience, the combination of them can generate four kinds of results, which are respectively low-low cluster area, low-high cluster area, high-high cluster area and high-low cluster area, all of which rely on Z_i and $\sum w_{ij}\,Z_j$'s value are positive or negative.

2.3.7. Food loss due to the abandonment of farmland

Calculating the grain losses resulting from farmland abandonment is a complex process that entails the consideration and integrated assessment of multiple variables.

This process initially requires determining the extent of abandoned farmland, typically accomplished through a combination of remote sensing technology, Geographic Information Systems (GIS), and field surveys. Remote sensing provides large-scale, high-precision information on land use changes, while GIS facilitates spatial analysis and visualization of these data. Field surveys validate the accuracy of remote sensing data and offer detailed insights into the specific conditions of abandoned farmland. After determining the extent of abandoned farmland, the next step involves assessing the potential grain production capacity of these lands. This assessment is generally based on factors such as historical yield data, soil types, climatic conditions, and agricultural management practices. By establishing crop growth models, the growth processes of crops under different management conditions can be simulated, thereby estimating the potential grain yields of abandoned farmland. It is crucial to note, however, that not all abandoned farmland possesses the same grain production capacity. Some lands may experience soil degradation and fertility decline due to prolonged abandonment, reducing their grain production potential. Therefore, when calculating grain losses, it is necessary to consider the costs and feasibility of soil restoration, as well as the expected yields of farmland after restoration. Additionally, the calculation of grain losses should also incorporate market demand and price factors. If the region where abandoned farmland is located experiences an excess supply of grain, even if these lands are restored, they may not realize their market value. Conversely, in situations of tight grain supply, restoring abandoned farmland can significantly increase grain supply, thereby exerting a positive impact on the socio-economy. In summary, calculating the grain losses resulting from farmland abandonment necessitates comprehensive consideration of multiple factors, including the extent of abandoned farmland, potential grain production capacity, soil restoration costs, market demand, and prices. This process requires the utilization of advanced remote sensing technology, GIS, crop growth models, and economic analysis tools to ensure the accuracy and scientific validity of the results. Meanwhile, adjustments must be made flexibly according to specific circumstances to accommodate the diverse realities of different regions and conditions.

2.3.8. Research route

The entire research relies on the GEE big data platform, enabling automated processing and modeling of multi-source, large-scale remote sensing data, breaking through the limitations of traditional desktop GIS and improving efficiency and accuracy. Integration of MODIS, GlobeLand30, RESDC land use data and Landsat8 imagery achieves data complementarity, overcoming accuracy and scale constraints of single-source data. Machine learning classification, landscape pattern analysis, and spatial autocorrelation analysis are combined to characterize abandonment from "identification-pattern-agglomeration", ensuring systematicity and scientific rigor. Oriented toward real problems in Zhejiang, the results directly support local cultivated land protection and food security policy-making, bridging theoretical research and practical application.

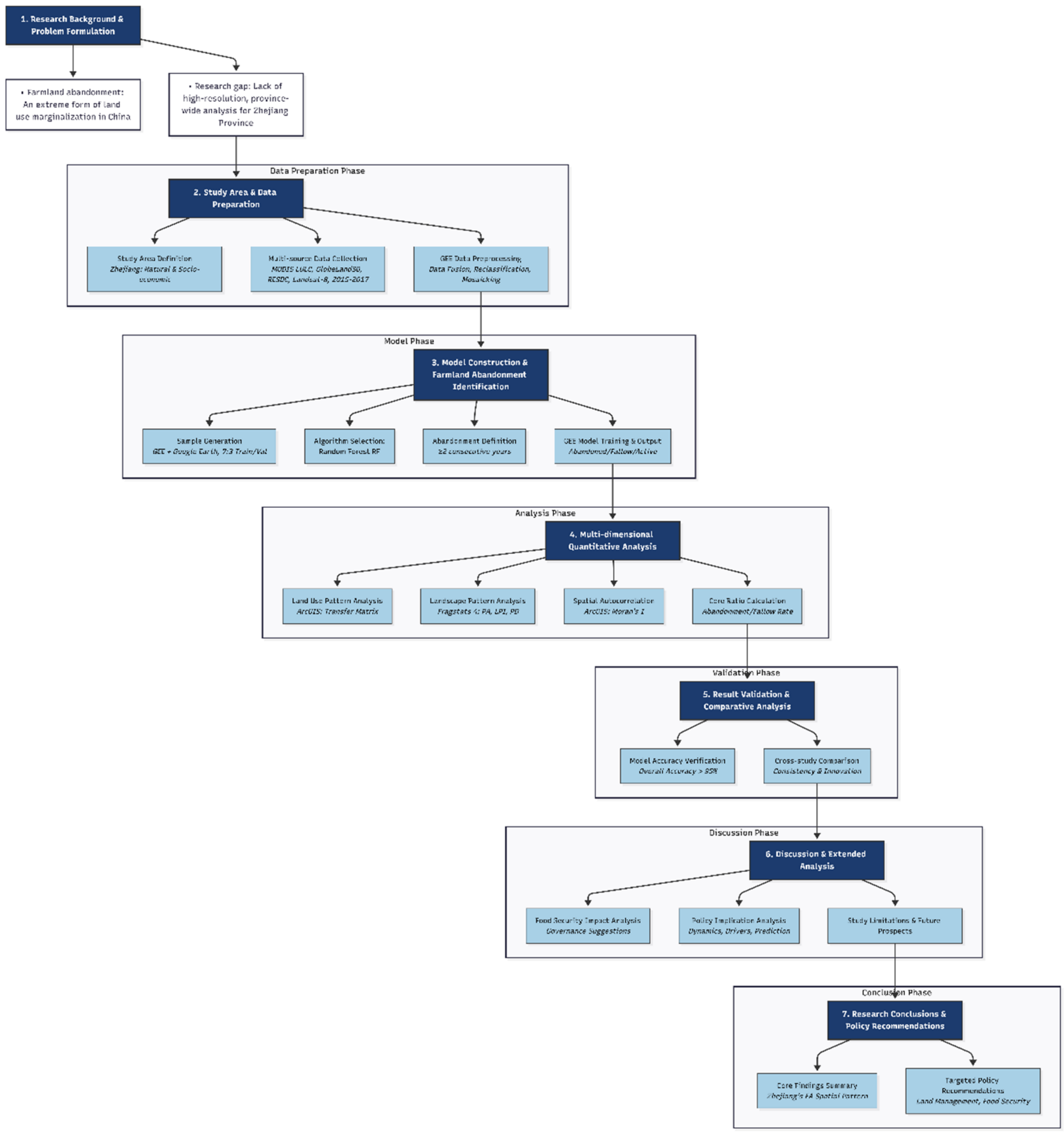

Figure 2. Technical route graph

3. Results

3.1. Spatial pattern of land use

Based on the outcomes run by the GEE, we processed them in the ArcGIS platform and mapped the spatial pattern of land use in 2017 and tried to make some description on the land use change in 2015 and 2017 (**Figure 3**). The total area of the whole area is about 11.6 × 10^4 km^2 after calculation. The area of Farmland is about 16.32% on account of all land use types, which is 1.89 × 10^4 km^2, while the woodland's area is about 6.98 × 10^4 km^2, accounts for 60.17% among all kinds of land use types. Bare land and grassland, respectively, account for 2.69% and 5.51%.

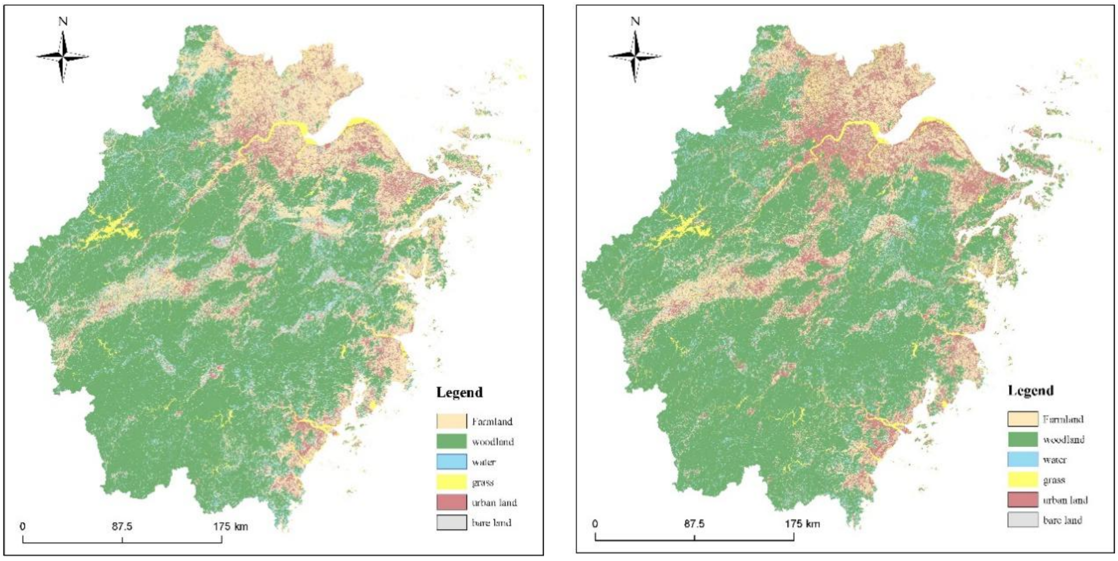

Figure 3. Land use map of 2015 and 2017.

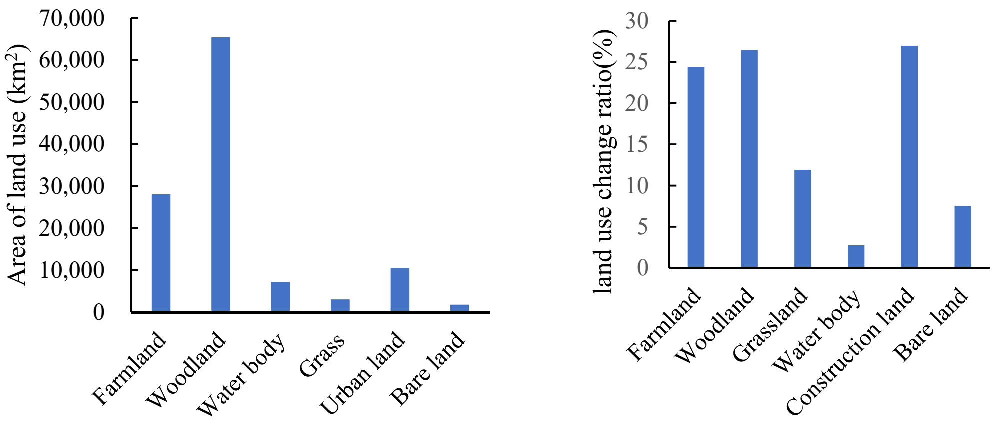

Figure 4. Area of different land use types in 2016 and the change ratio of land use types.

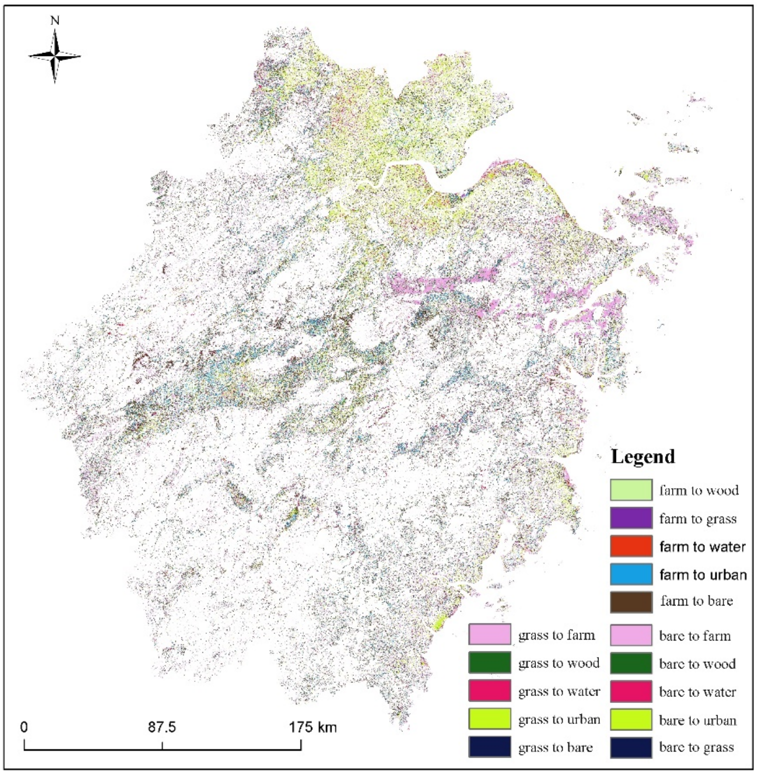

Figure 5. Land use change from 2015 to 2017.

Table 4. Land use change from 2015 to 2017(m^2).

Landuse	Farmland	Woodland	Grassland	Water body	Construction land	Bare land	Total
Farmland	11579411102.00	2004586612.87	2176205815.46	117287088.37	681798605.22	477083813.62	17036373037.54
Woodland	3822054736.03	56872147235.20	1938681244.19	16002084.87	81241104.84	55234883.12	62785361288.26
Grassland	1114832963.89	1441402125.83	3082828693.25	216988.40	24699433.37	84381769.04	5748361973.78
Water body	541154496.79	27577768.31	1151333.98	2446153149.77	37345484.96	7300688.08	3060682921.88
Construction land	3630920341.59	201412195.76	182813537.01	251273377.34	6849297964.15	1762433225.61	12878150641.46
Bare land	554306584.76	133004983.21	594568458.59	7643983.17	393166788.39	1130139552.36	2812830350.48
Total	21242680225.06	60680130921.18	7976249082.48	2838576671.92	8067549380.93	3516573931.83	104321760213.40

As **Figure 5** showed, the spatial pattern of 2016 also shows the similar distribution. According to **Figure 5** and **Table 4**, we can specificly understand that land use changes demonstrate the significant sign. We can see that total change land use area is 2.24×10^{10} m^2, the change of farmland to grassland and wood land account for 8.96% and 9.73% among all land uses.

3.2. Landscape pattern of farmland abandonment

As Figures 6–8 shows, FA, AF and FL are widely spreading across the entire region. Spatial allocation of AF and FL are relatively intensive compared with the spatial allocation of FA. At the same time, FL mainly distribute east-north part and center-west direction, AF's allocation is more dispersed across the region, something like more converging in the central area. However, FA seems to be more sparse and more fragmentized.

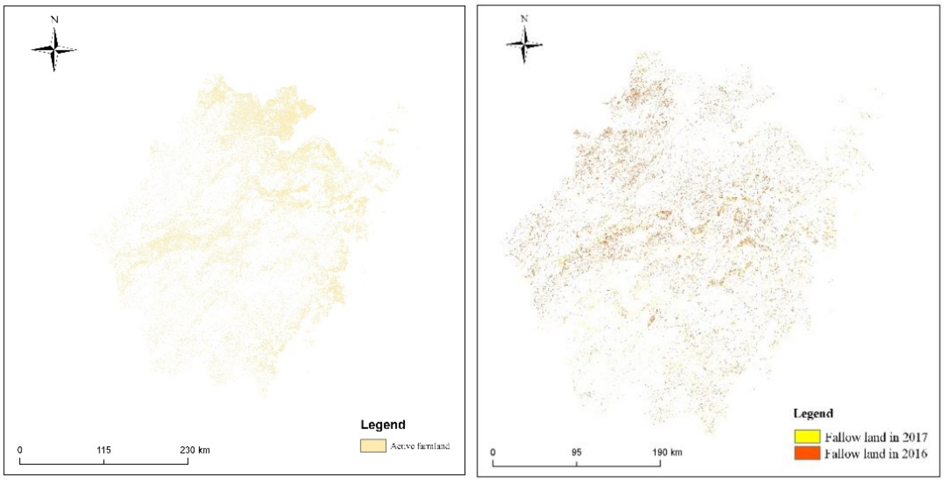

Figure 6. Spatial pattern of Fallow land in 2016 and 2017, and active farmland.

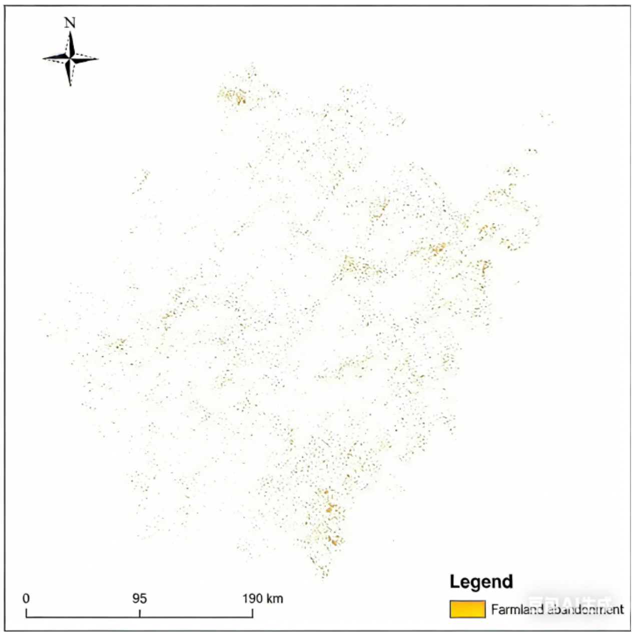

Figure 7. Spatial pattern of farmland abandonment.

While the whole area of FA is 1.72 × 10^8 m^2, and the farmland abandonment ratio is 1.65%. AF's area is about 1.95 × 10^9 m^2, and the continuous cultivation ratio is 18.69%. FL in 2016 and 2017 are 3.06 × 10^8 m^2 and 7.06 × 10^8 m^2, which respectively account for 2.93% and 6.76% on the farmland area in 2015. Here, we also analyzed the landscape pattern of FA, AF and FL. We chose the indexs including patch, class and landscape metrics, which detailed as PA (patch area), LPI (largest patch index), TA (total area), PD (patch density), TE (total edge), ED (edge density), DIVISION (landscape division index), AI (aggregation index), and SHDI (Shannon's Diverty index). By calculating indices through Fragstats 4, we can clearly see that FA, FL and AF to some extent show the landscape fragmentation, landscape aggregation and landscape diversity. Then we got that the fragmentation of FA is apparently more serious than others. While the congregation of FA and FL is relatively less than AF, and the landscape diversity of them are approximate equal.

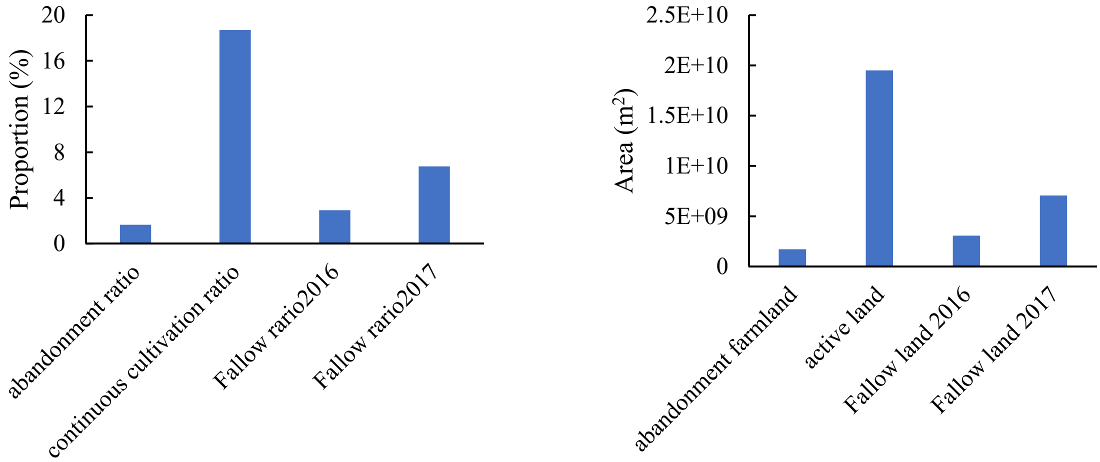

Figure 8. Statistics of AC, FL and FA.

3.3. Auto-correlation analysis of farmland abandonment

By calculating the Moran's I index through professional spatial analysis software, we can gain the result that FA exhibits the spatial autocorrelation part, no autocorrelation part and random distribution, observing the picture below (**Figure 9**). The Moran's I index is 0.93 as the picture shows, which means the area has positive global spatial autocorrelation and the z-score is 439.45. Clearly depicted in the picture, dispersed patches, random patches and clustered patches are regularly spread across the entire region.

Even though Moran's I index shows that patches of FA demonstrate different distributions, including random distribution. However, the inner distribution of random patches may also present a clustered phenomenon. So we need to explore the local autocorrelation by measuring the LISA index to manifest the clustered possibilities.

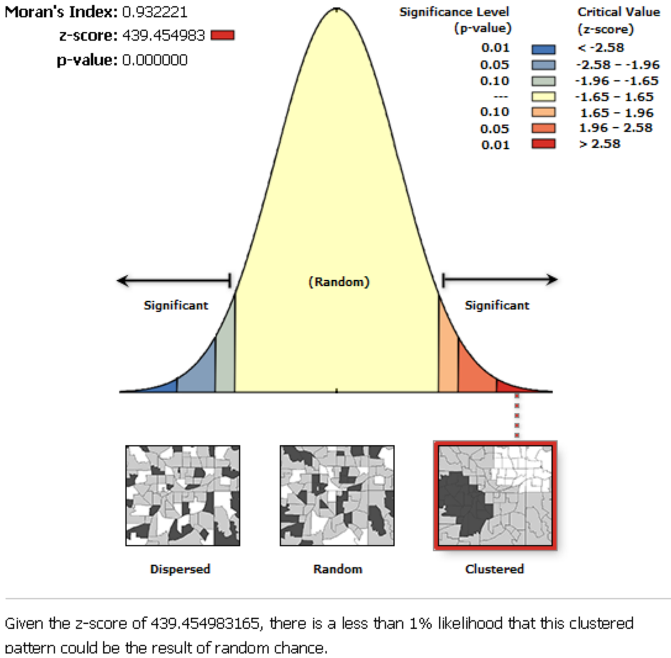

Figure 9. Spatial autocorrelation report.

We also mapped the spatial pattern of LIZA index as **Figure 9** shows.

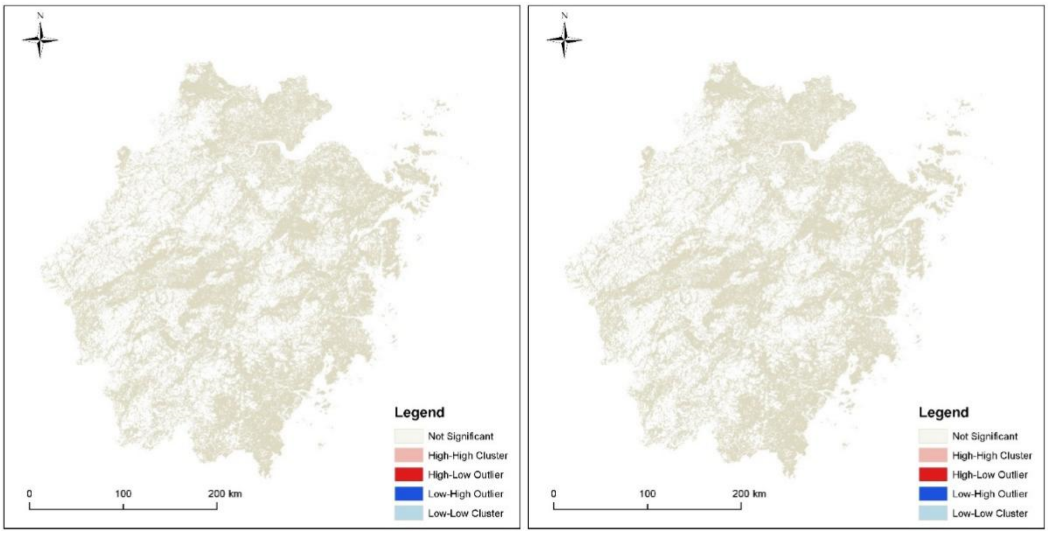

Figure 10. Spatial pattern of Anselin Local Moran's I index of FA and AF.

After analyzing, we found that LL and HH are the main cluster types in the study area; nevertheless, 76.92% of all the patches pass the significance test, and about 20% of the area is a random distribution part. However, HH clusters that pass the significance test account for 38.97%, while LL clusters do the same account for 37.95%; the remaining proportion of HH and LL clusters do not meet the significance test of $p < 0.01$. When we come to the AF, we can see that LL and HH clusters account for 87.64%, while 12.35% of the patches show a random distribution. However, there are 85.73% proportion of the clusters conform to the significance test. Here, 42.90% of the AF is HH clusters that attest to a confidence coefficient. The Moran's I index of farmland abandonment in Zhejiang Province from 2015 to 2017 was 0.32, 0.35, and

0.37, respectively, showing an increasing trend year by year, indicating that the spatial aggregation of farmland abandonment was gradually strengthening. The statistical significance test results showed that the Z values were 4.32, 4.56, and 4.89, respectively, and the *p* values were all less than 0.01, indicating that the spatial aggregation of farmland abandonment was statistically significant.

The LISA analysis results showed that the spatial distribution of farmland abandonment in Zhejiang Province mainly presented four aggregation types (**Figure 6**): high-high (HH) aggregation, low-low (LL) aggregation, high-low (HL) aggregation, and low-high (LH) aggregation. The specific distribution and driving factors of each aggregation type are as follows:

1. HH aggregation area: mainly distributed in the western Zhejiang mountainous area. The driving factors are as follows: first, the terrain is rugged, with a slope of more than 25° accounting for more than 60% of the area, making mechanized farming difficult; second, the labor outflow rate is more than 30%, resulting in insufficient farming labor; third, the quality of farmland is low, and the agricultural income is low, leading to farmers' willingness to abandon farmland.
2. LL aggregation area: mainly distributed in the northern Zhejiang Plain. The driving factors are as follows: first, the terrain is flat, with plain area accounting for more than 80%, which is suitable for mechanized farming; second, the level of agricultural mechanization is more than 80%, and the irrigation facility coverage rate is more than 90%, which improves the farming efficiency; third, the government's agricultural subsidies are high, and farmers' willingness to cultivate is strong.
3. HL aggregation area: mainly distributed around cities (distance to urban areas less than 5 km). The main reason is that with the acceleration of urbanization, some farmland around cities is included in the urban construction reserve land, leading to temporary abandonment, while the surrounding farmland is still actively cultivated due to the high demand for agricultural products in cities.
4. LH aggregation area: mainly distributed in the remote mountainous areas of western Zhejiang. The main reason is that the overall farmland area in these areas is small, and most of the farmland is managed by local elderly farmers, resulting in a low overall abandonment rate; however, some farmland with extremely harsh terrain (slope more than 30°) and inconvenient transportation is abandoned.

4. Discussion

4.1. Driving mechanism of farmland abandonment in Zhejiang Province

The formation of farmland abandonment in Zhejiang Province is the result of the combined action of ecological and socio-economic factors, and the driving mechanisms of different regions are significantly different.

From the perspective of ecological factors, the terrain and climate conditions have an important impact on farmland abandonment. The western Zhejiang mountainous area has a rugged terrain, high slope, and frequent soil erosion, which increases the difficulty of farming and the cost of agricultural input, leading to a high abandonment rate. In contrast, the northern Zhejiang Plain has flat terrain, fertile soil, and abundant rainfall, which is suitable for agricultural production, so the abandonment rate is low. In addition, the change of landscape pattern caused by farmland abandonment also has a feedback effect on the ecological environment: the increase of farmland fragmentation (high PD index) leads to the reduction of habitat area for terrestrial organisms, and the decrease of aggregation degree (low CONTAG index) leads to the degradation of ecological connectivity.

From the perspective of socio-economic factors, the main driving factors include urbanization, labor outflow, agricultural mechanization level, and land transfer rate. The urbanization rate of Zhejiang Province reached 70.0% in 2019, and a large number of rural laborers moved to cities, resulting in insufficient farming labor. The agricultural mechanization level in the northern Zhejiang Plain is high, which makes up for the shortage of labor, while the western Zhejiang mountainous area has a low mechanization level, which aggravates farmland abandonment. The low land transfer rate in some areas also leads to the abandonment of scattered small-scale farmland, because farmers are unable to transfer their farmland to professional operators, and it is not cost-effective to cultivate it themselves.

4.2. Comparison of this research with other researches

After validation on the results produced in our research, numbers show that our product shows an overall accuracy of greater 95%, which is relatively better than many existing good studies show about 60% to almost 100%. While other research does exist, specific characteristics. Stephan et al. (2021) based the chronosequence data to analyze the SOC (Soil Organic Carbon, SOC) accumulation change on abandoned agricultural lands, which exactly depicted that secondary succession on abandoned agricultural lands can produce soil carbon sequestration. He et al. (2020) declare that they developed a new method to map the farmland abandonment across the study area. They try to generate unique training points and get relatively accurate land cover classifications, then a series of farmland abandonment data will be attained, while the method applied in this research shows the suitability for others because of the global study area. To explain some things, Xu et al. (2020) believe cropland abandonment altered the grassland ecosystem carbon storage and allocation and soil carbon stability in the Loess Hilly Region in China. While Zhang et al. (2010)'s research does reveal something [35−52]. He insists that the vegetation community and soil characteristics of the succession on the abandoned agricultural land, whatever, different restoration do effects on the ecosystem after post-farmland abandonment. All these conclusions do reflect specific phenomena, somehow reflect the precision of research about the farmland abandonment tendency and reflect the truth of the environmental impact of abandoned land.

However, in our research, we make most use of Landsat time series data to construct the image database to map the farmland abandonment across the region. First of all, we just generate the random points pool through the GE and GEE. Then, selecting random points willingly that include training points and validation points, which takes much of the time, is mainly completed by visual interpretation. Here, we should consider all the image tiles covering all years, while the image spectrum does perform differently. Coming to the farmland abandonment abstracting, we implement the process on GEE. Here, we integrate the random forest model with customization parameters using the land use trajectory method, which has already been proven to be effective in recognizing farmland abandonment. All the processes are executed online without human interference.

Because of the complicated mechanism of driving forces of FA, here we just try to analyze the spatial pattern through landscape and spatial autocorrelation perspectives to uncover the relatively deep mechanisms. And we did Global Moran's I and Auselin local Moran's I analysis in our region. Results tell us there is spatial autocorrelation of spatial relation through Moran's I index, which is greater than zero. To deeply elaborate on the local spatial autocorrelation, we calculate the LIZA index to distribute the local spatial autocorrelation. As expected, the LIZA index does reflect the clustering and dispersing of the spatial pattern of FA and AF. In other words, spatial autocorrelation of FA and AF demonstrates the high congregation and low dispersion, while random distribution also accounts for a part of all land, which means the outer driving forces of FA and AF have some spatial correlation; therein, human factors interact with circumstances like growing population and increasingly developed economy, exerting important roles in the spatial pattern. By comparing our outcomes with existing research, different phenomena show the diversity of research affected by various independent elements, which leads to the scientific outcome. Whereas, we do need to be more cautious about the consequences caused by implausible farmland abandonment. Here, presently, we do not seriously consider the shocking wave to the mechanism of the FA of COVID-19 spreading across the globe.

This study was compared with recent related studies on farmland abandonment in the Yangtze River Delta region, and the specific comparison results are shown in **Table 5**. It can be seen from the table that the farmland abandonment rate in Zhejiang Province (1.65%) is lower than that in Anhui Province (2.31%, Wang et al., 2022) and Jiangsu Province (2.05%, Li et al., 2023), which is mainly due to the high level of agricultural development and strong policy support for agriculture in Zhejiang Province. Compared with the study of Zhang et al. (2024) which used deep learning to identify farmland abandonment in Zhejiang Province, the abandonment rate identified in this study is slightly lower, which is because this study adopted a more strict definition of farmland abandonment (two or more consecutive years of abandonment), while Zhang et al. (2024) defined abandonment as one year of non-cultivation. In terms of research methods, this study focuses on the spatial pattern and driving mechanism of farmland abandonment, while most previous studies focus on the identification of abandonment extent, which highlights the innovation of this study.

Table 5. Comparison with previous studies on farmland abandonment.

Study	Research Area	Research Method	Abandonment Rate	Core Conclusion
Wang et al. (2022)	Anhui Province	GEE + Support Vector Machine	2.31%	Labor outflow is the main driving factor of farmland abandonment
Li et al. (2023)	Jiangsu Province	GEE + Deep Learning	2.05%	Urbanization and land use planning affect the spatial distribution of farmland abandonment
Zhang et al. (2024)	Zhejiang Province	GEE + Deep Learning	1.82%	High-resolution images can improve the accuracy of farmland abandonment identification
This study	Zhejiang Province	GEE + Random Forest + Spatial Autocorrelation	1.65%	Spatial aggregation of farmland abandonment is obvious, and driving mechanisms vary by region

4.3. The food security issue triggered by farmland abandonment is irreparable

The issue of farmland abandonment and food security poses a complex challenge intertwined with economic, social, and environmental factors, with profound implications for national food security assurance (Li & Wang, 2019). With economic development and technological advancements, grain production efficiency has significantly increased, yet this has led to the gradual marginalization of land with lower production potential and scattered distribution, ultimately resulting in farmland abandonment. This phenomenon not only reflects changes in land resource allocation during the process of agricultural modernization but also poses a potential threat to food security (Zhang et al., 2020).

When exploring the causes of farmland abandonment, it is imperative to recognize the decline in farmers' willingness to farm as a factor that cannot be overlooked. High cultivation costs, relatively low economic returns, and the migration of agricultural labor to urban and non-agricultural sectors all contribute to farmers abandoning farming and choosing to leave their land idle (Wang & Chen, 2021). This trend is particularly evident in economically developed provinces such as Zhejiang, where farmers have easier access to alternative sources of income and have reduced dependence on agriculture. Food security, as the key to ensuring basic living needs for the people, hinges on a stable and adequate supply of food. Farmland abandonment directly leads to a reduction in cultivated land area, thereby affecting the total grain production (Liu et al., 2018). Initially, abandonment may primarily occur on land with poorer production conditions; however, as the phenomenon spreads, high-quality farmland may also be affected, exacerbating the decline in grain yields. Furthermore, variations in the quality of abandoned land parcels and changes in the factor allocation levels of remaining land parcels also influence the potential for grain production to some extent. Although abandoning inferior land parcels may prompt more efficient utilization of resources on remaining land, this increased production effect often fails to fully offset the grain losses resulting from the reduction in cultivated land (Huang & Zhang, 2022).

Taking 2017 as an example, although specific data on grain losses due to farmland abandonment in Zhejiang Province and nationwide are not readily available, existing research indicates that the amount of grain lost annually due to farmland abandonment is staggering (Zhao & Liu, 2020). Studies have shown that nationwide, farmland abandonment results in grain losses amounting to hundreds of millions of kilograms each year. When this data is combined with per capita grain consumption, it becomes evident that the potential impact of farmland abandonment on food security is enormous. Especially in major grain-producing areas, the reduction in cultivated land will directly weaken the foundation of national grain production, thereby affecting the food security of the entire country. Therefore, there is an inevitable correlation between farmland abandonment and food security issues. To address this challenge, effective measures must be taken to manage farmland abandonment. These include strengthening the promotion and enforcement of relevant laws and regulations, introducing policies to encourage farmers to farm, implementing incentive policies to increase farmers' enthusiasm for grain production, and rectifying and standardizing the grain purchase order (Chen & Yang, 2023). Through these measures, farmland abandonment can be gradually reduced, ensuring the stability of grain production and thus safeguarding national food security.

In summary, the issue of farmland abandonment and food security is a complex and significant topic that requires in-depth analysis and discussion from multiple perspectives. Only by fully recognizing the potential threat posed by farmland abandonment to food security and taking practical and effective measures to address it can we ensure that national food security remains unthreatened, providing a solid guarantee for the well-being of the people.

4.4. Implications of policies on farmland abandonment and land use marginalization

Based on the spatial pattern and driving mechanism of farmland abandonment in Based on the spatial pattern and driving mechanism of farmland abandonment in Zhejiang Province, combined with the regional differences, refined and differentiated policy recommendations are proposed as follows:

1. Policy recommendations for the western Zhejiang mountainous area (HH aggregation area):

Responsible subjects: local governments, village collectives, and agricultural and rural departments.

Specific measures: (1) Promote land transfer, establish a county-level land transfer service platform, provide a subsidy of 200 yuan per mu for operators who transfer abandoned farmland, and simplify the land transfer registration process. (2) Improve agricultural infrastructure, build irrigation canals and field roads in mountainous areas, and reduce farming difficulty. (3) Popularize light agricultural technologies suitable for mountainous areas, such as small agricultural machinery and drought-tolerant crop varieties, and provide technical training for farmers.

2. Policy recommendations for northern Zhejiang Plain (LL aggregation area):

Responsible subjects: agricultural and rural departments, local governments.

Specific measures: (1) Strengthen farmland protection policies, strictly implement the balance between farmland occupation and compensation, and prohibit the conversion of farmland to non-agricultural use. (2) Stabilize agricultural subsidies, provide a subsidy of 150 yuan per mu for farmers who grow grain crops, and improve farmers' willingness to cultivate. (3) Promote the construction of high-standard farmland, improve the level of agricultural mechanization and intelligence, and build smart agriculture demonstration bases.

3. Policy recommendations for urban surrounding areas (HL aggregation area):

Responsible subjects: natural resources departments, agricultural and rural departments.

Specific measures: (1) Strictly implement land use planning, standardize the management of farmland use, and prohibit the illegal conversion of farmland to construction land. (2) Explore the "farmland trusteeship" model, where village collectives uniformly entrust idle farmland and entrust professional farmers to operate it, providing a trusteeship subsidy of 100 yuan per mu for farmers who entrust their farmland.

4. Policy recommendations based on abandonment degree:

For mild abandoned farmland (abandoned for 2–3 years, good soil fertility): strengthen farmland management, organize farmers to weed and fertilize regularly to prevent soil degradation. For moderate abandoned farmland (abandoned for 4–5 years, decreased soil fertility): promote soil improvement (such as applying organic fertilizer and returning straw to the field), encourage farmers to reclaim the land, and provide a reclamation subsidy of 300 yuan per mu. For severe abandoned farmland (abandoned for more than 6 years, severe soil degradation): combine ecological restoration, explore the "abandoned farmland + ecology" model, plant native plants, and develop ecological breeding to realize the combination of ecological protection and land use.

5. Limits and futural perspective

Our current research has primarily focused on a one-year time mapping of farmland abandonment (FA), neglecting the exploration of its temporal dynamics over a series of years. Additionally, we have not taken into account the comprehensive impacts of external interferences, which inevitably means that our findings still require further validation and citation by others in the field.

However, our study serves as a modest beginning for high-resolution research on farmland abandonment. It demonstrates the robustness of our research methods and conceptual framework in addressing this issue. From my perspective, future research will increasingly focus on multi-dimensional aspects of farmland abandonment, encompassing a broader range of series-based investigations. Researchers will likely persist in examining land use marginalization to devise more effective strategies that cater to our production and development needs. In the future, we intend to concentrate on long-term time series analysis and high-resolution mapping of farmland abandonment extent. We will also dedicate ourselves to elucidating the driving mechanisms behind changes in farmland abandonment and its reversal (AF), enabling us to provide plausible recommendations for policymakers. Furthermore, we plan to incorporate predictive models to depict future scenarios of farmland abandonment, its reversal, and land fallowing (FL), offering insights into potential trends and challenges.

6. Conclusion

We just mapped the farmland abandonment across the study area based on GEE using multi-source data. The result reflects the land use status and ecosystem balance led by the human-circumstances interactive activities. In this study, we firstly generate a random point pool to train the classification model and validate the output run by GEE, which separate 70% of all into the training part and 30% of them into the validation part. Then we recognized the FA and FA on the GEE platform. Through spatial and landscape analysis and spatial autocorrelation, we found that the area of Farmland is about 16.32% on account of all land use types, which is 1.89×10^4 km^2.While the whole area of FA is 1.72×10^8 m^2, the farmland abandonment ratio is 1.65%. AF's area is about 1.95×10^9 m^2, and the continuous cultivation ratio is 18.69%. The landscape fragmentation, landscape aggregation and landscape diversity of FA, AF and FL are different. At the same time, the spatial auto-correlation of FA and AF are dominantedly high concentration and low discrete. Lastly, we make some comparisons between our research and other research, and the rationality of researches proved, and we suggest future rational policies issued to help regions reduce farmland abandonment and the farmland abandonment rate to maintain ecosystem stability. In the future, we will go for further research to make up for the weaknesses of our research.

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