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Spatial Distribution and Influencing Factors of Daylily Cultivation in the Farming–Pastoral Ecotone of Northern China

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Abstract: The farming–pastoral ecotone in northern China is an ecologically vulnerable area with low-quality arable land, and cash crops are an important economic source for local farmers. Although local governments have introduced supportive policies, there are still several factors that hinder the implementation of the policies: there is a lack of sufficient research on the distribution of specialty crops, and the driving factors for agricultural planting structure adjustment are not yet clear. In this study, the specialty cash crop of the daylily planting industry in Yunzhou District, in the Farming–Pastoral Ecotone in northern China, was selected as the research object. Field surveys were conducted to collect sample points and village-level survey data, which were further combined with Sentinel-1 and Sentinel-2 data, and vegetation indices. Support vector machine (SVM) and random forest (RF) classifiers were utilized to identify daylilies and compare the accuracy using different combinations of input data. Furthermore, the classification results were counted by village, and spatial autocorrelation was used to analyze the spatial distribution pattern of daylilies. Finally, in conjunction with the village-level survey data, Spearman correlation analysis, multiple regression trees (MRT), and random forests were employed to explore the driving factors of daylily cultivation. The results indicate that using an RF classification tree of 300 resulted in the optimal method, as it achieved the highest accuracy for crop classification. The overall accuracy and daylily classification accuracy were 94.6% and 94.75%, respectively. Daylily distributions were mainly concentrated near the Sanggan River, urban areas, and the tourism industry. The distribution area of daylilies in each village was concentrated in 13.4–38.8 hm^2. Spatial clustering showed more aggregation of low–low and high–high types. Labor force and daylily yield were identified as the most significant influencing factors. Further analysis of the different regions revealed the importance of industry support policies and technical training. This study provides data to support the distribution of specialty crops in Yunzhou District and a technical basis for adjusting agricultural planting structures.

Keywords: farming–pastoral ecotone; cash crops; daylily; vegetation index; driving factors

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1. Introduction

The farming–pastoral ecotone in northern China is in a semi-arid to semi-humid region. Although it boasts abundant land resources, it faces significant challenges such as severe soil erosion, low precipitation, high evaporation rates, poor soil quality, low vegetation cover, and serious land degradation and desertification. It is thus considered one of China's ecologically fragile areas [1,2]. The "Guidance on the Adjustment of Agricultural Structure in the Farming-Pastoral Ecotone in Northern China", issued by the Ministry of Agriculture and Rural Affairs in 2016, emphasized a need to accelerate adjustments to the structure of the agricultural industry in this region and to leverage the advantages of specialty industries [3]. The daylily (*Hemerocallis citrina*), a member of the *Hemerocallis* genus in the Asphodelaceae family, is a perennial herbaceous plant that not only has edible and

medicinal value but also functions as a windbreak and aids in sand fixation and soil and water conservation [4]. Yunzhou District, which is located in the farming–pastoral ecotone, is renowned as the "Hometown of Daylilies" as they have been cultivated there for over 600 years, and this area remains one of the major daylily production sites in China. Abundant sunshine and significant temperature variations, along with other favorable natural conditions, have nurtured the "Datong Daylily" variety in particular, which is popular both domestically and internationally. Cultivating daylilies as a specialty cash crop is economically beneficial and can increase a farmer's income, thereby helping to alleviate poverty and increasing prosperity in rural areas. According to the survey, the main crops planted in Yunzhou District are corn and daylilies. Maintaining a balance between the food crop and cash crop planting ratio can leverage the greatest advantage of Yunzhou District and drive economic development. Therefore, mapping the distribution of daylilies will provide a basis for planting structure adjustment in Yunzhou District.

Conducting field surveys to assess crop distribution over a large-scale area can be time consuming and labor intensive. The rapid development of remote sensing technologies, however, has offered a solution to this. Remote sensing image identification can be used to distinguish different land cover types and crops, based on their unique spectral reflection characteristics, which are due to factors such as their internal structures and phenological features. Crop remote sensing identification methods usually analyze the key phenological characteristics of crops in time-series data to facilitate crop identification. This approach helps to avoid the misclassification and omission issues that can occur when using single-date imagery to identify crop spatial distributions, as some objects can have the same spectrum [5–9]. Although optical remote sensing images provide a wealth of spectral information, sometimes synthetic aperture radar (SAR) is also utilized to distinguish between different vegetation or crops. This is because it can address the excessive cloudiness and low quality of the images obtained during the optimal seasonal period, which would otherwise make it impossible to achieve high-precision identification. SAR is not restricted by weather and lighting conditions, which means that it can compensate for the limitations of the optical data [10–13]. The most existing remote sensing classification studies have primarily focused on major food crops like wheat and rice. For these crops, readily available product data allow for the direct acquisition of land cover types and crop information. Cash crops, however, are rarely cultivated in large, contiguous areas, which creates greater challenges for their identification [14,15]. A lack of research into many cash crops has also hindered accurate assessments of their distributions in various regions and the subsequent optimization of cultivation practices. There is currently an urgent need for relevant studies in this area to address these issues.

After identifying the distribution pattern of crops, we will explore the driving factors that affect the planting of the daylily, which are also the driving factors for adjusting the planting structure in Yunzhou District. There are four key aspects to these factors: policy and training, individual farmers, productivity levels, and the market environment. In the realm of policy and training, agricultural policies, subsidies, government support, and a series of encouraging policies can help to guide the choice of crop type and promote the adjustment of agricultural planting structures [16]. Agricultural technology training allows farmers to better understand agricultural production and policy-related information, increasing the likelihood that they will carry out adjustments to their agricultural planting structures. For individual farmers, factors such as farmer age (labor force) and educational level can influence their agricultural production efficiency and their interpretation of new policies, subsequently affecting the adjustment of agricultural planting structures [17,18]. When agricultural income constitutes a higher proportion of a household's income, farmers tend to be more loyal to farming and more willing to experiment with planting specialty crops [19]. Through land transfer, farmland can be consolidated into contiguous areas, which facilitates large-scale mechanized farming, saves time and labor, and integrates fallow or idle land resources, thereby promoting agricultural planting structure adjustments [20,21]. For productivity levels, the intensification of cash crop cultivation can have

a stimulating effect on the yield of food crops [22]. The yield in a particular year can also influence farmers' planting decisions for the following year. Considering the market environment, fluctuations in crop prices can also influence a farmers' planting decisions. When faced with multiple choices, the way farmers make decisions also determines their agricultural income [23,24]. Adjusting the agricultural layout structure based on crop suitability has a significant impact on optimizing the allocation of arable land resources [25]. Many scholars tend to conduct detailed research on individual factors when studying crop driving factors, but lack a comprehensive exploration of the overall situation.

In response to the lack of research on the distribution of specialty crops and the unclear driving factors for agricultural restructuring, this study selects a typical region in the Farming–Pastoral Ecotone of northern China—Yunzhou District—to conduct relevant research. The cultivation of daylilies by the local government is typical and has been vigorously promoted. In recent years, with the gradual increase in agricultural structural adjustments, governments at all levels have been actively promoting the cultivation of specialty crops. With the rapid development of daylilies, one such specialty cash crop, the cultivation of daylilies also faces the aforementioned issues. The uncertainty regarding the distribution of daylilies across the entire region and the driving factors has consequently constrained the development of this industry. The use of daylilies in Yunzhou District was thus utilized as a case study in this investigation, and field surveys and household interviews were conducted in July and August 2021 to collect sample points and village-level survey data. Sentinel-2 and SAR data were combined with vegetation indices from different sample point types, and various classifiers were also utilized. The classification results were counted in village units and combined with village survey data to analyze the drivers affecting daylily cultivation. This investigation has the following two main aims: (1) to establish a high-precision method for daylily identification and analyze the spatial distribution using spatial autocorrelation methods; and (2) to identify the driving factors behind the distribution pattern of daylilies.

2. Materials and Methods

2.1. Overview of the Study Area

Yunzhou District stretches from 39°43′ N to 40°16′ N and from 113°20′ E to 113°55′ E. Yunzhou is in the middle of the farming–pastoral ecotone in northern China, with a total area of 1478 km^2, average elevation of 1347 m, annual average temperature of 6.4 °C, annual average precipitation of 389 mm, annual average frost-free period of 125 d, and annual active accumulated temperature of 2846.5 °C (Figure 1). The main crops in Yunzhou District include corn and potatoes, and the main cash crop is the daylily. The daylily is a perennial herbaceous plant that is drought-tolerant and prefers warm temperatures. Seedlings begin to grow when the average temperature is above 5 °C. Daylily bushes are large, with a plant height of about 80 cm and a plant width of about 90 cm, and the leaves are strap-shaped. When daylilies are planted for more than 10 years of gradual aging, the picking period is shortened, the dropped flowers and buds are increased, and the yield is decreased significantly. The growth and development of the daylily is generally divided into five periods, namely, the spring seedling growth period, the moss and bud stage, the flowering period (picking period), the autumn seedling sprouting period, and the winter dormant period. The daylily requires adequate irrigation throughout the growth process. Picking is usually in late June—early August; farmers mostly pick it two hours before flowering, which can ensure the yield and quality. In 2021, the total area of daylily planting in Yunzhou District reached 11,000 hm^2, with a peak production area of 6000 hm^2, producing 63 million kilograms of fresh vegetables [26]. Field management measures have a significant impact on the yield and quality of daylilies, with yields reaching 15,000–23,000 kg per hectare during high-yield periods.

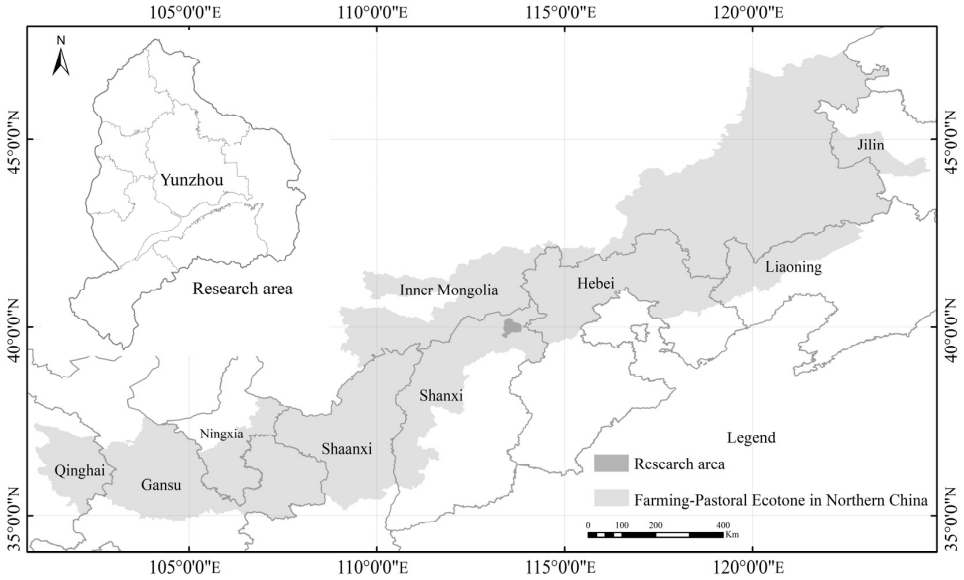


Figure 1. Geographical location of the research area.

2.2. Data Acquisition and Processing

2.2.1. Optical Image Data Acquisition and Processing

Eight issues of Sentinel-2 L1C images (dated 5 May, 19 June, 14 July, 13 August, 12 September, 2 October, 1 November, and 26 December 2021), covering the study area and <10% cloud, were screened. Sentinel-2 remote sensing data were provided by the data center (https://scihub.copernicus.eu/dhus/#/home, accessed on 14 March 2022) of the European Space Agency (ESA). L1C-level data consist of orthorectified orthoimages that have not been radiometrically calibrated or atmospherically corrected. Bands 1, 9, and 10 are used to study aerosols, water vapor, and cirrus clouds, respectively, with a lower spatial resolution (60 m), and consequently, these three bands were removed in this study. The Sentinel-2 data were first radiometrically calibrated and atmospherically corrected using the Sen2cor plug-in. The Sentinel-2 data consist of bands 2–4 at a 10 m resolution, while bands 5–12 have a 20 m spatial resolution (Table 1). After atmospheric correction, all 20 m resolution images were resampled to a 10 m resolution using nearest-neighbor interpolation with the SNAP 8.0 software. The data were then mosaicked, spatially registered, and vectorially cropped using ENVI 5.3.

Table 1. Selected Sentinel-2 bands and spatial and spectral resolutions.

Band	Central Wavelength/nm	Resolution/m
B2 (Blue)	490	10
B3 (Green)	560	10
B4 (Red)	665	10
B5 (Red Edge 1)	705	20
B6 (Red Edge 2)	740	20
B7 (Red Edge 3)	783	20
B8 (NIR)	842	10
B8A (Red Edge 4)	865	20
B11 (SWIR 1)	1610	20
B12 (SWIR 2)	2190	20

2.2.2. Radar Data Acquisition and Processing

As the Sentinel-2 optical imagery was partially obscured by clouds in the study area, SAR (Sentinel-1) data were downloaded for the entire reproductive period to provide additional crop information (dated 22 April, 4 May, 16 May, 21 June, 3 July, 27 July, 8 August, 20 August, 1 September, 13 September, 25 September, and 19 October 2021), as well as the

type of GRD; the strips were in the IW mode, and the polarization mode was VV+VH (Table 2). Preprocessing of the SAR data was performed using SNAP 8.0, including orbit correction, radiometric calibration, multi-temporal radar image filtering, multi-view, and terrain correction, to obtain results in dB units. ENVI 5.3 data were used for mosaicking, spatial registration, and other processing.

Table 2. Selected Sentinel-1 data parameters.

Acquisition Date	Polarization	Product Type	Resolution
22 April–19 October on 2021	VV + VH	GRD	5 × 10

2.2.3. Field Survey Data

This study utilized the Ovital mobile application for on-site data collection. As high-resolution images, such as those from GaoFen or Google Earth, were not available, the entire sample set was obtained solely through on-site data collection. A field survey of the research area was conducted from July to August 2021, and sample verification occurred from May to August 2022 (the entire reproductive period). According to the field survey data, the sample points include different land uses (water bodies, forests, and built-up land), unused land (barren grassland), and cultivated land (daylilies, corn, and nurseries) (Figure 2). With the support of visual interpretations of the land parcels, a total of 300 ground sample points were obtained by determining the number of each type based on the percentage in the region. A stratified random sampling method was used to ensure that the distribution of the training and test sets on each type of plot was consistent with the original dataset. In order to adequately represent all samples in both the training and test sets, approximately 60% of the sample set was selected as training samples and the remaining 40% was used to perform classification precision evaluation. The classification results were evaluated using a confusion matrix with the following elements: overall classification accuracy, Kappa coefficient, producer accuracy, user accuracy, and F1 score.

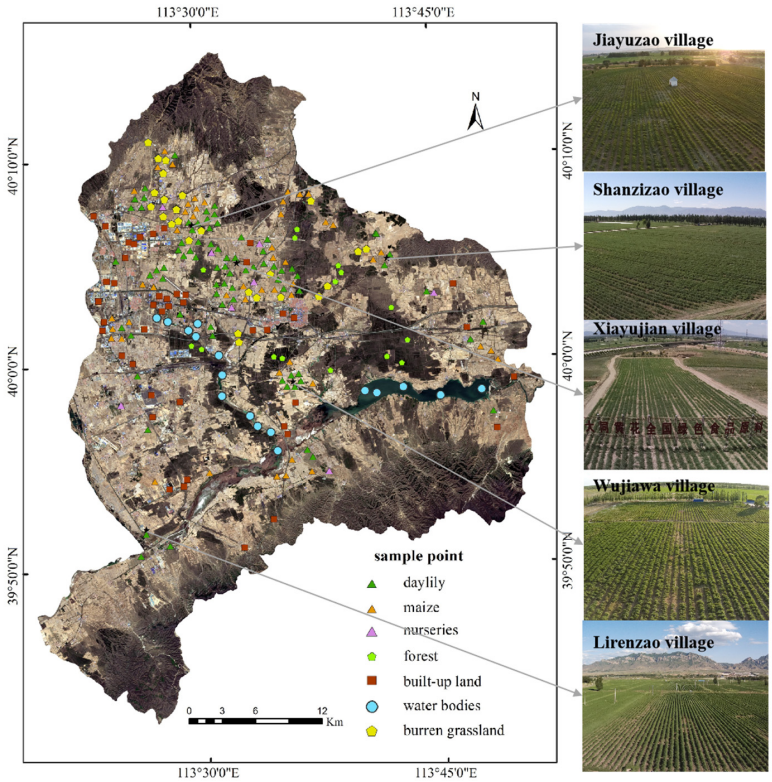


Figure 2. Demonstration site and sample points of the research area. (The image on the left does not contain spectral information, is from May, and has a sub-meter resolution.)

After identifying the distribution range of the daylily, we verified the situation of the villages on the ground and counted the areas of daylily cultivation by village. The survey data were counted by visiting the villages and learning about the situation of the villages from the village cadres, to explore the influence of socio-economic data on the range of daylily cultivation at the scale of the villages (Figure 3). The survey was conducted mainly in villages where the daylily was planted, and a small number of villages where the daylily was not planted were not surveyed (the detailed description can be found in Supplementary Materials).

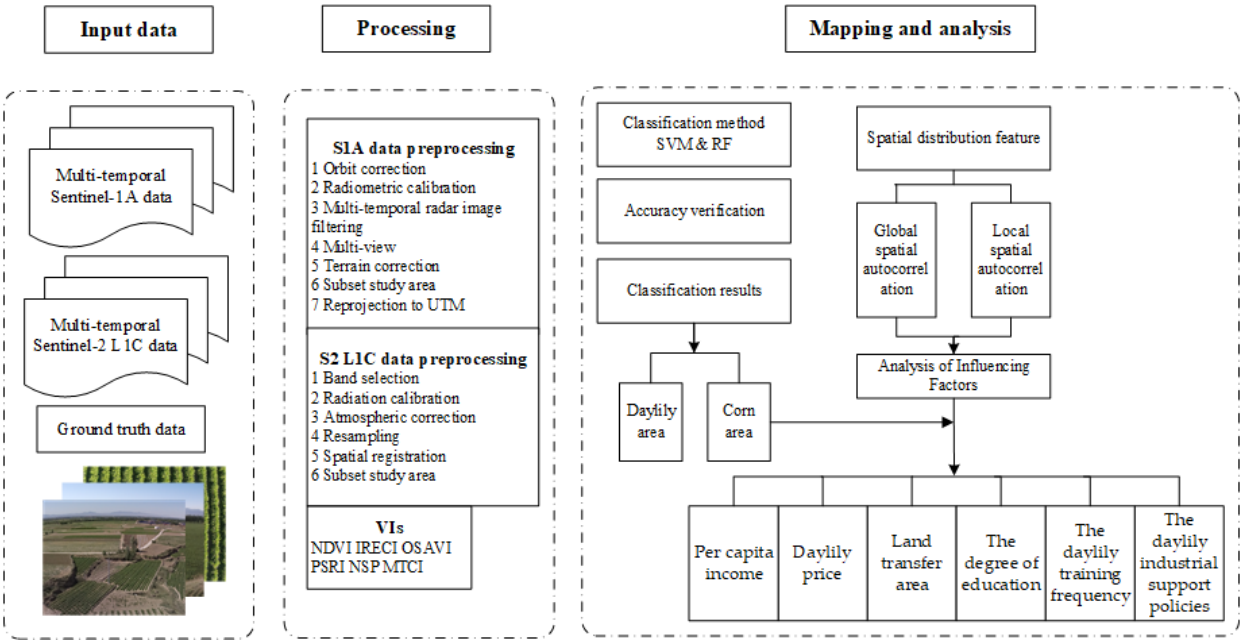


Figure 3. Workflow of mapping of daylilies and influencing factors using Sentinel-1 and -2 data.

2.3. Methodology

To address the issue of daylily distribution, we used remote sensing images to distinguish land use types and crops. Through the field survey, the crops grown on arable land in Yunzhou District were mainly daylily, corn, and nursery. The land use types distinguished in this study were barren grassland, forests, built-up land, and water bodies, whereas the three crops distinguished on cultivated land were daylily, corn, and nursery. Sentinel-2 and SAR data were used, and spectral curves and mean vegetation index curves were created using ENVI 5.3 to identify differences between crops and land types. The vegetation index was improved by subtracting the Normalized Difference Vegetation Index (NDVI) from the Plant Senescence Reflectance Index (PSRI) to enhance classification accuracy. Support vector machine (SVM) and random forest (RF) classifiers in ENVI 5.3 were employed to classify the different data combinations (Table 3). In this study, the kernel type of SVM was selected as the radial basis function, with gamma set to 0.125, resulting in higher and more stable classification accuracy; the penalty parameter was set to 100, because increasing or decreasing it would decrease the overall classification accuracy [27]. After testing, the number of decision trees in RF was set to 300 and the square root was chosen as the number of features [28]. Error matrices for overall classification accuracy and single-crop accuracy for daylilies were obtained using ground-truth measurement points.

$$NSP = |NDVI - PSRI| \quad (1)$$

Table 3. Different input data.

Type	Input Data
A	August spectral data and May vegetation indices such as OSAVI, IRECI, NDVI
B	September spectral data and May vegetation indices such as OSAVI, IRECI, NDVI
C	October spectral data and May vegetation indices such as OSAVI, IRECI, NDVI
D	August spectral data and May vegetation indices such as OSAVI, IRECI, NDVI, and SAR
E	NSP
F	August spectral data and May vegetation indices such as OSAVI, IRECI, NDVI, and NSP
G	August spectral data and May vegetation indices such as OSAVI, IRECI, NDVI, NSP, and MTCI
H	August spectral data and May vegetation indices such as OSAVI, IRECI, NDVI, NSP, MTCI, and SAR

Observations of the spectral curves of daylilies and corn showed that there were noticeable differences in August and September. In the visible light range, the spectral values of daylilies were found to be higher than those of corn. In the red-edge range, the spectral reflectance of corn increases sharply to reach its maximum in the near-infrared range. From the red-edge to the near-infrared range, the spectral reflectance of corn remains higher than that of daylilies. However, due to the influence of crop moisture content, the reflectance drops significantly, and corn reflectance becomes lower than that of daylilies. The spectral curves for November and December showed a consistent overall trend, with the corn reflectance being consistently higher than that of daylilies. The differences in these features of the optical remote sensing images for crop classification were ultimately selected for comparison in August, September, and November. The vegetation indices (Normalized Difference Vegetation Index (NDVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), and Inverted Red-Edge Chlorophyll Index (IRECI)) were selected for the early stages of growth in early May when the daylilies had already returned to green, while the corn had just begun to be sown. The MERIS terrestrial chlorophyll index (MTCI) had a high accuracy in estimating the chlorophyll content of corn, which improved the accuracy of distinguishing between daylilies and corn. July–August is a better time of year for distinguishing crops, but the optical imagery is cloudy and only the more appropriate two-scene imagery was selected in mid-July and mid-August. The July–August SAR data were utilized to supplement and increase the information (Figure 4) (the detailed description can be found in Supplementary Materials).

Firstly, the distribution of daylily cultivation in Yunzhou District was identified through remote sensing, and the area of daylily cultivation was counted with the village as the research unit. The spatial distribution pattern of daylily cultivation was analyzed using the spatial statistical analysis tool of ArcGIS 10.3. The spatial statistical method requires that global autocorrelation be performed on the data first to determine the degree of autocorrelation of the data in the whole region. Then, local spatial autocorrelation analysis and hotspot analysis are performed to explore the correlation of attributes at specific locations and in their neighboring regions within the region. In this study, the inverse distance weighting method was used to determine whether the data were spatially clustered and their degree of clustering, such as hot spots (areas of high-value clustering) and cold spots (areas of low-value clustering). The survey data were tallied by visiting the villages and asking the village cadre about the situation in each village to explore the impact of socio-economic data on the extent of daylily cultivation at the village scale.

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (2)$$

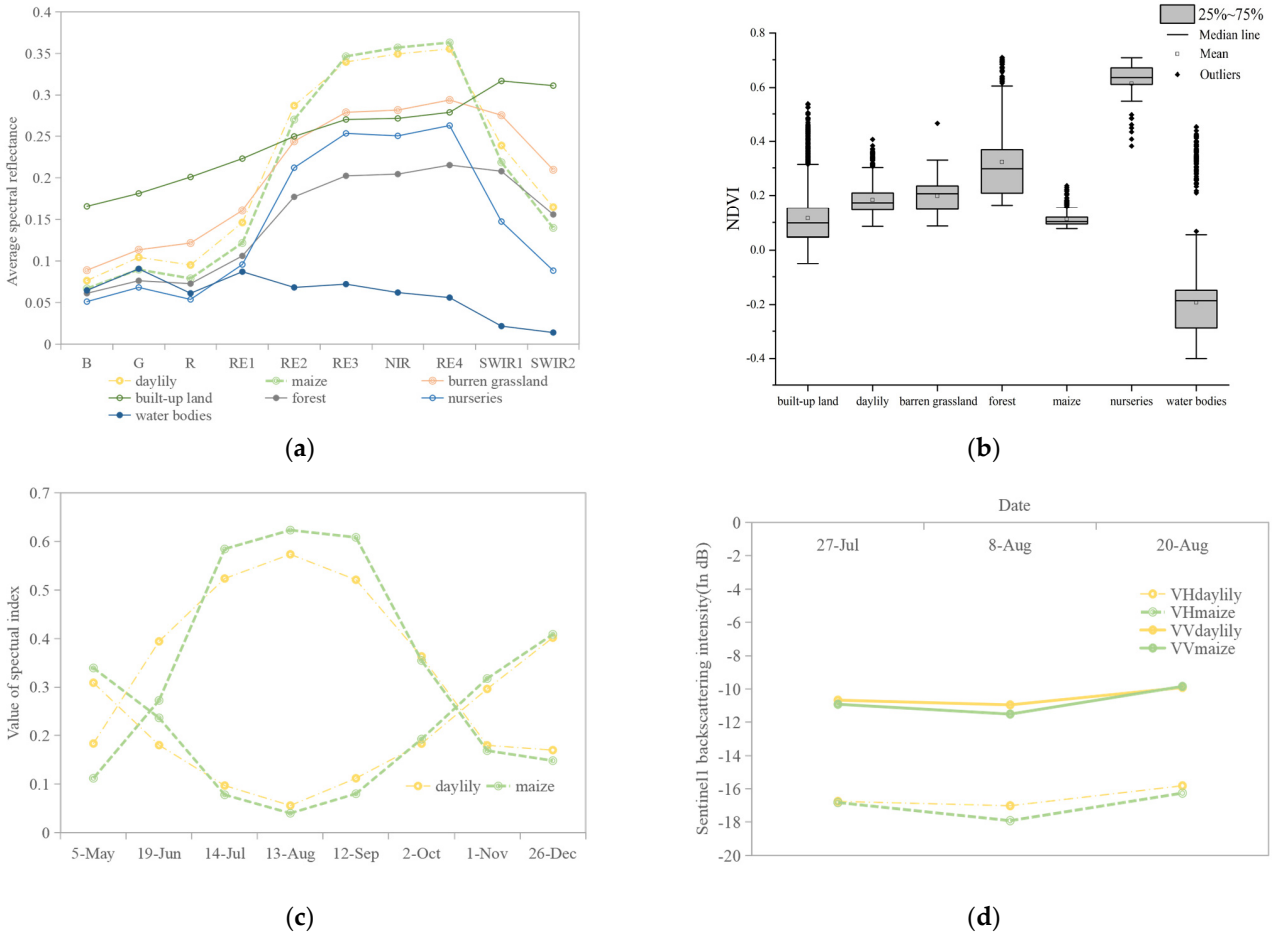


Figure 4. The main spectral curves, vegetation index curves, and backscatter curves. (**a**) spectral curve on 13 August, (**b**) NDVI box plot, (**c**) NDVI and PSRI mean curve, and (**d**) backscatter curve in July to August.

In Equation (2), Moran's I is the global Moran's index; x_i and x_j are the attribute values of location i and j, respectively; $\bar{x}$ is the average of all attribute values; w_{ij} is the spatial weight between regions i and j; n is the number of villages; and m is the number of neighboring cells of spatial unit i.

$$\text{Moran's I} = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^{m} w_{ij}(x_j - \bar{x}) \tag{3}$$

$$S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{4}$$

In Equations (3) and (4), Moran's I is the local Moran's index; x_i and x_j are the attribute values at locations i and j, respectively; $\bar{x}$ is the mean of all attribute values; S^2 is the variance of all attribute values; w_{ij} is the spatial weight between regions i and j; n is the number of villages; and m is the number of neighboring cells of spatial unit i.

The driving factors in this study were determined using the R 4.3.1 software and the Spearman method for correlation analysis. A correlation matrix was used to determine the associations between multiple sets of data. The planting area for daylilies in the various surveyed areas, obtained after classification, was analyzed for Spearman correlations with factors such as daylily prices, corn area, and land transfer scale, in order to identify significant factors related to their distribution patterns. Furthermore, the R 4.3.1 software, along with the MVPART wrap packages, was used to perform Multivariate Regression Tree

(MRT) classification for the daylily planting area and the factors significantly correlated with it. To determine the specific driving factors in different classification trees, the Random Forest package in R was employed for importance ranking with 500 trees and 100 iterations to calculate *p*-values.

3. Results

3.1. Classification Results

The SVM classifier achieved the highest OA and Kappa coefficient in the H data combination, at 94.9% and 92.74%, respectively. The next-best performance was observed in the A combination, which used only August optical imagery and May vegetation indices, achieving an OA of 94.8% and a Kappa coefficient of 92.46%. The E combination, which solely used improved vegetation indices for classification, had the lowest overall accuracy with an OA of 72.9% and a Kappa coefficient of 58.94%. The accuracy for each class when identifying daylilies may not be uniformly high. Therefore, the F1 score was used in conjunction with accuracy to assess precision. In the D combination, the daylily classification results achieved the highest UA and PA, with values of 90.45% and 93.09%, respectively. Next was the H combination, where the daylily classification results achieved a UA of 88.95% and a PA of 92.78%. The daylily classification accuracy in the C combination was the lowest, with a UA of 78.63% and a PA of 78.46% (see Table 4).

Table 4. Comparison of classification results' accuracy.

	OA (%)	Kappa (%)	UA (%)	PA (%)	F1 Score
SVM classified images					
A	94.8	92.46	88.27	91.47	89.84
B	92.2	88.75	85.53	85.71	85.62
C	89.5	84.67	78.63	78.46	78.54
D	**93.8**	**91.25**	**90.45**	**93.09**	**91.75**
E	72.9	58.94	83.37	75.91	79.47
F	94.7	92.30	87.27	90.62	88.91
G	94.7	92.30	87.09	90.62	88.82
H	**94.9**	**92.74**	**88.95**	**92.78**	**90.82**
RF classified images					
A	95.9	93.91	93.79	90.19	91.95
B	95.1	92.75	88.35	85.71	87.01
C	91.4	87.18	82.67	71.22	76.52
D	**96.5**	**95.04**	**94.26**	**93.39**	**93.82**
E	71.5	54.66	87.82	89.32	88.56
F	94.5	91.91	93.09	91.9	92.49
G	**96.4**	**94.69**	**94.14**	**92.54**	**93.33**
H	**94.6**	**92.35**	**95.19**	**94.32**	**94.75**

Bold text represents higher accuracy classification results.

The RF-based classification results showed that the D combination had the highest overall classification accuracy, with an OA of 96.5% and a Kappa coefficient of 95.04%. This was followed by the G combination with an OA of 96.4% and a Kappa coefficient of 94.69%. The E combination had the lowest overall accuracy in the RF-based classification results, with an OA of 71.5% and a Kappa coefficient of 54.66%. However, unlike the SVM classification, incorporating the new improved vegetation indices and MTCI index into the A combination during classification improved the accuracy for daylilies. The UA for daylilies increased from 93.79% to 94.14%, and the PA increased from 90.19% to 92.54%. The E combination, which solely relied on NSP data, achieved relatively high recognition accuracy for daylilies, with a UA of 87.82% and a PA of 89.32%, despite having lower overall accuracy.

The SVM classification was compared with that of the RF (Figure 5), and the results showed that with the SVM classification, many of the boundaries for corn were misclassified as daylilies. This study primarily focused on identifying daylilies, and the F1 scores were compared. Ultimately, this study determined that the H combination (August spectral data

and May vegetation indices such as OSAVI, IRECI, NDVI, and NSP, MTCI, and SAR) with RF classification using 300 trees was the best classification method as it yielded the most optimal crop classification results. Furthermore, the OA and the Kappa coefficient were 94.6% and 92.35%, respectively, while the UA and the PA for daylilies were 95.19% and 94.32%, respectively.

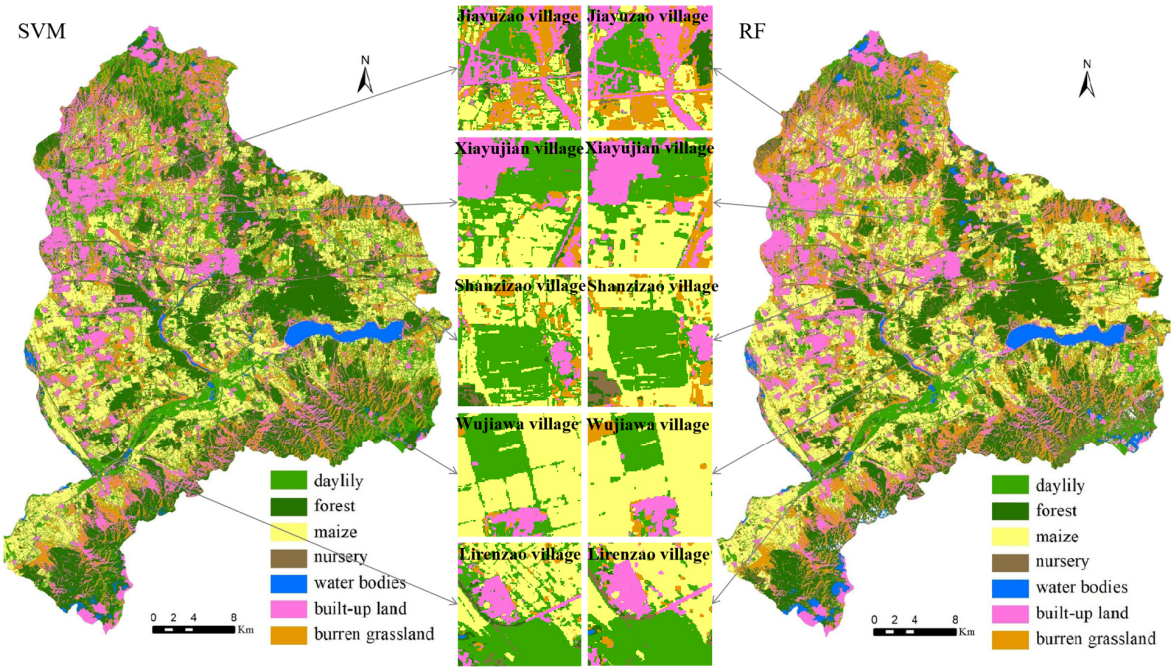


Figure 5. Classification results and demonstration zones. (The left figure shows the SVM classification, the right figure shows the RF classification, and the middle figures show the classification comparison of the five selected fields.)

3.2. Spatial Distribution of Daylilies

In Yunzhou District, daylilies were found to be primarily concentrated near the Sanggan River, urban areas, and Huanghua Park (Figure 6a). The daylilies identified in Section 3.1 were counted by village as a unit, and the distribution area of the villages in Yunzhou District was concentrated in 13.4–38.8 hm^2, and the spatial distribution characteristics were analyzed by using spatial autocorrelation (Figure 6b). The global spatial autocorrelation analysis for daylily distribution resulted in a z-score of 6.31, indicating that 99% of the daylily spatial distribution was clustered. In terms of quantity, areas with a high concentration of daylilies (high–high type) and areas with no or low daylily cultivation (low–low type) were more prevalent (Figure 6c,d). This means that villages with a larger area of daylily cultivation tended to be surrounded by other villages with a higher concentration of daylilies, and villages with lower daylily cultivation were found to typically be surrounded by villages with lower daylily cultivation, resulting in a more clustered spatial distribution.

The village survey data were organized into an Excel sheet, and the natural breakpoint method in ArcGIS 10.3 was used to classify the driving factors into five categories and to draw the spatial distribution maps of different factors (Figure 7). The degree of education showed a spatial distribution pattern of low in the center and south and high in the west, and villages with high educational attainment were sporadically distributed. The distribution characteristics of the workforce was similar to the education level, generally showing low in the center and south and high in the west and north, while the workforce was generally large, higher than 338 people in most regions, with villages with less than 380 people distributed sporadically. Per capita income showed a spatial distribution pattern of high in the west and low in the north, with per capita income in most regions ranging from CNY 7201 to 9200, and generally higher than CNY 9200 in the west. The daylily yield was higher in the center

than in the surrounding areas, with gentle terrain and better natural conditions in the central part, resulting in high agricultural output, and most areas had a yield of daylilies between 8250 and 12,750 kg/hm^2. The selling price of dried daylilies was high in the west, north, and east, and lower in the middle and south of the spatial distribution pattern, with most of the areas ranging from 285 to 315 CNY/hm^2. Industrial support policies included subsidies for daylilies based on a certain planting area, water conservancy facilities, government-led disaster insurance and price insurance, government-built workshops, drying equipment, and other facilities, with the government contacting the workers and providing a series of measures, and most of the villages had more than three support policies. The daylily technical training frequency in most areas was between 0.5 and 4 times/year; only one village reached 10 times/year or more. The overall spatial distribution pattern of land transfer area showed lower values in the central region and higher values in the surrounding areas, with the central land outflow areas all below 7.8 hm^2. The corn area showed a distribution pattern with lower values in the northwest and southeast, and higher values in the southwest and east, with most areas ranging from 97.1 to 194.5 hm^2.

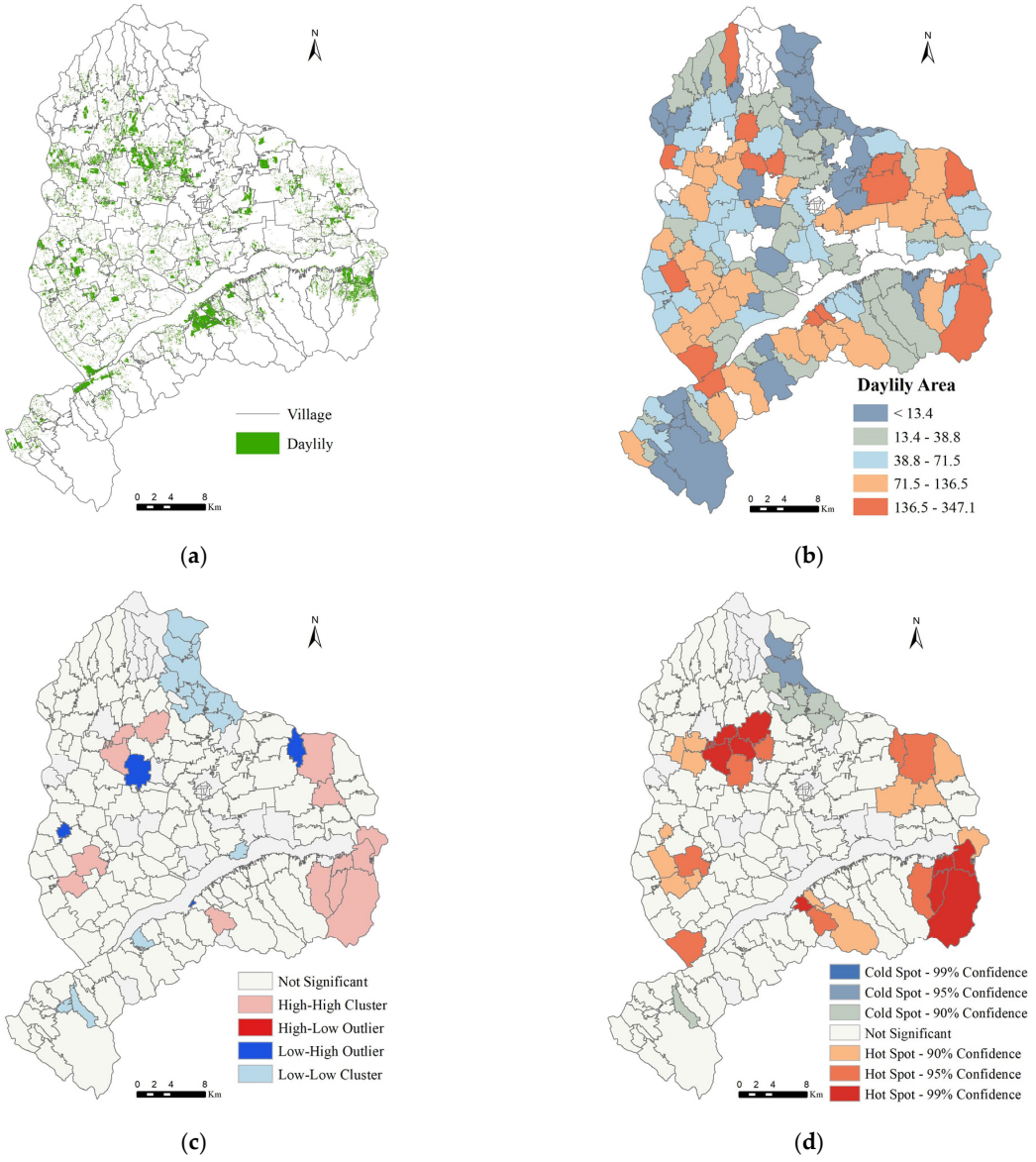


Figure 6. Spatial distribution of daylilies: (**a**) distribution of daylilies, (**b**) village statistics of daylily area, (**c**) local autocorrelation result, and (**d**) hot spot analysis.

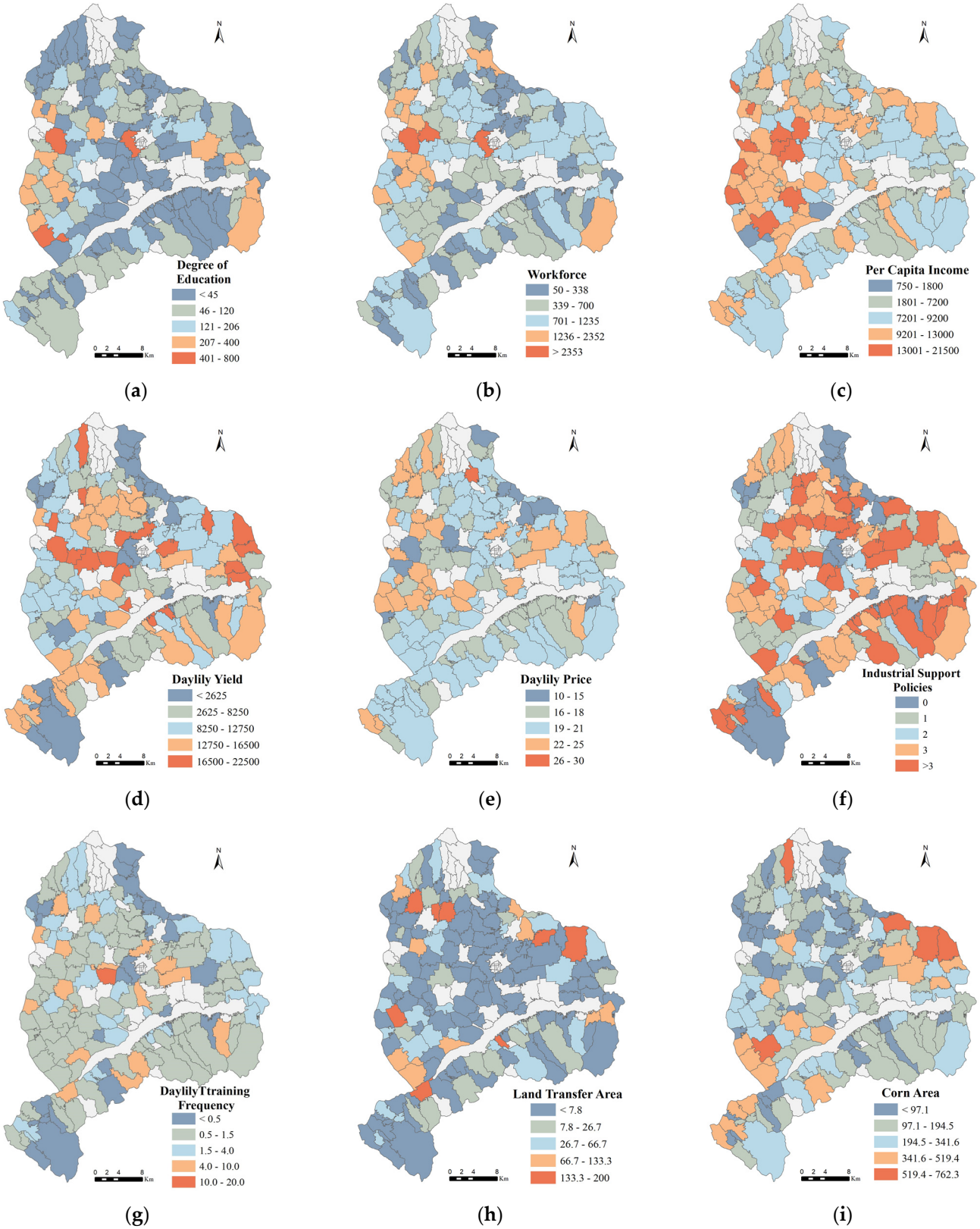


Figure 7. Spatial distribution of drivers: (**a**) degree of education, (**b**) workforce, (**c**) per capita income, (**d**) daylily yield, (**e**) daylily price, (**f**) industrial support policies, (**g**) daylily training frequency, (**h**) land transfer area, and (**i**) corn area.

3.3. Drivers

The Spearman correlation results indicated that the planting area for daylilies was significantly positively correlated with workforce, daylily yield, industrial support policies, daylily training frequency, farmers' education level, corn planting area, land transfer scale, farmers' per capita income, and daylily unit price. The correlation coefficients for these factors were determined to be as follows: 0.55, 0.53, 0.51, 0.42, 0.41, 0.26, 0.22, 0.2, and 0.18, respectively (significant at $p < 0.01$, except for daylily unit price, which is significant at $p < 0.05$) (Figure 8).

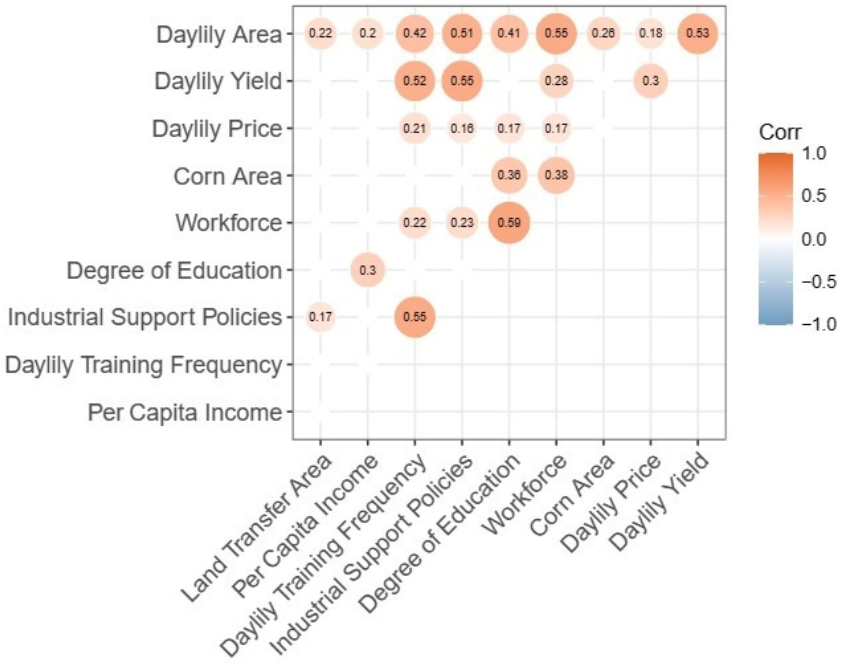
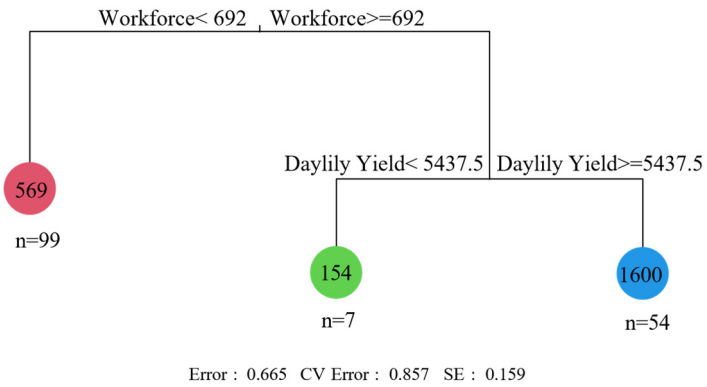


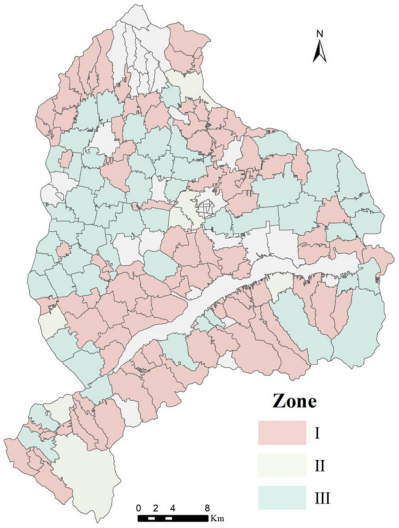
Figure 8. Driving factors' correlation map.

Using Multivariate Regression Trees (MRT), the 160 villages in Yunzhou District were divided into three groups (Figure 9a). The first split was based on villages with 692 people in the workforce as a node, and the second split occurred at a node with a daylily yield of 5437.5 kg/hm^2. The divisions of Yunzhou District were thus as follows: Region I, villages with a workforce of fewer than 692 people; Region II, villages with a workforce greater than or equal to 692 people and a daylily yield of less than 5437.5 kg/hm^2; Region III, villages with a workforce greater than or equal to 692 people and a daylily yield greater than or equal to 5437.5 kg/hm^2.

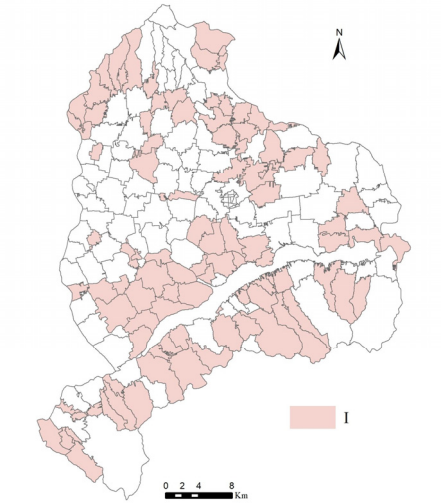
In subregion I, villages with a smaller labor force, the frequencies of daylily technical training, industrial support policies ($p < 0.01$), and education level ($p < 0.05$) were significantly and positively correlated with daylily cultivation (Figure 9b). Sub-area I was a more suitable area for cultivation, where most young people chose to go out to work, leaving behind some older farmers who were dependent on the land and were able to respond positively to the policy to grow daylilies. Whether it was fertilizing, watering, or harvesting, they were able to put a lot of energy into planting at each period. For Zone 1, it is necessary to strengthen publicity and education, increase farmers' understanding of policies, and attract more young and energetic villagers with ideas to join the development of the daylily industry.

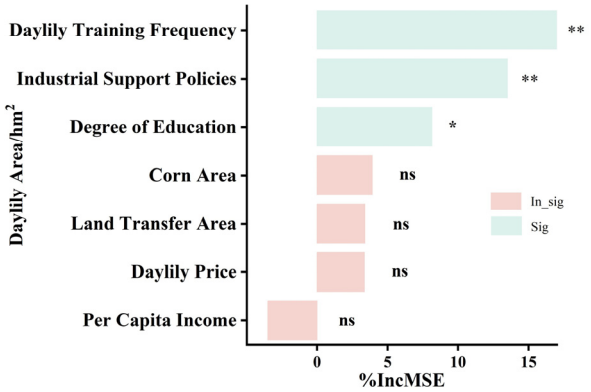
In subregion II, the workforce was sufficient but daylily yield was low, and the frequency of daylily technical training ($p < 0.05$) was significantly and positively correlated with daylily cultivation (Figure 9c). Sub-area II was an unsuitable area for planting; these villages were mainly located in urban centers and mountainous areas, which were greatly affected by topography, with dispersed plots of land, making planting difficult, with a low rate of return, and with a low willingness of farmers to plant daylilies.



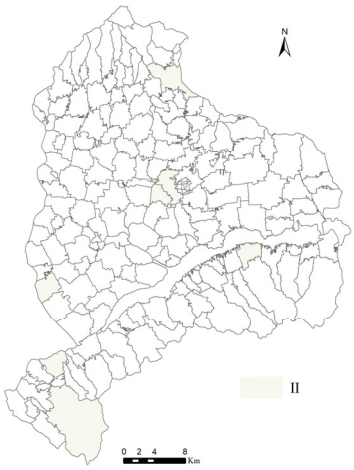


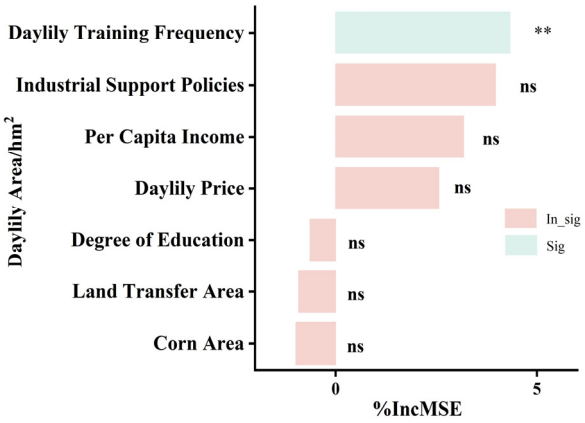
(**a**)





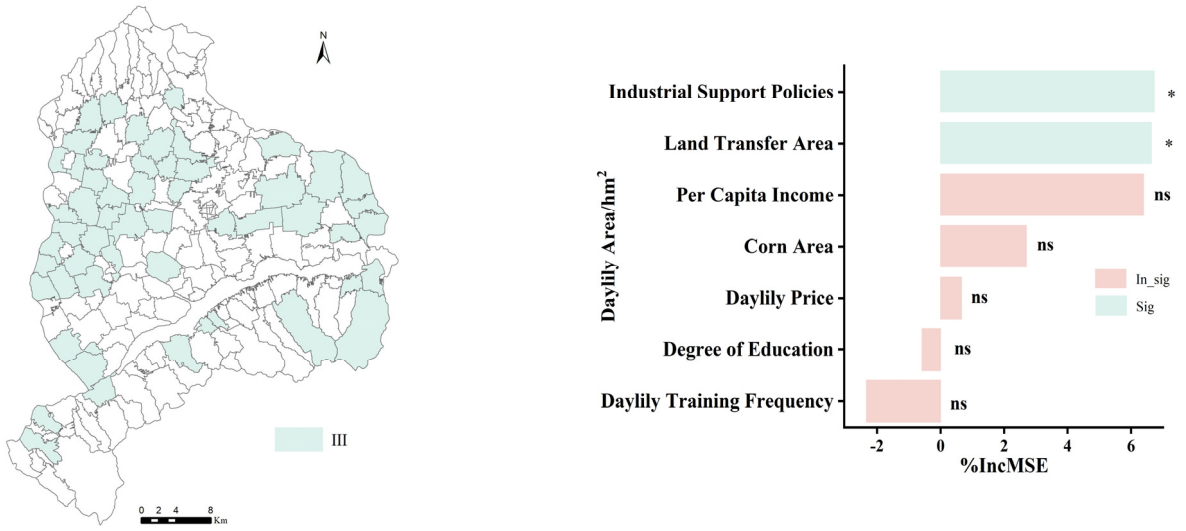
(**b**)





(**c**)

Figure 9. *Cont.*



(**d**)

Figure 9. Multiple Regression Tree (MRT) partition and importance ranking of different partition drivers: (**a**) MRT partitioning process and result, (**b**) subdivision I and importance ranking of drivers, (**c**) subdivision II and importance ranking of drivers, and (**d**) subdivision III and importance ranking of drivers (** indicates a significance level of 0.01, * indicates a significance level of 0.05, and ns indicates not significant).

In subregion III, the workforce was sufficient and daylily yield was high, and the industrial support policy and the land transfer area ($p < 0.01$) were significantly positively correlated with daylily cultivation (Figure 9d). Sub-area III was the most suitable planting area, which mostly relied on the development of cooperatives, unified management, and sending specialists to participate in technical training to learn more scientific and reasonable planting techniques to achieve high-yield daylily planting. The support policy should be optimized for sub-area III. Cooperative unified management cannot be limited to the unified planting of daylilies; unified raw material sales should be integrated into the agricultural project funds, with the implementation of precision support, by simply supporting the planting to the product processing, development, sales, and other changes in the whole industry chain, for the formation of the project superimposed effect, to create a daylily industry agglomeration area.

4. Discussion

4.1. Spatial Distribution of Daylilies

The spatial distribution of daylilies in Yunzhou District was primarily concentrated near the Sanggan River and urban areas. On one hand, daylilies require increased water supply after flowering, especially during the flowering period, to promote the normal development of their flower buds. Therefore, conditions of sufficient water supply are more conducive to the growth of daylilies. The availability of abundant water resources near the Sanggan River makes irrigation easier, leading to better growth conditions for the daylilies. This, in turn, increases the willingness of farmers to cultivate them. On the other hand, due to the short shelf life of fresh daylilies and the lack of advanced preservation techniques, exporting them can be challenging, which limits their market reach [29]. Farmers near the urban areas have the advantage of a favorable geographic location, which makes them more inclined to cultivate daylilies. Fresh daylilies incur significant losses during storage and transportation, and farmers located far from urban areas face limitations when selling fresh daylilies.

Wang you Avenue near Tangjiabao village in Yunzhou District is a typical example of the integration of agriculture and tourism, with a large and concentrated area of daylily

cultivation. The government has now fully integrated Wang you Avenue, the Daylily Park, Datong Volcanic Cluster, the Sanggan River Wetland Park, and other tourism resources to help promote the development of the daylily industry. Activities such as daylily sightseeing, harvesting activities, and daylily exhibitions and sales can strengthen the tourism industry. Policy drives the distribution and scale construction of daylily planting. In terms of the daylily planting scale, more daylily plantings were found in the low–low and high–high clusters than in the high–low and low–high ones, which is consistent with the spatial layout of cotton in Xinjiang [30]. The choice of crop grown by farmers is often influenced by policies and surrounding farmers [31], and this gradually affects the agricultural structure.

4.2. Drivers of Daylily Cultivation

The main drivers of daylily cultivation were labor, yield, and policy training. As daylily cultivation is a labor-intensive industry, the demand for labor is high during the harvest season [32]. To ensure daylily quality, farms are usually harvested before daylilies open the next day (before 8:00 in the morning). The harvest season is concentrated, and during the peak period, it takes 10–12 h a day, and the harvesting conditions are generally poor [33]. On average, it takes two people to harvest 667 m^2 of daylilies. Labor consequently has a significant impact on whether farmers grow daylilies and the scale of cultivation. The higher the daylily yield, the greater the income, and this consequently stimulates the daylily industry to grow. Daylily yield, however, is largely affected by natural factors. Farmers also need to carefully consider fertilization and irrigation, according to regulations, when cultivating daylilies. In 2020, General Secretary Xi Jinping proposed the "small daylily, big industry" in his inspection of Shanxi Province, which pointed the way for Datong to develop its specialty and advantageous industries [34]. The government should focus on local conditions, formulate support policies, and vigorously develop specialty industries. Currently, Yunzhou District has implemented many policies that benefit farmers to encourage Yunzhou District farmers to plant daylilies. These industrial support policies have improved farmers' willingness to plant daylilies. Technical training can also help farmers to understand the characteristics of daylilies, how to accurately apply fertilizer and irrigation, and how to provide adequate nutrient supplementation at the correct time. These changes will help to improve the yield of daylilies and reduce fertilizer pollution.

However, the area of food crops, the unit price of daylilies, and the per capita income do not have a significant impact on daylily cultivation. Although there are studies showing that farmers planting cash crops often obtain resources such as credit and management training, which are beneficial for planting food crops, cash crops and food crops are synergistically efficient [22,35]. However, growing daylilies requires more labor and effort than other cash crops, and the cost of harvesting is high. This may be the reason why cash crops and food crops in Yunzhou District do not currently have a synergistic relationship. The price of daylilies is determined by the yield and market of the current year, which may affect farmers' planting decisions for the next year but has no significant impact on the current year. When households have multiple sources of income, they are less dependent on daylily cultivation.

4.3. Advantages and Limitations of Classification and Identification

This study has aimed to accurately identify daylilies. For other land cover types, the use of optical imagery August data and NDVI May data were sufficient for classification and identification. Daylilies are perennial herbaceous plants that are cultivated on arable land. The primary focus of this study was to develop a method by which to differentiate between daylilies and corn cultivated on arable land. Some previous studies have investigated the use of remote sensing data for the identification of annual cash crops, while others have focused on the identification of perennial grasslands. However, research regarding the use of remote sensing data for the identification of perennial herbaceous plants, specifically on arable land, has been limited. This study aims to fill this research gap. In this study, comparing the two classifiers SVM and RF determined that RF has higher classification

accuracy than SVM. The identified daylily area was found to be highly consistent with the daylily cultivation area in Yunzhou District that has been reported online [26]. Shaohong used remote sensing data to classify wetlands and compared support vector machines, artificial neural networks, and random forest classifiers, and found that RF classification accuracy was the highest with 93% overall accuracy [36]. Linhui constructed an object-oriented random forest (RF) scheme by using GF-2 as a data source and combining spectral, vegetation index, topography, and other features to identify forest types in a forest field in Heilongjiang, and the overall accuracy reached 83.16% [37].

To determine the input data, the NSP index was proposed to maximize the differentiation between daylilies and corn. The use of this single index performed well with the RF classifier, which aligns with findings from previous studies [38,39]. When comparing different input data, Sentinel-1 and Sentinel-2 were found to complement each other effectively, leading to improved classification accuracy, and this was also supported by previous research [10]. Comparisons of the different classifiers showed that the SVM quickly achieved a high classification accuracy for single-crop classifications, which was consistent with the findings of Liu [40].

While the daylily is a perennial herbaceous plant and corn is an annual herbaceous plant, their phenological characteristics are generally similar, except for the fact that the daylily germinates earlier than corn, and corn grows faster after sowing. These characteristics, however, are not easily distinguishable in 10 m resolution Sentinel images. It is thus necessary to combine multi-temporal data and vegetation indices to amplify the spectral differences between the daylily and corn. This study has achieved a high level of accuracy when distinguishing between the daylily and corn. However, differentiating between barren grassland and daylilies, especially in areas with trees along the roadsides and at the boundaries of cultivated land, can be challenging due to the presence of mixed pixels. In this study, the classification accuracy for barren grassland was found to be relatively low. This could be attributed to the spectral similarity between barren grassland and daylilies or the limited spatial resolution of the satellite imagery, which makes it difficult to distinguish fine-scale features like barren grassland. Further research or the use of higher-resolution imagery might help to improve the accuracy of barren grassland classification.

4.4. Implications

The 20th National Congress of the Communist Party of China encourages the development of specialty industries, the acceleration of the transformation of cash crops, and the realization of rural revitalization [41]. In recent years, local governments have adhered to the development of specialty industries as their main focus and have optimized and adjusted the industrial planting structure. This paper uses the daylily industry in Yunzhou District, which is in the middle of the farming–pastoral ecotone, as a case study. It has aimed to establish a set of high-precision daylily identification methods; explore the factors affecting the distribution patterns of daylilies; and determine the policy supports with large impacts on the planting scale of daylilies as a specialty cash crop.

When selecting socio-economic factors in this study, factors such as income level, labor force, government support policies, etc., were considered, all of which may affect the planting situation of daylilies. In addition, the classification images obtained through remote sensing can provide spatial data on the range and distribution of daylily fields within villages. Using the village as the study unit, the distribution of daylily cultivation was correlated with different aspects of socio-economic factors, and the suitability of daylily cultivation in different sub-regions and the main driving factors were identified. Overall, government support policies and training in daylily technology were important in influencing the area under daylily cultivation. This study can provide decision makers with information on the impacts of daylily cultivation on local livelihoods and on the ecological environment, and can also provide a basis for determining the optimal ratio of food crops to cash crops to be planted in Yunzhou District. However, there is no further research on

how these socio-economic factors specifically affect the expansion or contraction of the daylily planting range.

5. Conclusions

Daylilies, as perennial plants with well-developed root systems, exhibit strong drought resistance, making them suitable for cultivation in arid and semi-arid regions [42]. Yunzhou District, located in the central part of the farming–pastoral ecotone, utilizes daylilies as a specialty cash crop to address the challenges of soil erosion, limited precipitation, and high evaporation. Daylilies have thus been identified as a leading industry for poverty alleviation and wealth generation in Yunzhou District due to their ability to thrive in such natural conditions.

In response to issues such as the unclear distribution of cash crops in the Farming–Pastoral Ecotone and the unclear driving factors for agricultural structural adjustment, this paper takes the example of the specialty crop, the daylily, in Yunzhou District for exploration. The results show that it is feasible to use Sentinel-2 and radar (SAR) data to identify daylilies with high precision by combining multiple vegetation indices. In Yunzhou District, daylilies are mainly distributed in the vicinity of the Sanggan River, urban areas, and Daylily Park. In terms of village statistics, the area of daylily cultivation is mainly distributed in 13.4–38.8 hm^2. In terms of quantity, daylilies planted in clusters of low–low and high–high types are more numerous than those of high–low and low–high types. Labor, daylily yield, and policy training are important factors affecting the distribution patterns of daylilies. The daylily is a labor-intensive crop, and labor-abundant areas tend to be able to support larger areas of daylily cultivation. The yield of daylilies, influenced by natural conditions and farming techniques, determines the feasibility and attractiveness of daylily cultivation. Government policy support and training play a key role in guiding farmers toward efficient daylily cultivation. The government should rely on big data support to continuously monitor the distribution of daylilies as a way to optimize policies. In particular, it should increase policy efforts and training frequency for regions with large daylily planting areas, abundant labor force, and good natural conditions to optimize the crop planting structure. It is crucial to explore the complex interplay of socio-economic factors in the cultivation of the daylily. Remote sensing technology provides a valuable tool for capturing the dynamics of agricultural cultivation, making the decision-making process for agricultural policies and practices more efficient and precise.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13040439/s1, References [43–49] are cited in the Supplementary Materials.

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Data Availability Statement: The datasets generated in this study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

References

1. Wang, X.; Li, Y.; Gong, X.; Niu, Y.; Chen, Y.; Shi, X.; Li, W.; Liu, J. Changes of soil organic carbon stocks from the 1980s to 2018 in northern China's agro-pastoral ecotone. *CATENA* **2020**, *194*, 104722. [CrossRef]
2. Xiang, D.; Verbruggen, E.; Hu, Y.; Veresoglou, S.D.; Rillig, M.C.; Zhou, W.; Xu, T.; Li, H.; Hao, Z.; Chen, Y.; et al. Land use influences arbuscular mycorrhizal fungal communities in the farming–pastoral ecotone of northern China. *New Phytol.* **2014**, *204*, 968–978. [CrossRef]

3. The State Council. Farming-Pastoral Ecotone: China's Optimized Layout of New Space for Agricultural Development. Available online: https://www.gov.cn/xinwen/2016-12/02/content_5142230.htm (accessed on 14 August 2023). (In Chinese)
4. Qing, Z.; Liu, J.; Yi, X.; Liu, X.; Hu, G.; Lao, J.; He, W.; Yang, Z.; Zou, X.; Sun, M.; et al. The chromosome-level Hemerocallis citrina Borani genome provides new insights into the rutin biosynthesis and the lack of colchicine. *Hortic. Res.* **2021**, *8*, 89. [CrossRef]
5. Boschetti, M.; Busetto, L.; Manfron, G.; Laborte, A.; Asilo, S.; Pazhanivelan, S.; Nelson, A. PhenoRice: A method for automatic extraction of spatio-temporal information on rice crops using satellite data time series. *Remote Sens. Environ.* **2017**, *194*, 347–365. [CrossRef]
6. Chen, Y.; Lu, D.; Moran, E.; Batistella, M.; Dutra, L.V.; Sanches, I.D.A.; da Silva, R.F.B.; Huang, J.; Luiz, A.J.B.; de Oliveira, M.A.F. Mapping croplands, cropping patterns, and crop types using MODIS time-series data. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *69*, 133–147.
7. He, Y.; Dong, J.; Liao, X.; Sun, L.; Wang, Z.; You, N.; Li, Z.; Fu, P. Examining rice distribution and cropping intensity in a mixed single- and double-cropping region in South China using all available Sentinel 1/2 images. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *101*, 102351. [CrossRef]
8. Sitokonstantinou, V.; Papoutsis, I.; Charalabos, K.; Arnal, A.; Andrés, A.; Zurbano, J. Scalable Parcel-Based Crop Identification Scheme Using Sentinel-2 Data Time-Series for the Monitoring of the Common Agricultural Policy. *Remote Sens.* **2018**, *10*, 911. [CrossRef]
9. Sonobe, R.; Yamaya, Y.; Tani, H.; Wang, X.; Kobayashi, N.; Mochizuki, K. Mapping crop cover using multi-temporal Landsat 8 OLI imagery. *Int. J. Remote Sens.* **2017**, *38*, 4348–4361. [CrossRef]
10. Adrian, J.; Sagan, V.; Maimaitijiang, M. Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2021**, *175*, 215–235. [CrossRef]
11. Onojeghuo, A.O.; Blackburn, G.A.; Wang, Q.; Atkinson, P.M.; Kindred, D.; Miao, Y. Mapping paddy rice fields by applying machine learning algorithms to multi-temporal Sentinel-1A and Landsat data. *Int. J. Remote Sens.* **2018**, *39*, 1042–1067. [CrossRef]
12. Orynbaikyzy, A.; Gessner, U.; Conrad, C. Crop type classification using a combination of optical and radar remote sensing data: A review. *Int. J. Remote Sens.* **2019**, *40*, 6553–6595. [CrossRef]
13. You, N.; Dong, J. Examining earliest identifiable timing of crops using all available Sentinel 1/2 imagery and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2020**, *161*, 109–123. [CrossRef]
14. d'Andrimont, R.; Taymans, M.; Lemoine, G.; Ceglar, A.; Yordanov, M.; van der Velde, M. Detecting flowering phenology in oil seed rape parcels with Sentinel-1 and -2 time series. *Remote Sens. Environ.* **2020**, *239*, 111660. [CrossRef]
15. Di, Y.; Dong, J.; Zhu, F.; Fu, P. A robust but straightforward phenology-based ginger mapping algorithm by using unique phenology features, and time-series Sentinel-2 images. *Comput. Electron. Agric.* **2022**, *198*, 107066. [CrossRef]
16. Popescu, A.; Alecu, I.N.; Dinu, T.A.; Stoian, E.; Condei, R.; Ciocan, H. Farm Structure and Land Concentration in Romania and the European Union's Agriculture. *Agric. Agric. Sci. Procedia* **2016**, *10*, 566–577. [CrossRef]
17. Liu, S.; Zhang, P.; Marley, B.; Liu, W. The Factors Affecting Farmers' Soybean Planting Behavior in Heilongjiang Province, China. *Agriculture* **2019**, *9*, 188. [CrossRef]
18. Xia, T.; Wu, W.; Tang, H.; Zhou, Q.; Yang, P.; Li, Z.; Liu, Z.; Yu, Q. Influencing Mechanism of Family Attributes on Choosing Crops—A Case Study in Binxian County of Heilongjiang Province. *Agric. Food Sci.* **2013**, *46*, 3257–3265.
19. Wang, S.; Liu, C.; Han, L.; Li, T.; Yang, G.; Chen, T. Corn Grain or Corn Silage: Effects of the Grain-to-Fodder Crop Conversion Program on Farmers’ Income in China. *Agriculture* **2022**, *12*, 976. [CrossRef]
20. Jiang, Y.; Qi, M. Analysis on the characteristics of the structural changes of agricultural products in China before and after land transfer. *Jiangxi Soc. Sci.* **2017**, *37*, 81–89.
21. Peng, J.; Chen, J.; Su, C.; Wu, Z.; Yang, L.; Liu, W. Will land circulation sway "grain orientation"? The impact of rural land circulation on farmers' agricultural planting structures. *PLoS ONE* **2021**, *16*, e0253158. [CrossRef]
22. Strasberg, P.J. *Smallholder Cash Cropping, Food Cropping, and Food Security in Northern Mozambique: Research Methods*; Michigan State University, Department of Agricultural, Food, and Resource Economics: East Lansing, MI, USA, 1996.
23. Klasen, S.; Priebe, J.; Rudolf, R. Cash crop choice and income dynamics in rural areas: Evidence for post-crisis Indonesia. *Agric. Econ.* **2013**, *44*, 349–364. [CrossRef]
24. Lee, H.; Bogner, C.; Lee, S.; Koellner, T. Crop selection under price and yield fluctuation: Analysis of agro-economic time series from South Korea. *Agric. Syst.* **2016**, *148*, 1–11. [CrossRef]
25. Song, G.; Zhang, H. Cultivated Land Use Layout Adjustment Based on Crop Planting Suitability: A Case Study of Typical Counties in Northeast China. *Land* **2021**, *10*, 107. [CrossRef]
26. Datong Municipal People's Government. Daylily Industry Bigger Farmers Better Days Datong Yunzhou District all-round Promotion of High-Quality Development of Industry Rich People Paths. Available online: https://www.dt.gov.cn/dtszf/bumdtpd/202205/7155edc00e3c40a2b1c91f2757e7dbe6.shtml#:~:text=2021%E5%B9%B4%E8%AF%A5%E5%8C%BA%E9%BB%84,%E8%8F%9C1680%E4%B8%87%E6%96%A4%E3%80%82 (accessed on 14 March 2023). (In Chinese)
27. Jaramillo, F.; Orchard, M.; Muñoz, C.; Antileo, C.; Sáez, D.; Espinoza, P. Online estimation of the aerobic phase length for partial nitrification processes in SBR based on features extraction and SVM classification. *Chem. Eng. J.* **2018**, *331*, 114–123. [CrossRef]
28. Yi, Z.; Jia, L.; Chen, Q. Crop Classification Using Multi-Temporal Sentinel-2 Data in the Shiyang River Basin of China. *Remote Sens.* **2020**, *12*, 4052. [CrossRef]
29. Fafchamps, M.; Shilpi, F. The spatial division of labour in Nepal. *J. Dev. Stud.* **2003**, *39*, 23–66. [CrossRef]

30. Yu, Y.; Yu, G.; Wei, J. Analysis of spatial changes and influencing factors of cotton production layout in Xinjiang under the background of supply-side reforms. *J. Arid. Land Resour. Environ.* **2019**, *33*, 74–80. (In Chinese)
31. Ren, J.; Li, F.; Yin, C.; Zhang, J. Uncovering the Deviation of Farmers' Green Manure Planting Willingness and Behavior. *Sustainability* **2022**, *14*, 14315. [CrossRef]
32. Zhang, X.; Ma, H.; Wei, S.; Yang, L. Design of DayLily Robot Recognition System Based on ZYNQ. In Proceedings of the 2021 International Conference on Networking, Communications and Information Technology (NetCIT), Manchester, UK, 26–27 December 2021; pp. 154–157.
33. Feng, J.; Zhao, X.; Zhu, T.; Li, T.; Qiu, Z.; Li, Z. Detection Mature Bud for Daylily Based on Faster R-CNN Integrated With CBAM. *IEEE Access* **2023**, *11*, 81646–81655. [CrossRef]
34. The State Council. Rich Flowers Bloom, Small Daylily into Big Industries. Available online: http://www.yunzhou.gov.cn/yzqrmzf/tpxw/202105/4a7b6d9bc3424677af4dc8260cdd8c94.shtml (accessed on 10 August 2023). (In Chinese)
35. Govereh, J.; Jayne, T.S. Cash cropping and food crop productivity: Synergies or trade-offs? *Agric. Econ.* **2003**, *28*, 39–50.
36. Tian, S.; Zhang, X.; Tian, J.; Sun, Q. Random Forest Classification of Wetland Landcovers from Multi-Sensor Data in the Arid Region of Xinjiang, China. *Remote Sens.* **2016**, *8*, 954. [CrossRef]
37. Li, L.; Jing, W.; Wang, H. Extracting the Forest Type From Remote Sensing Images by Random Forest. *IEEE Sens. J.* **2021**, *21*, 17447–17454.
38. Fang, W.; Zhu, H.; Li, S.; Ding, H.; Bi, R. Rapid Identification of Main Vegetation Types in the Lingkong Mountain Nature Reserve Based on Multi-Temporal Modified Vegetation Indices. *Sensors* **2023**, *23*, 659. [CrossRef]
39. Sumner, Z.; Varco, J.J.; Dhillon, J.S.; Fox, A.A.A.; Czarnecki, J.; Henry, W.B. Ground versus aerial canopy reflectance of corn: Red-edge and non-red edge vegetation indices. *Agron. J.* **2021**, *113*, 2782–2797. [CrossRef]
40. Liu, P.; Choo, K.-K.R.; Wang, L.; Huang, F. SVM or deep learning? A comparative study on remote sensing image classification. *Soft Comput.* **2017**, *21*, 7053–7065. [CrossRef]
41. The State Council. Xi Jinping: Hold High the Great Banner of Socialism with Chinese Characteristics and Unite for Building a Modern Socialist Country in All Aspects—Report at the 20th National Congress of the Communist Party of China. Available online: https://www.gov.cn/xinwen/2022-10/25/content_5721685.htm (accessed on 10 August 2023). (In Chinese)
42. Wang, M.; Sun, Y. Fruit trees and vegetables for arid and semi-arid areas in north-west China. *J. Arid. Environ.* **1986**, *11*, 3–16.
43. Frampton, W.J.; Dash, J.; Watmough, G.; Milton, E.J. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS J. Photogramm. Remote Sens.* **2013**, *82*, 83–92. [CrossRef]
44. Kanke, Y.; Tubaña, B.; Dalen, M.; Harrell, D. Evaluation of red and red-edge reflectance-based vegetation indices for rice biomass and grain yield prediction models in paddy fields. *Precis. Agric.* **2016**, *17*, 507–530. [CrossRef]
45. Ramoelo, A.; Cho, M.A.; Mathieu, R.; Madonsela, S.; van de Kerchove, R.; Kaszta, Z.; Wolff, E. Monitoring grass nutrients and biomass as indicators of rangeland quality and quantity using random forest modelling and WorldView-2 data. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *43*, 43–54. [CrossRef]
46. Seager, S.; Turner, E.L.; Schafer, J.; Ford, E.B. Vegetation's red edge: A possible spectroscopic biosignature of extraterrestrial plants. *Astrobiology* **2005**, *5*, 372–390. [CrossRef]
47. Wu, C.; Niu, Z.; Tang, Q.; Huang, W.; Rivard, B.; Feng, J. Remote estimation of gross primary production in wheat using chlorophyll-related vegetation indices. *Agric. For. Meteorol.* **2009**, *149*, 1015–1021. [CrossRef]
48. Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. *Monitoring Vegetation Systems in the Great Plains with Erts*; NASA: Washington, DC, USA, 1974; p. 351.
49. Cui, B.; Huang, W.; Ye, H.; Chen, Q. The Suitability of PlanetScope Imagery for Mapping Rubber Plantations. *Remote Sens.* **2022**, *14*, 1061. [CrossRef]

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