Monitoring and Modelling Abandoned Agricultural Land Based on Multisource Data Integration

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Abstract. Given the sustained growth of the global population, the problem of abandoned agricultural land (AAL) has gradually attracted the attention of governments and scholars. Here, four high-resolution remote sensing data sources (Sentinel-2A satellite, Resources satellite 3, Gaofen-1 satellite, and Gaofen-2 satellite) and two geographic information survey data sources (land use data and returning farmland to forest data) were used in combination. An integrated method of combined annual and interannual detection was used to monitor AAL. The integrated method produced total abandonment information and distinguished the types of AAL (completely AAL, half-AAL, and transitional AAL). By data mining the monitoring results, eight driving factors of abandonment were determined at the plot scale, including village distance, height difference, highway distance, plot area, fractal dimension index, shelter forest, irrigation condition and neighbourhood characteristics. The logistical regression results showed that seven independent variables except village distance had a significant impact on abandonment, and the prediction accuracy of the model was 95.4\%. This study can be applied to monitoring AAL and analysing the driving forces of abandonment.

Keywords. Abandoned Agricultural Land; Multisource Data; Integrated Method; Data Mining; Logistic Regression

1. Introduction
According to a calculation by the Food and Agriculture Organization of the United Nations (FAO), in 2017-2018, the consumption rate of the world grain inventory was 25.8\%, which exceeded the alert level of 18\%, and the food security of world grains was in a tenuous balance. In 2018, 800 million people suffered from undernutrition. Approximately 70\% of those starving live in rural areas in less developed and developing countries [1]. According to the Second National Land Survey of China, non-irrigated dry land accounted for 54.9\% of the total farmland as of December 2013, and hillside land accounted for 27\% (slope angle greater than 6 degrees). Therefore, among the existing farmland types in China, a large proportion is dry land and sloping land with poor farming conditions, and a large extent of farmland is vulnerable to the threat of abandonment. The negative impacts of abandoned agricultural land (AAL) include the loss of agricultural production [2], the destruction of rural landscapes [3], an increased probability of wildfires [4-5], reduced incomes for farmers [6], and an increased risk of village marginalization [7]. The positive impacts of AAL include forest restoration [6], the promotion of biodiversity [8], an increase in soil carbon sinks [9-11], reduced soil erosion [12-13] and improved soil fertility [14].
Popular AAL research topics for scholars include the impacts of abandonment driving forces and AAL impacts at different levels, including farmers, villages, counties, cities, and countries [15], all of which require an in-depth understanding of the AAL situation in a region. There are two main research methods for collecting information in this field: the questionnaire survey method and the recognition method, which is based on remote sensing technology [16-18]. The questionnaire survey method is good for studying the driving forces of AAL, whereas methods based on remote sensing technology help in understanding the temporal and spatial distribution characteristics of AAL.

The existing remote sensing extraction methods for AAL mainly include visual interpretation [19], supervised classification [20-22], object-oriented classification (rule-based) [23], direct change detection [24], post-classification change detection [25-26], and vegetation index change detection [27].

Cheng used the normalized difference vegetation index (NDVI) products of Moderate Resolution Imaging Spectroradiometer (MODIS) data combined with various types of growth cycle characteristics to comparatively analyse and identify AAL with an accuracy rate of 90% [27]. Witmer used Thematic Mapper (TM) images to identify AAL caused by war in Yugoslavia, and the classification accuracy was 82.5% [24]. Prischepov used TM/Enhanced Thematic Mapper (ETM) data to classify Lithuania [21]. The overall AAL classification accuracy was 90%, indicating that using multitemporal data was much more accurate than using single-phase data and that the data should include spring, summer, and autumn with the texture features of crops before sowing and after harvesting as the main basis for identifying cultivated land and grassland. Stefanek used Landsat and European remote sensing satellite (ERS) synthetic aperture radar (SAR) data to study land trajectories and cultivated land reclamation in Ukraine [23]. The overall classification accuracy ranged from 87.2% to 97.4%. Löw revealed that the stratification-based classification with a fusion of the classification results with random forest (RF) and support-vector machine (SVM) classifiers was statistically more accurate than non-stratified single classifications [22]. Landsberg indicated that a supervised classification method and high-resolution images should be used and that a study area should be narrowed to improve AAL extraction accuracy [28].

The problems associated with monitoring AAL by remote sensing are as follows: (1) obtaining cloudless data coverage with high spatial and temporal resolution is difficult. AAL is challenging to identify because it is usually fragmented and scattered throughout small abandoned land parcels [29]; (2) Distinguishing AAL from grassland, bare land and shrubs is difficult [30]; (3) Conducting regional/local studies to develop indicators to assess the risk of farmland abandonment is needed [5]. In this study, multisource data integration and intra-year and inter-year detection integration are used to determine the precise classification of AAL. Then, the remote sensing monitoring results and multisource data are mined to extract the potential driving factors. Finally, a logistic regression model is built to analyse the driving factors and degree of influence of land abandonment at the plot scale and to explore the general law of land abandonment in semi-arid areas of China.

2. Materials and Methods

2.1. Definition of AAL

This study adopted the definition of AAL provided by the Institute for European Environmental Policy (IEEP) and extended it according to the situation of the research area, which is “farmland where the main vegetation is natural” [19]. The definition divides AAL into three types: complete AAL is “farmland that has not been cultivated for at least two years,” half-AAL is “farmland that has not been cultivated for one year,” and transitional AAL is “returning farmland to forest” (RFF). The definitions of the three types of AAL are shown in table 1.
Table 1. Definitions of abandoned agricultural land (AAL) types. This table includes the IEEP’s definition of AAL.

| AAL type   | Definition                                                                 | Uncultivated time | Vegetation cover                     |
|------------|---------------------------------------------------------------------------|-------------------|--------------------------------------|
| Completely AAL | Complete abandonment of farmland management, and the vegetation naturally returns to a forest or grassland ecosystem | 2 years or more   | Mostly weeds, a few shrubs (Helingeer County) |
|            | Farmland with a low management level that is not completely abandoned; the economic output is zero or very low, but other forms of income can be supported | 1 year            | Sparse weeds                        |
| Half-AAL   | Land use types converted from farmland                                    | 1 year or more    | Sparse weeds, shrubs                 |

2.2. Research Area Overview
Helingeer County is located in the south-central region of Inner Mongolia (39°58’–40°41’N latitude, 111°26’–112°18’E longitude) and is one of the counties under the jurisdiction of Hohhot, the capital of Inner Mongolia. In 2016, the total area was 3,436 km², farmland accounted for approximately one-third of the county area, and the cultivated area of crops was 700.6 km². The main crops were corn, millet, soybean, and potato. The altitude ranged from 1,400-2,028 m, and the annual average precipitation was 392.8 mm. The county belongs to the transitional zone of Inner Mongolia and the Loess Plateau. Mountainous and loess hilly areas account for 77.7% of the county’s area; the northwestern part, which belongs to the edge of the Tumochuan Plain, covers 22.3% of the county area (figure 1).

![Figure 1](image1.png)

Figure 1. Map of the geographical location of the research area. The green line is China’s provincial border.

2.3. Data Sources
The remote sensing (RS) data sources included 8 m and 16 m multispectral images from the Gaofen-1 satellite (GF-1), 4 m multispectral images from the Gaofen-2 satellite (GF-2), 6 m multispectral
images from the Resource satellite 3 (ZY-3), and 10 m multispectral images from the Sentinel-2A satellite (S-2A). Among them, the ZY-3 was launched in 2012, the GF-1 was launched in 2013, the GF-2 was launched in 2014, and the S-2 was launched in 2015. All these satellites are still in service. These satellites have the same wavelength and similar resolutions, which is convenient for comparison and image fusion. In line with Prishchepov [21], RS data for different seasons were obtained in spring (May), summer (July to August), and autumn (late September to October) from 2014 to 2017, for a total of four years and 12 periods. The imaging interval of the data in the same season was no more than 15 days (table 2).

Table 2. Data sources used in this study, including 4 remote sensing data sources and 2 geographic information data sources.

| Data name                  | Number of data | Data type | Resolution (m) | Period covered | Data source                                      |
|----------------------------|----------------|-----------|----------------|----------------|-------------------------------------------------|
| Gaofen-1 (GF-1)            | 28 scenes      | L1A       | 8              | 2014-2016      | Chinese Land Survey and Planning Institute (CLSPI) |
| Gaofen-2 (GF-2)            | 14 scenes      | L1A       | 4              | 2015           | CLSPI                                           |
| Resource-3 (ZY-3)          | 4 scenes       | L1A       | 6              | 2016           | CLSPI                                           |
| Sentinel-2A (S-2A)         | 17 scenes      | L1C       | 10             | 2016-2017      | European Space Agency (ESA)                     |
| Land use                   | 4 years        | Vector    | 1:10000        | 2014-2017      | CLSPI                                           |
| Returning farmland to forest (RFF) | 3 years       | Vector    | 1:10000        | 2015-2017      | Helingeer County Forestry Bureau                 |

The land use data were derived from the Second National Land Survey. The survey contributed to a 1:10,000 land use database that covered the whole country, and the land change survey and database are updated every year. Airborne RS, aerospace RS, and ground surveys were used in the survey. To ensure the accuracy of the investigation, the Land Survey Ordinance was applied, and we strictly controlled quality in all aspects of the investigation. The findings regarding land ownership were considered authoritative [31]. In this study, we assumed that the land use data were accurate.

2.4. Principles and Methods
The specific steps are shown in figure 2: (1) pre-process the RS data; (2) co-register the RS data, including relative radiation normalization and registration; (3) use annual and interannual detection methods to extract the AAL [26, 27]; (4) assess the accuracy of the results of the integrated method; (5) extract eight potential abandonment driving factors based on the results of the AAL extraction and multisource data; (6) invert the driving factors of abandonment by a logistical regression model; and (7) combine the RS monitoring results with the model inversion results and evaluate the driving forces of AAL.

2.4.1. Multisource Data Preprocessing. From the image sequences, the image with the best data quality was selected as the reference image, and the remaining images were corrected. In this study, of the data sources, S-2A had the best comprehensive performance because the S-2A data were L1C, the service time was shortest, and the reliability was high (table 2).

Regarding radiometric correction, according to the calibration equation and calibration coefficient of the sensor, the recorded quantized digital number (DN) value was converted to the apparent radiance of the corresponding field of view. This process assigns the pixel values of different images the same dimension level. Then, the surface reflectance is obtained by atmospheric correction.

In this study, nine of the 12-quarter RS datasets used were clear sky data, and the other three periods had a cloud content of no more than 5%. The cloud-covered areas were replaced by GF-1-WFV (16 m) data in the same quarter. Large cloud-covered areas without replaceable data were eliminated in post-processing; small cloud-covered areas were regarded as sources of error.
Figure 2. Flowchart describing the main steps of this study. The green boxes are the main logistical steps implemented in this study, the blue boxes are the secondary contents, and the boxes filled with blue are the tertiary contents. GF-1, Gaofen-1 satellite; GF-2, Gaofen-2 satellite; ZY-3, Resource satellite 3; S-2A, Sentinel-2A satellite; RFF, returning farmland to forest; RS, remote sensing; GIS, geographic information system; DEM, digital elevation model; and FDI, fractal dimension index.

2.4.2. Multisource Data Co-registration. Since the five sensors used in this study had the same wavelengths and similar spatial resolutions in the four visible and near infrared (NIR) bands, the data were suitable for data co-registration.

The co-registration process included multisource and multi-period data. Relative radiometric normalization was implemented using the following steps: (1) based on radiometric calibration and atmospheric correction, all data were resampled to a 10 m spatial resolution, up-sampled using quadratic linear interpolation, and down-sampled using pixel aggregation. (2) All data were divided into 12 groups, with each group representing a seasonal dataset. (3) According to the overlapping-region histogram matching method, each group of data was categorized and normalized, which enhanced the radiation consistency within the same group of data. (4) Twelve sets of data were output to the ENVI standard format with a 4 band and 10 m resolution, and the administrative boundary of Helingeer County was cut out.
The purpose of relative radiometric normalization [32] was to reduce the relative errors in the different data sources and smooth the NDVI mutations. The co-registration results of ZY-3 (figure 3a, left) and S-2A (figure 3a, right) in summer 2016 were used as an example. In the true colour images, the ZY-3 and S-2A data showed significant differences, but in the NDVI images, the ZY-3 and S-2A data showed no significant differences in the overlay comparison. The vegetation index of continuous features between different images was consistent, indicating that the co-registration results were of acceptable high quality. The methods used in this study were mainly based on NDVI images. Therefore, we paid more attention to the consistency of the NDVI for the different data sources.

![Figure 3](image_url)  
*Figure 3. Evaluation of the co-registration results: (a) true colour image and (b) normalized difference vegetation index (NDVI) image. S2-A on August 7, 2016 (right), and ZY-3 on July 22, 2016 (left). The NDVI differences between the images have been eliminated.*

2.4.3. Threshold Test. A threshold setting should consider the time span of the data, the main crop types, the planting system, and interannual rainfall changes [33]. The image thresholds in any two seasons differ, and therefore, it was necessary to analyse the images comprehensively based on statistical data and on-the-spot situations. Based on the sample database established by the field investigation in the study area (82 points, each point represents a homogeneous landscape of 1/30 ha), we calculated the range of the NDVI changes in farmland cover in the different periods with SPSS 20 (developed by IBM corporation, Amundke, New York, USA) software and then used the results for the threshold segmentation of annual and interannual detections (figure 4).

As shown in figure 4, the range of the NDVI changes between the AAL and the main crops was significantly different, which was the basis of the threshold segmentation. The range in the NDVI soybean changes was close to that of AAL, which was one of the main error sources restricting the use of this method. The main crops were sown in May and harvested from the end of September until the middle of October. The planting system was one season per year. There were two NDVI features that showed the greatest differences between the AAL and crops: the maximum NDVI value and the range of the NDVI changes [20]. The NDVI of the crops after harvesting in autumn decreased suddenly, causing substantial NDVI changes; at the same time, weeds continued to grow for a period of time. Therefore, we mainly used the range of the NDVI changes to distinguish between crops and AAL.
Figure 4. Normalized differential vegetation index (NDVI) change separation chart of the land cover types: (a) spring-summer 2016; (b) summer-autumn 2016; and (c) changes in summer from 2015 to 2016. The x-axis is an equi-spaced scale, and the y-axis is the result of subtracting the NDVI of the 2 phases. The green line is the threshold segmentation line.

2.4.4. Integrated Method. The integrated method included two annual detection methods and one interannual detection method, which are described as follows:

Annual detection: Using the farmland vector layer in the land use data as a mask layer [31], the method extracted cultivated land from the mask layer and then subtracted cultivated land from farmland to obtain uncultivated land, which was the AAL. First, the RS image was masked with the farmland vector layer to remove the disturbance due to changing ground objects outside the farmland vector layer range, and the farmland patch set was regarded as the piecewise function set $F_1$. The seasonal changes in NDVI were detected in spring-summer and summer-autumn, and the results were recorded as $D_1$ and $D_2$, respectively. The two results intersected, and the cultivated land was extracted and recorded as $A_1$. Change detection applied the image difference method of threshold segmentation based on the statistical results are presented in figure 5, and the change threshold was corrected by combining prior knowledge obtained from field surveys. Finally, uncultivated farmland was obtained by subtracting the cultivated land from the total farmland, which was the AAL, denoted as $A_1$. The formula was as follows:

$$A_1 = F_1 - D_1 \cap D_2$$

(1)

Interannual Detection: The land cover of the AAL before and after abandonment differed. The field investigation showed that the land cover of the study area was mainly grassland with sparse weeds in the newly abandoned agricultural plot, whereas the vegetation in the long-abandoned plot was dense.
In the first year, due to previous tillage measures, the weed types were mainly low-spreading pioneer plants that were relatively sparse, and the spectral features ranged between grassland and bare land. First, the RS image mask was applied to the farmland vector layer to delimit the region of interest (ROI). Then, the ROI of the summer RS images in the previous two years was detected, and the patches of farmland with an NDVI that was significantly smaller than those in the previous years were extracted, which were denoted as $D_3$. Then, set $A_2$ of the newly increased AAL patches was determined:

$$A_2 = D_3$$ (2)

The single method has both advantages and disadvantages in the process of extracting AAL. Most AAL can be extracted by annual detection, but it is impossible to extract AAL when the land use type has been converted from farmland to other land types. The interannual detection method can extract the type of land use from AAL converted from farmland, but only the increase in AAL is extracted, not the total AAL. The extraction of AAL through the single method is limited, and the total AAL (set $A$) can be obtained by coupled annual and interannual detection methods.

$$A = A_1 \cup A_2$$ (3)

After combining the RFF data, the type of AAL was distinguished as formula (4) - (6), where $A$ is the total AAL, $A_1$ is the result of annual detection, $A_2$ is the result of interannual detection, $A_T$ is transitional AAL, $A_H$ is half-AAL, $A_C$ is completely AAL, and $T$ is RFF (RFF is the GIS data collected from government departments rather than RS data).

$$A_T = T$$ (4)

$$A_H = A_2 - A_2 \cap A_T$$ (5)

$$A_C = A - A_T - A_H$$ (6)

2.5. Accuracy Evaluation

The accuracy evaluation was combined with field verification and visual interpretation. On the map of AAL in 2017, 450 random points (pixel size was 1/30 ha) with a uniform distribution were generated by ArcGIS 10.5 (developed by ESRI company, Redlands, California, USA) software, of which 230 points were extracted by the interannual detection method and 220 points were extracted by the annual detection method. The minimum point distance was 150 m. Field verification was performed at 120 of the 450 verification points, and we visually interpreted the S-2A data at the remaining 330 verification points. The classification results generated 200 random points from the integrated method in 2015, and the classification accuracy was evaluated by the visual interpretation of GF-2 (the spatial resolution was 4 m) data.

2.6. Data Mining

Using the integrated method results and multisource data, eight driving forces of abandonment were sorted at a plot scale (table 3). The principles of setting the independent variables were as follows: (1) data information was obtained by the integrated method; (2) expert knowledge was used; and (3) the variables were independent.

The formula of the fractal dimension index (FDI) was as follows where $Z_i$ is the perimeter of the plot, and $A_i$ is the area of the plot:

$$FDI = 2 \ln(Z_i/4)/\ln(A_i)$$ (7)

A total of 407 random points were generated in the joint-change detection and extraction results, including 150 random points generated for cultivated land and 257 random points generated for AAL. Local encryption was carried out in some areas where abandonment was severe. In addition, the random point set was divided into 327 training sets and 80 verification sets for cross validation to
evaluate the accuracy of the model. In statistics, cultivated land and AAL samples should be evenly distributed, and one-fifth of the samples should be reserved for verification. Eight kinds of information from the plots where the random points were located were sorted, and a logistic regression model was built to analyse the data.

### Table 3. Independent variable setting. FDI, fractal dimension index.

| Independent variable | Description |
|----------------------|-------------|
| Village distance     | Distance of the plot from the centre of the village (km) |
| Height difference    | Height difference between the plot and the village datum level (m) |
| Highway distance     | Closest distance between the plot and an asphalt road (km) |
| Plot area            | Plot area of cultivated land or AAL (km$^2$) |
| FDI                  | Shape complexity index of a plot (1-2) |
| Shelter forest       | Orderly progressive variables: 0, 0.5, and 1 in turn according to the size of the surrounding shelter forests (0-1) |
| Irrigation condition | Dummy variable: dry land 0, irrigated land 1 |
| Neighbourhood        | Dummy variable: isolated 0, adjacent to other AAL 1 |

### 3. Results

#### 3.1. Analysis of Integrated Methods to Extract Results

Distinguishing between cultivated land and AAL is easy when the threshold value is accurate. The boundary of the cultivated land-AAL vector, which was identified through the annual detection method, was superimposed on the true colour summer image of the same year (using the results extracted from S-2A in 2017 as an example). Visual verification showed that the extraction results were in line with the actual situation (figure 5c).

Similarly, when the threshold value is accurate, interannual detection can also extract AAL. By analysing the true colour RS images (figures 5a and 5b) from summer 2016 and 2017 in a certain part of the study area, intuitively, the plots were determined to have been planted one year before and abandoned one year later (using the S-2A and ZY-3 extraction results from 2016 to 2017 as an example).

The extraction results for all types of AAL from 2014 to 2017 are shown in figure 6. The results showed that the cultivated land was mainly distributed on the plain in the northwestern part of the county as well as in the areas along the two rivers. The AAL was mainly distributed in the loess hilly areas in the southwestern and southeastern regions (the total accuracy of the extraction results was 97.3% in 2017).

The types of AAL from 2015 to 2017 were divided with 2014 as the base year. The types were mainly completely AAL, with less half-AAL and transitional AAL. Most of the AAL was distributed in the loess hilly regions, and less was distributed on the plains. The transitional AAL in the study area was mainly RFF. Consistent with Gellrich [25] and Kuemmerle [26], distinguishing reforestation areas was necessary. Since 2015, 6.7 km$^2$ of farmland has been planted as RFF every year, with an average distribution in all villages under the jurisdiction of the county. The average abandonment rate was 36.5% in four years, of which 32.9% was completely AAL, 3% was half-AAL and 0.6% was transitional AAL.
Figure 5. Local extraction results of the annual and interannual detection methods: (a) before abandonment, (b) after abandonment, and (c) annual detection results.

Figure 6. Integrated method extraction results: (a) 2014, (b) 2015, (c), 2016, and (d) 2017.
3.2. Accuracy Assessment
From the accuracy assessment, the overall detection accuracy of the annual, interannual, and integrated methods was more than 97%, which indicates that the AAL extraction results were authentic and reliable and that the methods were feasible. The main causes of precision loss were the following: (1) transitional AAL and half-AAL had relatively fewer random points because of their relatively smaller areas, and the information about transitional AAL was incomplete. (2) In some areas with poor planting conditions, soybean plants were low in number and sparse, and the NDVI variation gradient was small, which was easily confused with AAL. (3) Finally, there were inevitable system differences among the multisource data points. Although the system differences were weakened by various correction methods, the system errors could not be completely eliminated.

3.3. Logistic Regression Results
A total of 407 random points were generated for the complete AAL and cultivated land extracted by the integrated method (figure 7). Whether a plot was abandoned or not was recorded as the dependent variable; cultivated land was recorded as 0, and AAL was recorded as 1. All the independent variables in table 4 were normalized and unified in the same dimension. SPSS 20 software was used to build a logistic regression (LR) model and analyse the driving forces of AAL.

![Random point distribution map](image_url)

**Figure 7.** Random point distribution map.

Forward LR was conducted for 327 training samples, and the output of the model is shown in table 4. Seven independent variables passed the saliency hypothesis test, while village distance did not pass the saliency hypothesis test and was excluded from the model. At step 7 of the forward LR, 312 samples were predicted correctly, 15 samples were predicted incorrectly, and the prediction accuracy was 95.4%.
Table 4. Variable analysis table. B, partial regression coefficient; S.E., standard error; df, degrees of freedom; Sig., significance; and Exp (B), odds ratio.

| Step 7                  | B     | S.E.  | df | Sig. | Exp (B) |
|-------------------------|-------|-------|----|------|---------|
| Irrigation condition (1)| -3.006| 0.873 | 1  | 0.001| 0.05    |
| Neighbourhood(1)       | 2.987 | 0.803 | 1  | 0    | 19.817  |
| Height difference      | 4.412 | 1.892 | 1  | 0.02 | 82.403  |
| Shelter forest         | -4.746| 1.147 | 1  | 0    | 0.009   |
| Plot area              | -26.334| 7.57  | 1  | 0.001| 0       |
| FDI                    | 24.17 | 7.695 | 1  | 0.002| 3.14E+10|
| Highway distance       | -2.332| 0.612 | 1  | 0    | 0.097   |
| Constant               | -22.346| 8.453 | 1  | 0.008| 0       |

A receiver operating characteristic curve (ROC) was used to evaluate the accuracy of the model. The area under the ROC curve (AUC) of the training set was 0.994, and the AUC of the verification set was 0.803. These results show that the prediction results of the model are satisfactory.

4. Discussion

4.1. Analysis of the Driving Forces of Abandonment

Irrigation conditions: Compared with that of dry land, the effect of irrigated land on abandonment had the opposite effect. The average annual rainfall in the study area was 392.8 mm, which is less than the general standard of dryland farming (400 mm), and the rainfall was mostly concentrated in July-August. Spring drought is a serious condition that results in challenges and risks for dryland farming.

Neighbourhood characteristics: The partial regression coefficient was positive, indicating that compared with the surrounding land without AAL, the surrounding land with AAL was more likely to be abandoned. On the one hand, farmers’ decision-making is easily influenced by adjacent farmers; on the other hand, the land conditions in some areas were similar, the probability of abandonment was similar, and AAL will spread to land with similar conditions.

Height differences: The partial regression coefficient was positive; that is, the greater the height difference was, the greater the abandonment probability was. Height difference is directly related to the cost of land labour and restricts the use of agricultural machinery. For the self-sufficient elderly peasant group, failure to invest in large labour costs leads to the abandonment of such farmland; for the young and middle-aged peasant groups with relatively higher labour investments, high costs mean low profits, and based on the principle of profit maximization, this condition may also lead to the abandonment of such farmland.

Shelter forest: The partial regression coefficient was negative; that is, the more trees there were, the lower the abandonment probability was. Some previous studies have noted that seed rain in forests can lead to abandonment, but our model analysis did not support this view. The protection of shelter forests on farmland has the following benefits: on the one hand, farmland with shelter forests has a strong ability to resist wind, sand, drought and waterlogging, and its output is relatively stable. On the other hand, this protection can also increase the soil nutrient content and improve the quality of farmland. In addition, relatively large shelter forests may symbolize a good ecological environment that indirectly reflects the soil quality, water resource abundance and liveability of the area where a plot is located.

Plot area: The coefficient of the partial regression was negative, which indicated a negative effect of abandonment. A relatively larger plot area is more suitable for intensive cultivation with large-scale agricultural machinery, which greatly improves planting efficiency and planting profits, which is in line with farmers' planting preferences. In contrast, the smaller a plot area is, the higher the fragmentation level is, and therefore, the land is difficult to manage and easy to abandon.
FDI: The FDI represents the complexity of a plot shape. The ideal plot shape of farmland that is suitable for cultivation should be regular. A complex plot shape of mostly contour shapes with topographic fluctuations or those with relatively higher levels of fragmentation indirectly indicates the complex topography and fragmentation of a plot; therefore, the possibility of abandonment is higher.

Highway distance: In this study, the highway distance was the distance between the plot and an asphalt road, and the distances to soil roads were not calculated. The partial regression coefficient was negative, which indicates that the abandonment probability decreases as the highway distance increases. Highway distance should have a positive impact on abandonment, but the model inversion indicated the opposite result. Possibly, the closer a highway is, the higher the urbanization level is. Industrial pollution may lead to abandonment. Abandonment may also be caused by the agricultural labour force shifting to industry and the service industry. In contrast, the farther away a highway is, the simpler the industrial form is. Intensive agriculture can appear, and abandonment is thus inhibited. In addition, the inversion results also showed that agricultural travel and transportation in this area were more dependent on soil roads and less dependent on asphalt roads.

Village distance: The effect of this variable on abandonment was not significant. Recently, small tractors have become popular, and a distance of several kilometres from villages is not a limiting factor.

4.2. Evaluation of Methods and Policy Recommendations
Currently, RS monitoring methods and driving-force research are separate. Most scholars studying the RS monitoring method of AAL have only performed qualitative analyses on the driving forces. Scholars who have studied the driving forces of abandonment have often lacked the spatial distribution information of AAL because the analysis data have usually been from farmer questionnaires. In fact, the monitoring of AAL requires a deep understanding of AAL, and the study of the driving forces of abandonment requires precise extraction of AAL. The advantage of the integrated method is that it distinguished the three types of AAL and extracted the eight driving factors. This method can be used not only for monitoring AAL but also for evaluating the driving forces of abandonment, which makes the study results directly applicable to AAL management.

Since 2018, China's agricultural sector has implemented a 'farmland protection subsidy (FPS)'. The prerequisite for obtaining this subsidy is that farmland is not abandoned and that farmland productivity is not reduced. AAL has become a sensitive issue. Many farmers do not explain their actual abandonment situation because of self-protection. According to the China Rural Land Contract Law (2018 Amendment), "farmers who have abandoned farmland for more than two years in a row will have their land management rights terminated and may be fined." The amendment of this bill shows the determination of the management department to curb farmland abandonment. Several factors need to be improved, including distinguishing the location conditions and driving forces of abandonment, managing by classification and avoiding one size fits all. In this study, the RS monitoring results showed that AAL mainly occurred in mountainous areas. The results of the model inversion showed that the main driving forces of abandonment were physical geographical conditions, infrastructure and an intensive level of agriculture. These factors do not depend on the will of farmers. Therefore, the rationality of FPS requires further research by decision-making departments and the scientific community. In addition, the AAL was widely distributed in the southwestern portion of the study area, and the type was mainly completely AAL. It is necessary to recognize that the decline in rural areas is difficult to reverse; redistributing and planning farmland and woodlands, village relocation and ecological restoration should be carried out according to local conditions.

5. Conclusions
AAL is a complex human land interaction system driven by multiple driving forces, and the monitoring method of AAL is the foundation of studying the driving forces. At present, issues related to high-precision unsupervised threshold segmentation technology have not been resolved by the academic community. The current unsupervised threshold segmentation algorithm has difficulties
meeting the accuracy requirements; supervised threshold segmentation relies on prior knowledge and sample statistics, and the level of automation and intelligence is insufficient. In the future, it will still be necessary to develop an unsupervised threshold segmentation algorithm with high accuracy and robustness that can decrease the labour and time costs of AAL monitoring and reduce human error.

The study of AAL should be carried out in a broader context, taking into account the impact and interaction of global climate change, ageing population structure and population distribution in relation to urbanization. The impacts of global warming on China are mainly the decline in the East Asian monsoon, the aggravation of waterlogging in the south and droughts in the north [34]. In the future, serious drought may aggravate abandonment in northern China. In 2016, the National Development and Reform Commission predicted that China's long-term urbanization level would reach 70% in 2030 (56.1% in 2016). With the migration of the agricultural population to the city, AAL will also rise. At the same time, China is also facing social problems such as low fertility rates and an ageing population. Negative population growth is likely to occur in the near future, and the agricultural labour force has been distributed in an inverted pyramid. In the future, the issue of AAL may be concentrated. Therefore, research in this field should be more forward-looking and dynamic, balancing the relationship among food security, ecological security and social and economic development, and should provide a basis for the government's decision-making.

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