Exploring the characteristics and driving forces of orchard expansion in ecological fragile region: A case study of three typical counties in the Loess Plateau

Qiyuan Hu[1], Xiang Gao[1], Sijia Wang[1], Qihan Wang[1], Yuting Qin[1], Weiyi Zhang[1], Fei Lun[1] and Zhuo Li[2]*

[1]College of Land Science and Technology, China Agricultural University, Beijing, China, [2]Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources, Shenzhen, China

The Loess Plateau exemplifies the type of ecologically fragile region that faces severe poverty challenges in China. Orchards have expanded rapidly over the past few decades and now constitute a considerable part of local economy. Not only do the characteristics of orchard expansion affect local economic development, but also exert additional pressure on the ecological environment. Therefore, it is essential for sustainable development on the Loess Plateau to investigate the characteristics and driving forces of orchard expansion. The Fuxian, Luochuan, Huangling, three typical orchard planting counties were chosen as the study area. Firstly, the orchard was extracted from the land use/cover classification from 1990–2020. It broadens the research approach to the identification of expansion cash crops by using the combination of linear spectral mixture analysis (LSMA) and decision tree. Secondly, the spatiotemporal dynamics of orchard expansion were quantitatively investigated based on spatial geometry center shift, physical geographical features, landscape pattern and orchard planting suitability. Then, we constructed an evaluation indicators system to detect the feature importance and partial dependence of different factors by random forest regression. It is more innovative to employ the machine learning method to investigate driving forces. Finally, the linkages between planting suitability and orchard expansion were further discussed, and subsequent policies were proposed. Findings demonstrated the orchard had continuously expanded over the past 30 years, with the fastest expansion rate during 1990–2005. Increased cohesion was accompanied by a shift in the orchard's spatial distribution to the north central region and highly suitable planting regions. Slope turned out to be the primary factor affecting the orchard expansion. In the future, regions with aging orchard but high planting suitability should be the preferred choice for orchard expansion. Additionally, the transportation connectivity and governmental assistance are crucial considerations for the future planning of the orchard.

1 Introduction

The Loess plateau (LP) is a globally well-recognized ecological fragile region (Fu et al., 2017; Fu, 2022), with severe social-ecological issues, including soil erosion (Zhou et al., 2016; Lu et al., 2022), water shortage (Feng et al., 2016) and poverty (Patrick, 2016). The conflict between socioeconomic development and environmental protection is a crucial challenge that needs urgent solutions. Orchard planting is characterized by high economic benefits and now serves as the backbone of the local economy in the LP (Chen et al., 2021). In addition, with the improvement of the dietary structure (Guo et al., 2022), the LP, one of the largest apple planting regions, has gone through significant orchard expansion in recent decades (Yang et al., 2020). Thus, the spatiotemporal dynamics of agricultural land will not only affect the local socio-economy, but also on its ecological condition.

Previous researches on agricultural land in the LP has focused on its economic benefits and associated environmental effects along with the land use/cover change (Zhao et al., 2018; Liang et al., 2018; Li et al., 2021; Huo et al., 2022; Xiao et al., 2022). There are many excellent reviews promoting sustainable agricultural land management in the LP, which also provide valuable instruction for socioeconomic development. However, the existing studies paid much attention to traditional food crops (Tracy, 2020; Wang et al., 2022a; Wang et al., 2022b; Chen et al., 2022; Wu et al., 2022; Wang and Cheng, 2022), while cash crops still remained unclear. Consequently, it is necessary to explore the spatiotemporal dynamics of orchard expansion and its driving forces in order to propose optimizing strategies for orchard planting in the LP.

Much work so far in terms of orchard expansion can be divided into three aspects: 1) identification of orchard expansions (Dong et al., 2013; Jason et al., 2017; Sun et al., 2017; Kaspar and Jefferson, 2018; Lin et al., 2022). Depending on multiple spectral indices and phenological information, much attention has been paid to identifying the expansion of different orchards. Zhu et al. (2020) extracted apple orchards in Qixia county from 2000–2017 by using normalized difference vegetation index (NDVI) time series and phenological vegetation information. Xuan et al. (2018) applied the random forest method to extract citrus orchards by using NDVI, soil-adjusted vegetation index (SAVI) and normalized difference moisture index (NDMI). Based on the phenological difference. The selection of the appropriate spectral indices and the extraction of the corresponding phenological information is a major challenge for different regions and different fruit tree species; 2) analysis on the characteristics of orchard expansion, including landscape pattern (Guzmán et al., 2022), dynamics (Dibs et al., 2017; Peña-Cortés et al., 2021) and planting suitability (Wu et al., 2022). As for analyzing the characteristics of orchard expansion, current studies are based on a single perspective. Naqash and Wani. (2019) discovered the spatiotemporal dynamics of orchard expansion in Kashmir Valley and proposed policy suggestions from the perspective of pest control. Guzmán et al. (2022) analyzed the landscape pattern of olive orchards expansion in Spain. A comprehensive investigation of the spatiotemporal dynamics of orchard expansion based on multiple perspectives is still lacking; 3) driving mechanism of orchard expansion (Xiao et al., 2015; Zhang et al., 2017). Driving force analysis based on statistical regression models (e.g., logistic regression model) is a common method for analyzing the driving mechanisms of orchard expansion. Although abundant potential determinants have been selected to figure out the driving mechanism, the underlying response mechanism is not further used to suggest new policy actions. More effort is needed to determine how to provide sustainable orchard management practices based on the understanding of the driving forces.

In general, scholars have made certain achievements in the study of orchard expansion. However, the comprehensive exploration of orchard expansion dynamics in the ecological fragile region and their driving forces are still lacking. Northern Shaanxi is one of the most vital regions for orchard cultivation in the LP. Therefore, this study takes the three typical apple orchard planting counties as the study area. The spatiotemporal dynamics of orchard expansion have been analyzed from the perspectives of spatial geometry center shift, physical geographical features, landscape pattern and orchard planting suitability. It broadens the research approach to the identification of expansion cash crops in ecologically vulnerable areas. Furthermore, it is more innovative to employ the machine learning method to investigate driving forces and put forward matching policies in order to promote the apple industry in the LP.

The specific objectives of this study are: 1) to map the land use/cover classification of the study area and identify orchard expansion from 1990 to 2020; 2) to analyze the spatiotemporal dynamics of orchard expansion based on the spatial geometry center shift, physical geographical features, landscape pattern and orchard planting suitability; 3) to reveal the potential determinants and analyze its driving forces based on the parameter of feature importance and partial dependence; 4) to propose optimistic strategies for local orchard expansion based on above findings for better agricultural land management and ecological conservation.

2 Materials and methods

2.1 Overall workflow

Figure 1 shows the overall workflow of this study. The whole research is carried out in two steps. Firstly, based on the three
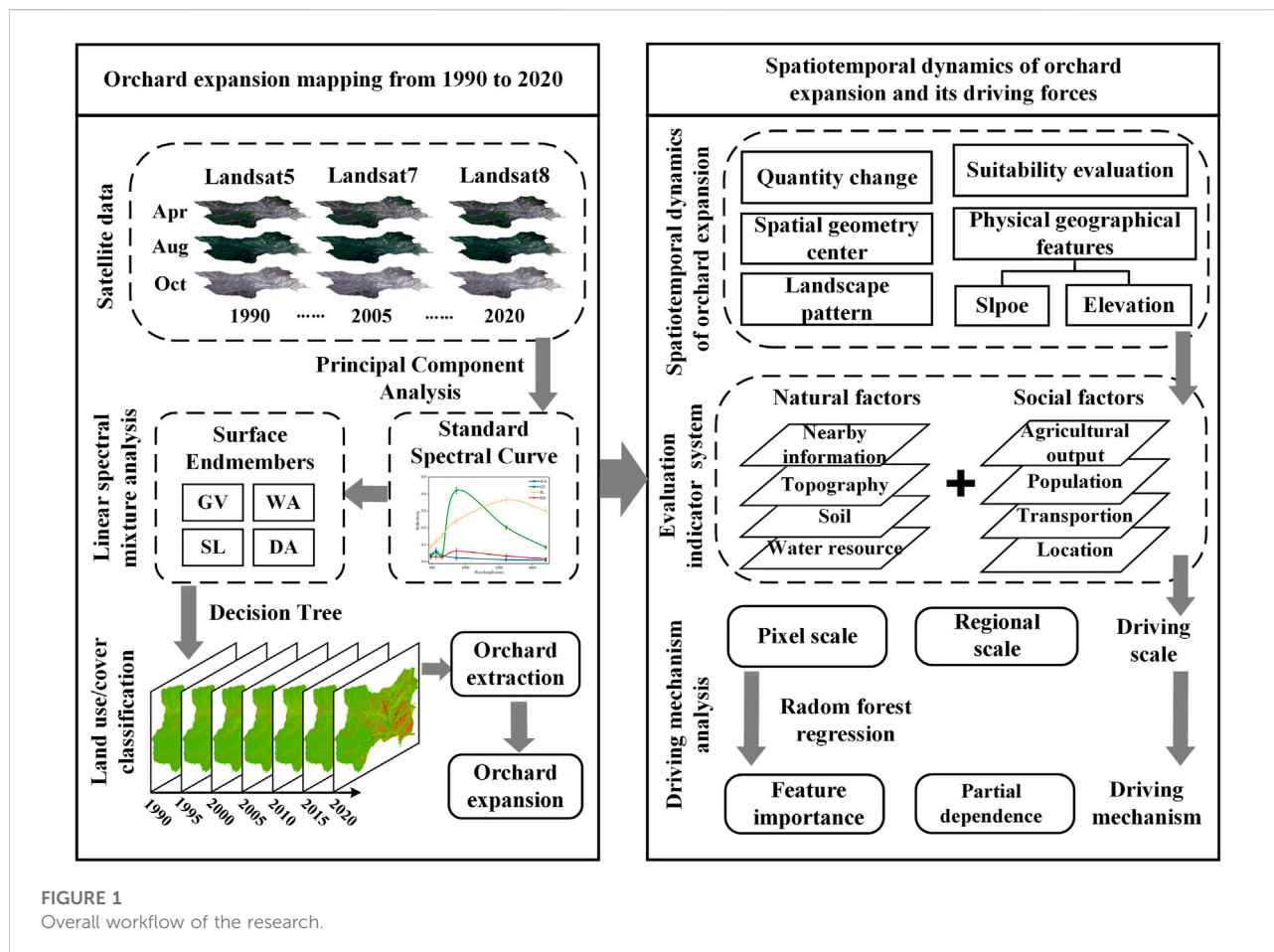
FIGURE 1
Overall workflow of the research.

temporal remote sensing data, the land use/cover classification of the study area from 1990 to 2020 was obtained by using a combination of the LSMA and the decision tree. The spatial distribution of orchard expansion was then available by extracting the orchards. Secondly, the spatiotemporal dynamics of orchard expansion were investigated from the perspectives of spatial geometry center shift, physical geographic features, landscape pattern and planting suitability. Combined with the constructed evaluation system of influencing factors, the feature importance and partial dependence of different factors were analyzed by using random forest regression.

2.2 Study area

The counties of Fuxian, Luochuan and Huangling in Yan'an City, Shaanxi Province were selected as the study area (Figure 2). The three counties are situated between $108°29'–109°42'$N and $35°44'–36°23'$E, covering an area of 8,278 km². These counties are located in the middle part of the LP, where the ecological environment is fragile and soil erosion is serious. This area

belongs to the temperate continental monsoon climate, with sufficient sunlight and pleasant weather. The terrain in the study area is complex, including river valley terrace, low hills and loess valleys. The local government attaches great importance to the investment and policy support of the apple industry, guiding the farmers and promoting the fruit industry. At present, this area has become one of the largest apple production areas in China, of which Luochuan county's apple yields rank the first, known as the "apple capital".

2.3 Data source

2.3.1 Satellite data

In this study, the surface reflectance data from Landsat TM/ETM +/OLI C2L2 products with radiometric calibration, geometric correction, and atmospheric correction were used. The Landsat satellite images have a 16-day return time and 30 m spatial resolution, which are available from 1972 to the present (Roy et al., 2014) and have been widely used in land use/cover classification (Azzari and Lobell, 2017; Jin et al., 2019;
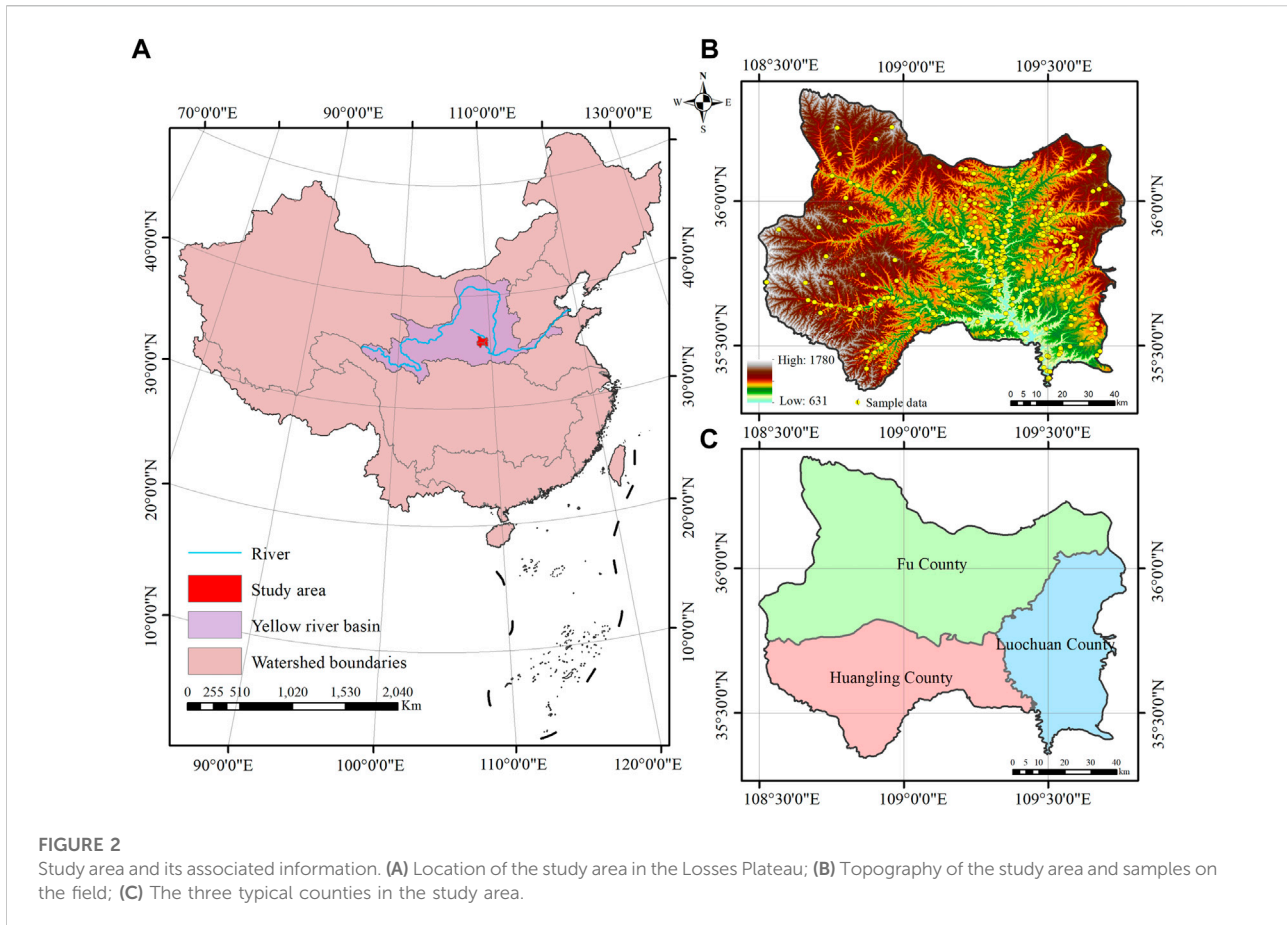
FIGURE 2
Study area and its associated information. **(A)** Location of the study area in the Losses Plateau; **(B)** Topography of the study area and samples on the field; **(C)** The three typical counties in the study area.

Souza et al., 2020). All images are freely available on the website of the United States Geological Survey (https://earthexplorer.usgs.gov). In this study, the "landsat_gapfll.sav" plug in of ENVI version 5.3 software (Exelis Visual Information Solutions, Inc., Boulder, CO, United States) was used to compensate for the loss of ETM + data. The cloud coverage of the images used in this study was less than 8%, and the cloud areas were not in the study area. Thus, no additional cloud removal processing was required.

In the study area, the periods of significant physical characteristics of the orchards include: 1) growth period (April-May): the period when fruit trees start to sprout and grow leaves; 2) peak period (August-September): the period when fruit trees have the largest green leaf area; 3) deciduous period (October-November): the period when most deciduous forests have turned yellow and deciduous, while fruit trees are still covered with green leaves without significant deciduousness. To distinguish different land types in the study area, Landsat satellite images for April, August and October of 1990, 1995, 2000, 2005, 2010, 2015, and 2020 were used in this study, among which Landsat5 TM images were used for 1990, 1995, 2005, and 2010, Landsat7 ETM+ images were used for 2000, and Landsat8 OLI images were used for 2015 and 2020. The images used in this study are shown in Table 1.

2.3.2 Field data

To obtain reference samples for decision tree construction and validation samples for land use/cover classification, we collected field data in July 2021, using a portable GPS satellite positioning navigator to collect the geographic coordinates and the land use/cover type. In addition, we selected sample sites for different land use/cover types that have not changed between 1990 and 2020 based on visual interpretation of high-resolution historical images from Google Earth. In the study area, we selected 758 sample points of various types, including 167 orchards, 162 cultivated land, 197 forest land, 47 grassland, 119 water, 18 bare land, and 48 construction land (Figure 1B).

2.4 Orchard expanding mapping

2.4.1 Linear spectral mixture analysis

The theoretical assumption of the LSMA is that the radiant brightness of the ground target pixel received by the sensor is only related to the proportion of the area occupied by each element (Li et al., 2021). Therefore, the reflectance of the ground target pixel is a linear combination of each endmember

TABLE 1 Details of satellite data used in this study.

Year	Satellite	Product	Date	Cloud coverage (%)
2020	Landsat8	OLI TIRS C2T2	4/25	0
			8/2	0
			9/30	5
2015	Landsat8	OLI TIRS C2T2	4/28	0
			8/15	1
			10/2	0
2010	Landsat5	TM C2L2	4/30	0
			6/30	0
			10/7	0
2005	Landsat5	TM C2L2	4/19	0
			9/10	0
			10/9	8
2000	Landsat7	ETM C2L2	5/12	0
			9/17	0
			9/23	0
1995	Landsat5	TM C2L2	4/23	0
			8/13	0
			9/22	2
1990	Landsat5	TM C2L2	4/7	0
			8/29	0
			10/8	6

reflectance within the pixel, with the proportion of the area occupied by each endmember as a weight (Small, 2003). In the unit pixel, endmember abundance values (EMA) are calculated by the area percentage of each standard endmember at the subpixel level based on the pixel spectrum. The EMA with specific physical meaning, in contrast to other traditional vegetation indices, such as NDVI, NDMI and SAVI, can better reflect the information of landscape features (such as plants, soil, water, and so on) (Li et al., 2021). The selection of appropriate spectral indices is a major challenge for different regions when conducting land use/cover mapping. Thus, using the LSMA to convert raw spectral data from remote sensing images into physically meaningful EMA is beneficial to land use/ cover classification.
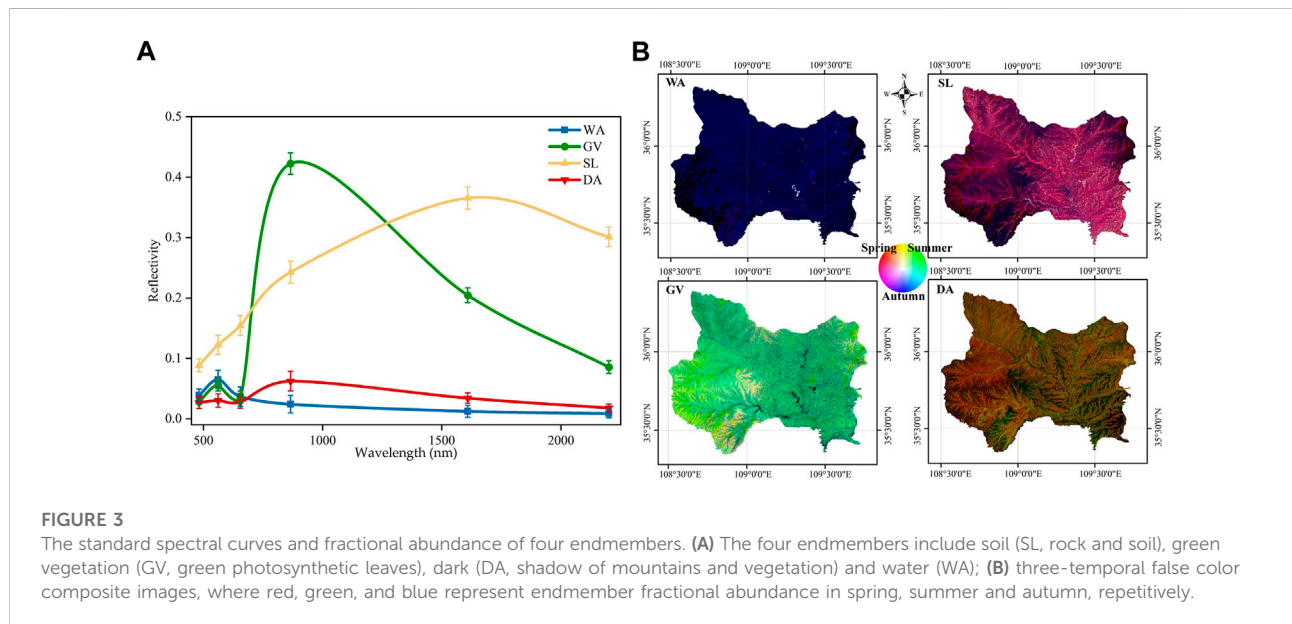
Before the LSMA, there are two critical steps: principal component analysis (PCA) and endmember selection. Firstly, we used the PCA method to extract the main feature information of spectral space. Taking the PCA method results in 2020 as an example, the cumulative contribution of the top three principal components in three seasonal images exceeded 98% (Table 2),

showing that the top three principal components of all images contained nearly all the spectral information. Consequently, we can determine that the intrinsic dimension of spectral information is three. According to the convex geometry theory, the number of endmembers is generally one more than the intrinsic dimension of the spectral space (Boardman, 1993). Therefore, we can select four pure spectral endmembers in the study area. Secondly, we built scatter grams based on the top three principal components to select pure endmembers. According to the spectral curve of points at the top of the scatter grams and the true color composite images, we determined four endmembers in the study area: soil (SL, rock and soil), green vegetation (GV, green photosynthetic leaves), dark (DA, shadow of mountains and vegetation) and water (WA).

There will be slight differences when extracting the endmember spectrum from the images of different satellite sensors (Han et al., 2022). To limit the influence of different sensors on the LSMA, we used the average values of six common bands (blue, green, red, near-infrared, and

TABLE 2 Principal component analysis of the top three principal components in 2020.

Image time	Principal component	Contribution rate (%)	Cumulative contribution rate (%)	Eigenvalue					
				Blue	Green	Red	NIR	SWIR1	SWIR2
2020-04	PC1	78.15	78.15	0.20	0.25	0.42	0.14	0.53	0.62
	PC2	19.32	97.47	0.06	−0.05	0.12	−0.97	−0.06	0.18
	PC3	2.03	99.50	−0.20	−0.37	−0.57	−0.10	0.68	0.07
2020-08	PC1	60.64	60.64	−0.12	−0.20	−0.23	−0.67	−0.53	−0.38
	PC2	36.32	95.96	0.17	0.21	0.38	−0.70	0.24	0.48
	PC3	2.84	98.80	0.25	0.37	0.55	0.21	−0.64	−0.11
2020-10	PC1	89.90	89.90	0.11	0.18	0.24	0.49	0.65	0.49
	PC2	6.63	96.53	0.02	−0.06	0.00	−0.85	0.34	0.41
	PC3	2.75	99.28	−0.34	−0.48	−0.60	0.13	0.45	−0.14

FIGURE 3
The standard spectral curves and fractional abundance of four endmembers. **(A)** The four endmembers include soil (SL, rock and soil), green vegetation (GV, green photosynthetic leaves), dark (DA, shadow of mountains and vegetation) and water (WA); **(B)** three-temporal false color composite images, where red, green, and blue represent endmember fractional abundance in spring, summer and autumn, repetitively.

shortwave-infrared 1/2) from three data sources to construct a standard endmember library (Figure 3A). These endmember spectra have been proven to be effective and stable (Sun and Liu, 2015; Sun et al., 2019). Finally, we estimate the EMA through the LSMA. The EMA results in 2020 are shown in Figure 3B.

2.4.2 Decision tree

In this study, the land use/cover types were selected into seven categories: Orchard, forest, grassland, water, cultivated land, construction land, and bare land. And we utilized the

decision tree classification for land use/cover classification. Decision tree is a well-recognized classification method that does not need complex data processing and simply requires categorization based on the classification criteria and specific features (Mahesh and Paul, 2003; Thoreau et al., 2009). The decision tree was built by the LSMA results, ground features, and the phenological information of different crops. The segmentation threshold was determined by repeated experiments based on the histogram of the training samples' EMA. The decision tree is shown in Figure 4. And the specific classification rules are as follows:
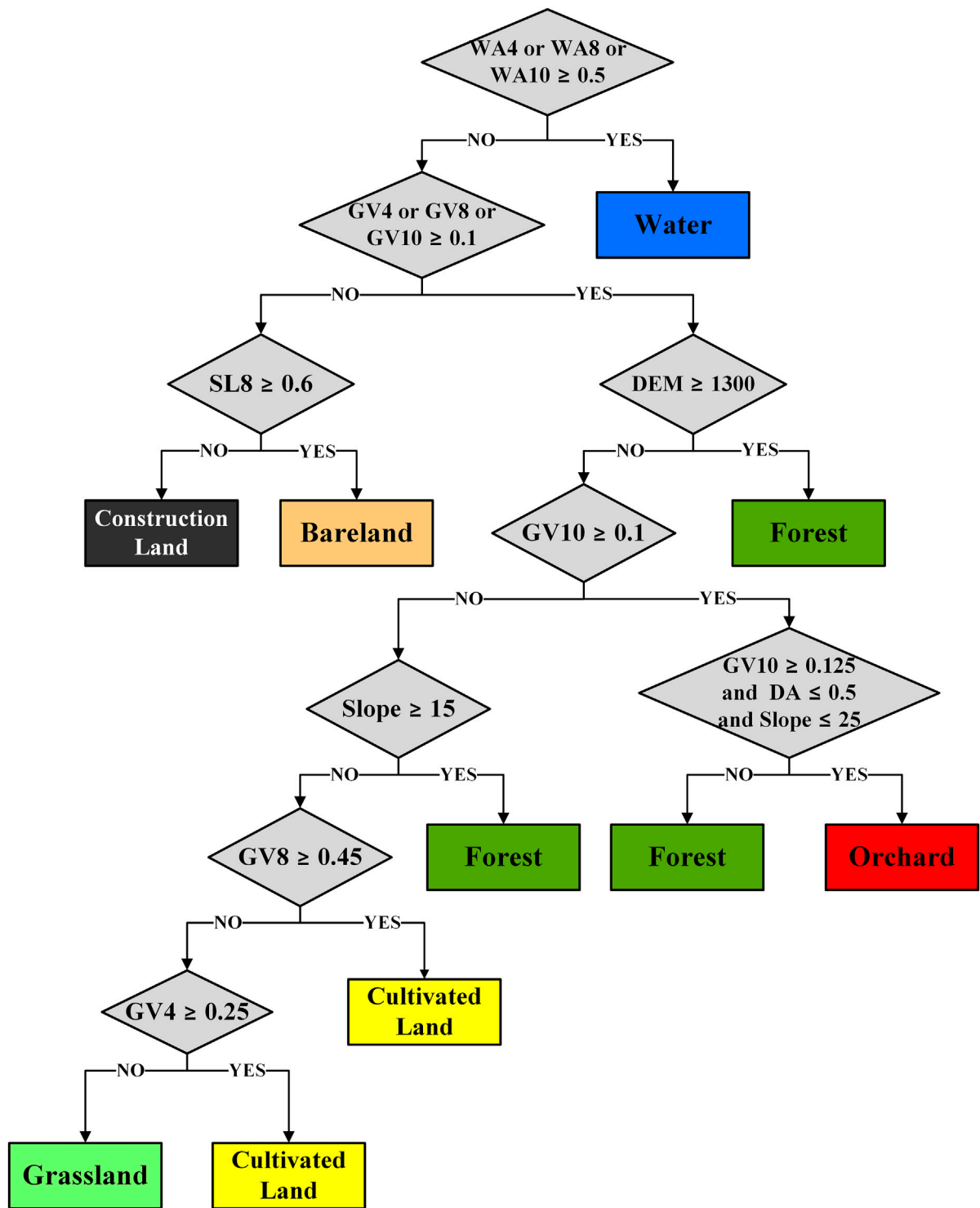
FIGURE 4
The land use/cover classification decision tree in this study.

(1) The water area is extracted by the three seasonal EMA of WA, and the threshold values are WA4 or WA8, or WA10 ≥ 0.5.

(2) The vegetation area and non-vegetation area are divided by the three seasonal EMA of GV, and the threshold values are GV4 or GV8, or GV10 ≥ 0.1.

(3) The bare land and construction land within the non-vegetation area are divided by the summer EMA of SL, and the threshold value is SL8 ≥ 0.6.

(4) The orchard, forest, grassland, and cultivated land are divided by the autumn EMA of GV, and the threshold value is GV10 ≥ 0.6.

(5) Using slope and elevation to further extract forest, and the threshold values are DEM ≥1,300 m and slope ≥15.

(6) Using slope and autumn EMA of GV and DA to further divide the orchard and forest, threshold values are GV10 ≥ 0.125 and DA ≤ 0.5, and slope ≤ 25.

(7) The grassland and cultivated land are divided by spring and summer EMA of GV, and the threshold values are GV8 ≥ 0.45 and GV4 ≥ 0.25.

2.5 Driving force of orchard expansion

2.5.1 Evaluation indicator system

While factors like soil condition, topography and climate have a more localized impact on orchard expansion, regional development has a more external socioeconomic impact. Thus, the influencing factors were selected at the pixel and regional scale and from natural and social dimensions. The evaluation indicator system was shown in Table 3. Due to the favorable climate condition for apple planting, climate change is not considered as the chief factor for local orchard expansion. Therefore, at the pixel scale, the factors were selected from three perspectives of terrain, soil and field conditions, including elevation, slope, soil organic matter, pH, surrounding land types. In terms of social factors, we considered the transportation convenience, the distance to the urban areas and the water sources, which influence the human management processes of irrigation, harvesting and fertilization. At the regional scale, four impact factors, namely average elevation, average elevation standard deviation, average slope and average slope standard deviation, were selected to reflect the differences in natural conditions of each township. For social factors, the population and agricultural output were selected to reflect the differences in socio-economic development of each township. In summary, a total of 17 impact factors were selected to explore their driving effects on orchard expansion.

2.5.2 Random forest regression

Random forest is a machine learning algorithm proposed by Breiman. (2001), which can be used to conduct classification and regression (Tang et al., 2022). It consists of many independent decision trees, and each decision tree is constructed as a random sampling process (Song et al., 2022). The regression algorithm obtains the average of the regression results of all decision trees as the final model output. Then, the random forest regression can quantitatively assess the feature importance and partial dependence based on the existing data through modeling (Liu et al., 2021). The feature importance of each factor is an important parameter, which

reflects their relative contributions to the dependent variable. Partial dependence can explain how one or two factors influence on the identified outcome of a machine learning model (Friedman, 2001). In this study, the feature importance is to investigate different influencing factors to orchard expansion. And the partial dependence is to explain the marginal effect of each influencing factor on the orchard expansion (Heilmayer and Brey, 2003). They are both especially suited for the investigation of the forces that influenced agricultural land evolution, particularly when delving into its complex, non-linear driving processes. Therefore, a random forest regression was chosen to explore the mechanisms behind the orchard expansion dynamics in the Loess Plateau. The analysis was performed using the "sklearn" package in Python.

2.6 Orchard planting suitability evaluation

Orchard location decisions and policy suggestions can benefit from a better understanding of the spatial connection between orchard planting suitability and orchard expansion. The suitability evaluation of orchard planting is divided into two parts, including land suitability and climate suitability. According to the soil environment and geographical conditions of the Loess Plateau, 13 indicators were selected considering land conditions, soil conditions, fertility status and climate conditions. Soil is the fundamental factor, providing moisture and nutrients for the growth of orchard cultivated. Topographical conditions are closed related to the growth of apple tree. The difference in elevation, slope and aspect can have a great impact on sunlight exposure, irrigation and soil erosion. Climatic conditions are also key factors, which strongly determine the phenological period of orchard planting. Due to data limitations and a lack of meteorological data at the orchard scale, we use meteorological station data for spatial interpolation, and use the natural breakpoint method for suitability classification. The specific evaluation indicators system was shown in Table 4. Based on the actual state of orchard planting in the study area, the opinions of local experts, and related literature and standards, the indicators affecting the growth of apple tree were divided into three classes: highly suitable, moderately suitable and generally suitable. The weight of the index is determined by the analytic hierarchy process in this study. According to the evaluation indicators system, all raster data were resampled and projected into the CGS_WGS 1984. Finally, we used the spatial analysis tool in ArcGIS 10.2 to predict the distribution of orchard planting suitability. The equation is as follows:

$$S = \sum_{i=0}^{n} w_i \times u_i$$

where S is the comprehensive score of the orchard planting suitability evaluation; w_i is the weight of the i factor; u_i is the score of the i factor; and n is the number of evaluation factors.
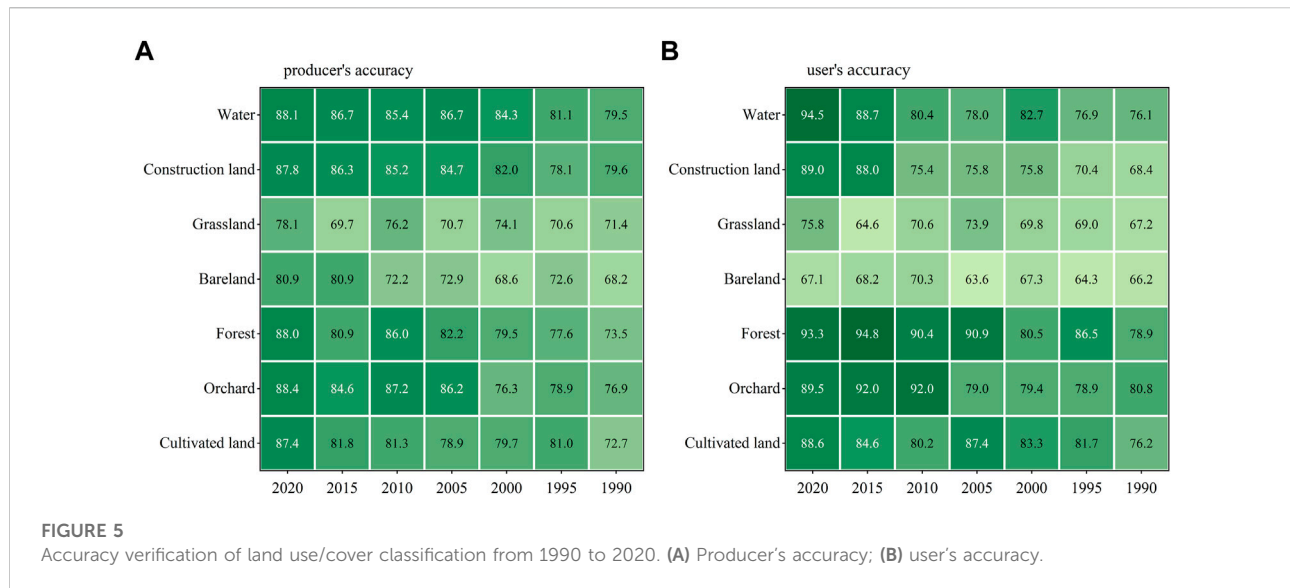
TABLE 3 Descriptive statistics of the selected Evaluation indicator of orchard expansion.

Scale	Dimension	Indicators	Average	STD	Max	Min
Pixel	Topography	Elevation (m)	1,126.1	85.7	1,240.8	929.1
		Slope (°)	7.0	1.8	10.7	5.0
		Aspect	171.7	15.8	198.0	145.6
	Soil	Soil organic matter (g/kg)	13.0	1.3	16.2	10.7
		PH	8.1	0.1	8.3	8.0
		Soil type	—	—	—	—
	Neighborhood information	Proportion of adjacent forest (%)	66.1	10.5	86.4	48.9
		Proportion of adjacent farmland (%)	4.7	2.2	10.7	1.8
	Reachability	Distance from water (m)	6,189.1	3,977.8	17,198.5	907.1
		Distance from main roads (m)	2,062.9	1.699.5	9,044.5	723.6
		Distance from urban area (m)	19,502.0	11,397.1	47,254.7	4350.1
Regional	Topography	Average elevation (m)	1,095.1	121.3	1345.6	882.0
		Standard deviation of elevation (m)	96.0	23.3	158.5	71.8
		Average slope (°)	13.2	2.3	19.4	9.5
		Standard deviation of slope °	7.6	1.0	10.8	6.2
	Socio-economic	Total Population	18,616.1	14,882.9	68,395.0	3758.0
		Agricultural output (Billion)	1.2	0.6	3.4	0.3

TABLE 4 The evaluation indicators system for orchard planting suitability.

Dimension	Indicators	Highly suitable (0.8, 1]	Moderately suitable (0.6, 0.8]	Generally suitable (0, 0.6]
Land suitability	Elevation (m)	900~1,200	<900	>1,200
	Slope (°)	3~10	<3∪(10, 15]	>15
	Aspect	135~225	[90, 135]∪(225, 270]	[0, 90]∪(270, 360]
	PH	6~8	—	<6∪>8
	Soil type	[loessal soil, alluvial soil]	dark loessal soil	—
	Soil organic matter (g/kg)	>20	10~20	<10
	Nitrogen (mg/kg)	>0.9	0.6~0.9	<0.6
	Phosphorus (mg/kg)	>20	8~20	<8
	Potassium (mg/kg)	>200	120~200	<120
Climate suitability	Temperature (°C)	8.5~12.5	[5, 8.5)∪(12.5, 16]	<5∪>16
	Precipitation (mm)	500~800	800~1,500	<500∪>1,500
	Minimum summer temperature (°C)	13–18	[11, 13)∪(18, 25]	<11∪>25

A producer's accuracy

	2020	2015	2010	2005	2000	1995	1990
Water	88.1	86.7	85.4	86.7	84.3	81.1	79.5
Construction land	87.8	86.3	85.2	84.7	82.0	78.1	79.6
Grassland	78.1	69.7	76.2	70.7	74.1	70.6	71.4
Bareland	80.9	80.9	72.2	72.9	68.6	72.6	68.2
Forest	88.0	80.9	86.0	82.2	79.5	77.6	73.5
Orchard	88.4	84.6	87.2	86.2	76.3	78.9	76.9
Cultivated land	87.4	81.8	81.3	78.9	79.7	81.0	72.7

B user's accuracy

	2020	2015	2010	2005	2000	1995	1990
Water	94.5	88.7	80.4	78.0	82.7	76.9	76.1
Construction land	89.0	88.0	75.4	75.8	75.8	70.4	68.4
Grassland	75.8	64.6	70.6	73.9	69.8	69.0	67.2
Bareland	67.1	68.2	70.3	63.6	67.3	64.3	66.2
Forest	93.3	94.8	90.4	90.9	80.5	86.5	78.9
Orchard	89.5	92.0	92.0	79.0	79.4	78.9	80.8
Cultivated land	88.6	84.6	80.2	87.4	83.3	81.7	76.2

FIGURE 5
Accuracy verification of land use/cover classification from 1990 to 2020. **(A)** Producer's accuracy; **(B)** user's accuracy.

3 Results

3.1 Land use/cover classification and accuracy verification

Our findings indicated the LSMA model combined with the decision tree had great applicability for multi-year land use classification, especially for identifying orchard expansion. The land use/cover classification results of the study area from 1990 to 2020 were presented in Figure 6. The accuracy verification (Figure 5) was carried out based on independent random sampling validations obtained from the field survey. The overall accuracy of classification results from 1990 to 2020 ranged from 74.2% to 86.0%, with kappa coefficients ranging from 0.70 to 0.84. The producer's accuracy and user's accuracy of orchards, cultivated land, water bodies and forest were above 72%.

As shown in Figure 6, the study area has more than 80% of forest throughout all time periods. While the cultivated land dropped year over year and the size of construction land and water did not vary significantly. On the contrary, the orchard and grassland showed an overall increasing trend. In particular, the orchard experienced the greatest increase from 1990 to 2020, tripling in the total area from 1990 to 2020. Orchards now account for 7.94% of the total area, up from 2.94% in 1990. For the three counties, Luochuan, Fuxian, and Huangling, their orchard areas are currently 4.5, 2.1, and 1.8 times larger than they were in 1990, while Luochuan County experiencing the most growth. Comparatively speaking, the cultivated land shrunk by a total of 27,610 ha, representing 71% cultivated land of the study area in 2020. In Luochuan and Fuxian counties, the amount of cultivated land declined by 12,098 and 15,315 ha, with 49% and 46% decreased rate, respectively. The amount of bare land, water
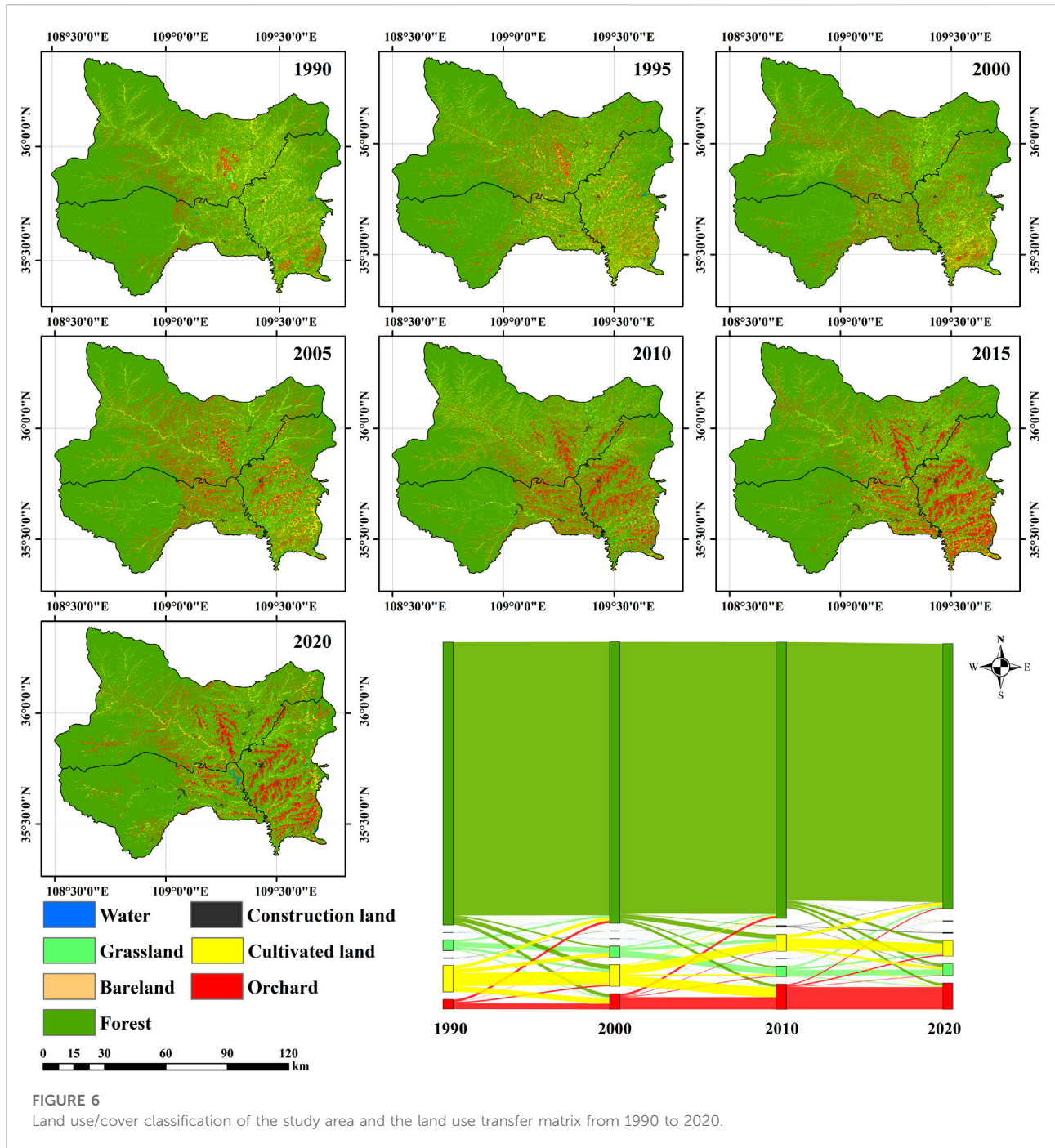
bodies, and construction land has increased year by year while the amount of grassland has fluctuated downward.

According to the analysis of land use transfer matrix, the cultivated land, which has been converted to orchards with a total of 32,309 ha, accounts for 49.2% of total orchards. This is followed by forest, with a total of 11,833 ha converted to orchards in the study area, contributing 18% of the total orchards. With 16,254 ha of cultivated land turned into orchards, Fuxian converted the most cultivated land, contributing 67.1% to its current orchard area. Huangling and Luochuan converted 1,452 and 14,603 ha of arable land into orchards over the three decades, contributing 17.2% and 58.9%, respectively. The fastest land use change occurred between 1990 and 2000, when 81,116 ha were primarily transferred from arable land to orchards. The rate of change in land use from 2000 to 2010 is comparable to that from 1990 to 2000. From 2010 to 2020, the rate of land use change slowed down, with just 1,694 ha of arable land being converted to orchards.

3.2 Orchard expansion characteristics

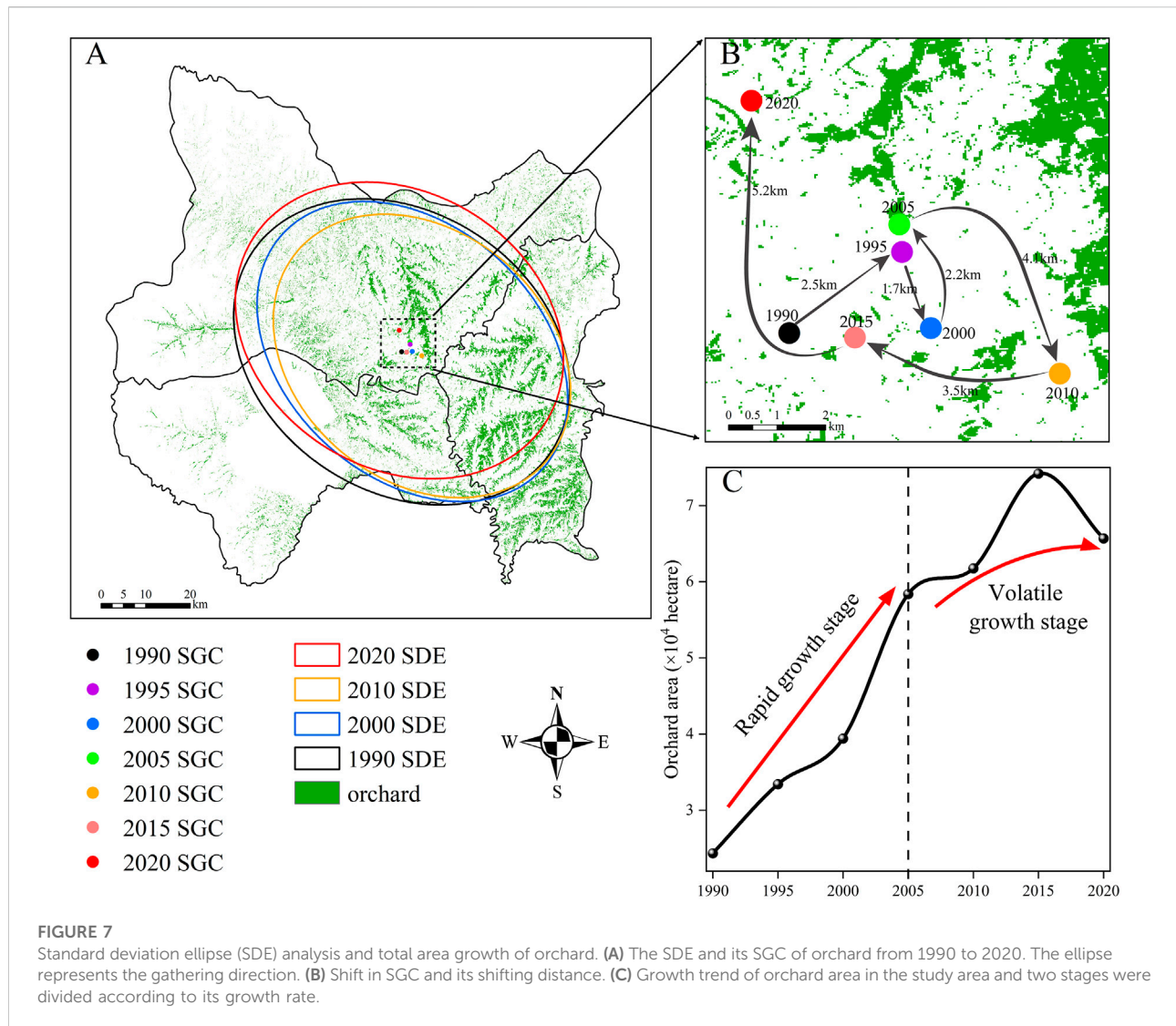### 3.2.1 Spatiotemporal characteristics

We found that the orchard area increased rapidly in the first fifteen years but increased slowly in the last fifteen years during the study period (Figure 7C). The whole study period can be divided into two stages: 1) rapid growth stage: from 1990 to 2005. Due to the encouragement of the local government in the process of reform and opening up, the apple planting area in the study area increased from 24,338 ha to 51,379 ha, an increase of about 111%. The orchard area of Fuxian, Huangling and Luochuan increased by 13,298, 3,151 and 10,592 ha, with growth rate up to 158%, 38% and 101%, respectively; 2) volatile growth stage: as the

FIGURE 6
Land use/cover classification of the study area and the land use transfer matrix from 1990 to 2020.

areas suitable for apple cultivation were gradually occupied, the expansion gradually slowed down. From 2005 to 2020, apple orchard increased by only 14,267 ha. In 2020, the total area of orchards in the study area was 67,646 ha, of which the orchard area in Fuxian, Huangling and Luochuan were 18,140, 6,735 and 29,296 ha, respectively. The orchard planting area of Luochuan has always been larger than that of Fuxian and Huangling, but its growth rate has gradually decreased. The expansion rate of

orchards in Huangling has gradually exceeded that of Luochuan. The planting area of each county has increased by more than 300%.

Due to the local policies and climate change, orchard expanded continuously between 1990 and 2020, initially to the northeast, then to the southeast, and finally to the northwest. In the horizontal direction, the spatial geometry center (SGC) of the orchard shows the trend of eastward expansion before 2010 and
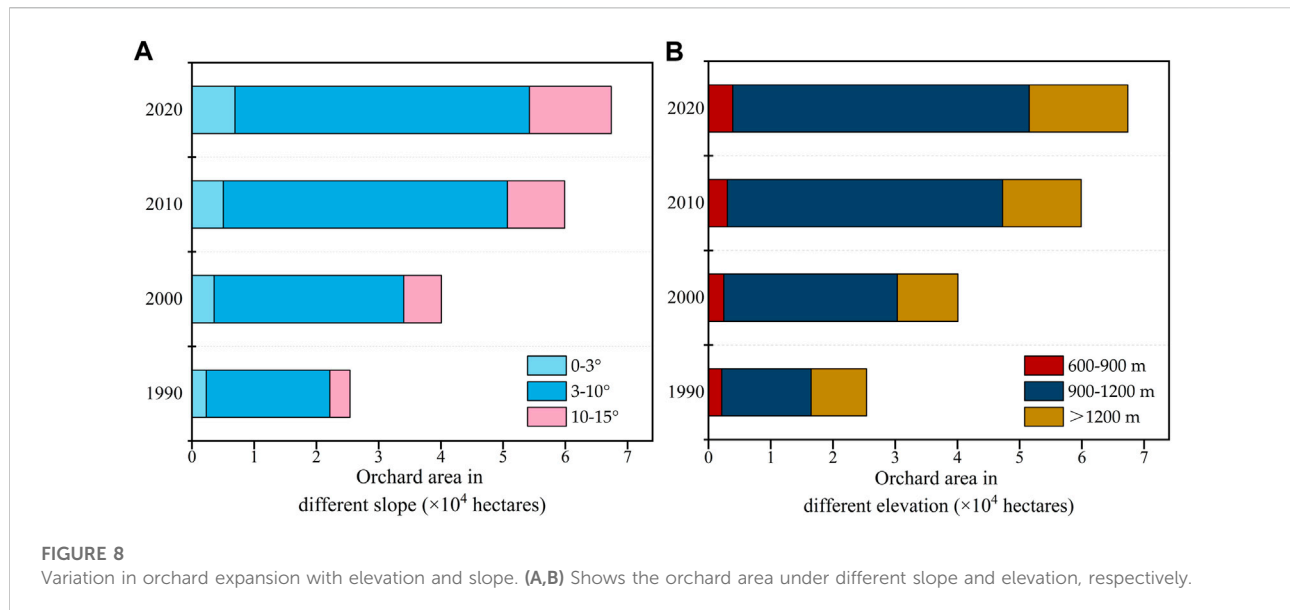
FIGURE 7
Standard deviation ellipse (SDE) analysis and total area growth of orchard. **(A)** The SDE and its SGC of orchard from 1990 to 2020. The ellipse represents the gathering direction. **(B)** Shift in SGC and its shifting distance. **(C)** Growth trend of orchard area in the study area and two stages were divided according to its growth rate.

then shows the trend of westward expansion. In the vertical direction, the SGC of the orchard generally shows a trend of expansion to the north (Figure 7B), with a shifting distance up to 5.2 km from 2015 to 2020.

3.2.2 Physical geographical feature

Orchard expansion has been increasingly occurring in areas at elevations of 600–900 m and above 1,200 m. We divided the elevation into three intervals of 600–900 m, 900–1,200 m and above 1,200 m based on the natural breakpoint method. The characteristics of orchard expansion at these three elevation intervals were studied in 1990, 2000, 2010 and 2020, respectively. Overall, from 1990 to 2020, orchard expansion mainly occurred in the area at 900–1,200 m, with an expansion area of 33,273 ha and growth rate up to 213% (Figure 8A). As a result of favorable soil, light and rainfall, as well as convenient proximity to transit hubs, apple orchards have

primarily settled in a region between 900 and 1,200 m in altitude. Higher quality land resources at lower elevations are mostly used by residents for food production and housing, hence the orchard planting area around 600–900 m elevation was the smallest in the area. Besides, we found that the expansion of orchard was most obvious in the area at 900–1,200 m elevation between 2000 and 2010. However, the area at 900–1,200 m, which is the most suitable area for orchard planting, was gradually filled with orchards.

Slope is one of the most important factors to consider in apple planting. According to the natural-geographical conditions of the study area, we divided the slope into three intervals of 0–3°, 3–10°, and 10–15°, respectively. It is clear from Figure 8B that the orchards in the study area are mainly distributed in the area with slopes of 3–10°. Analyzing the characteristics of orchard expansion in each period, we found that the orchards in the study area expanded significantly to the area with slopes of

FIGURE 8
Variation in orchard expansion with elevation and slope. **(A,B)** Shows the orchard area under different slope and elevation, respectively.

3–10°from 1990 to 2010, and the expansion rate decreased after 2010. In contrast, the trend is reversed for slopes of 0–3° and 10–15°.

3.2.3 Landscape pattern analysis

In this study, we used landscape metrics to analyze the landscape pattern of orchard planting area. As a whole and for different land use/cover types, we selected 6 and 4 landscape metrics, respectively. The ecological significance of each landscape metrics is shown in Supplementary Table S1.

The number of patches (NP) and patch density (PD) in Fuxian, Luochuan, and Huangling counties increased between 1990 and 2020, with 17.9% and 17.2% growth rate, respectively (Supplementary Table S2). The ratio of the area of the largest patch to the total landscape area (LPI) decreased by about 5%. The landscape shape index (LSI) increased by 3%. The spread ability index (CONTAG) decreased from 62.31 to 60.28. The Shannon Diversity Index (SHDI) increased by 5%. The above results show that from 1990 to 2020, with the expansion of orchards, the land use type of the study area changed greatly. In addition, human activities have increased the landscape's complexity and fragmentation, while also having an impact on the biological environment.

From Figure 9, it can be seen that the number of patches (NP) of orchards continued to increase by about 63.8% during 1990–2020, while the patch density (PD) continued to decrease. Meanwhile, these two indices of cropland had completely opposite trends to those of orchards. The shape indices (LSI) of all categories decreased during the study period, indicating that the landscape shapes of all categories are becoming simpler. The separateness index (SPLIT) of grassland, forest land, and arable land increased during the

study period, while the separateness index of orchard decreased. Based on the above results, it can be concluded that between 1990 and 2020, the orchards were characterized by larger planting areas, more aggregated patches, less fragmentation, and simpler shapes. However, a decline in arable land and a more dispersed pattern of grassland, forest, and cropland have resulted from the expansion of orchards.

3.2.4 Orchard expansion varied with planting suitability

Orchards can be planted across the entirety study area, as shown by the planting suitability assessment, with the exception of a few spots at elevations above 1,200 m. The planting suitability evaluation of land suitability evaluation indicators were shown in Supplementary Figure S1. The highly land suitable areas for orchard planting in the study area are mainly concentrated in the central and southwestern parts. The total highly suitable area is 335,371 ha, accounting for about 39.1% of the study area, while the moderately suitable and generally suitable account for 35.1% and 25.8%, respectively. The suitability zones in the north western part of the study area are more dispersed, mainly due to the large variation in soil texture types. The overall climatic suitability of the study area is excellent, with highly suitable regions accounting for over 80%. This is due to the fact that the average annual rainfall and average temperature are in the optimum range for orchard cultivation, thus having a positive effect on apple cultivation. Orchards were primarily dispersed in regions with high suitability, with 84.5% of the total orchard area in 2020. Over the last three decades, orchards expanded mainly into highly suitable regions, covering 37,839 ha, followed by 3,347 ha in moderately suitable regions and 2,006 ha in generally suitable regions.
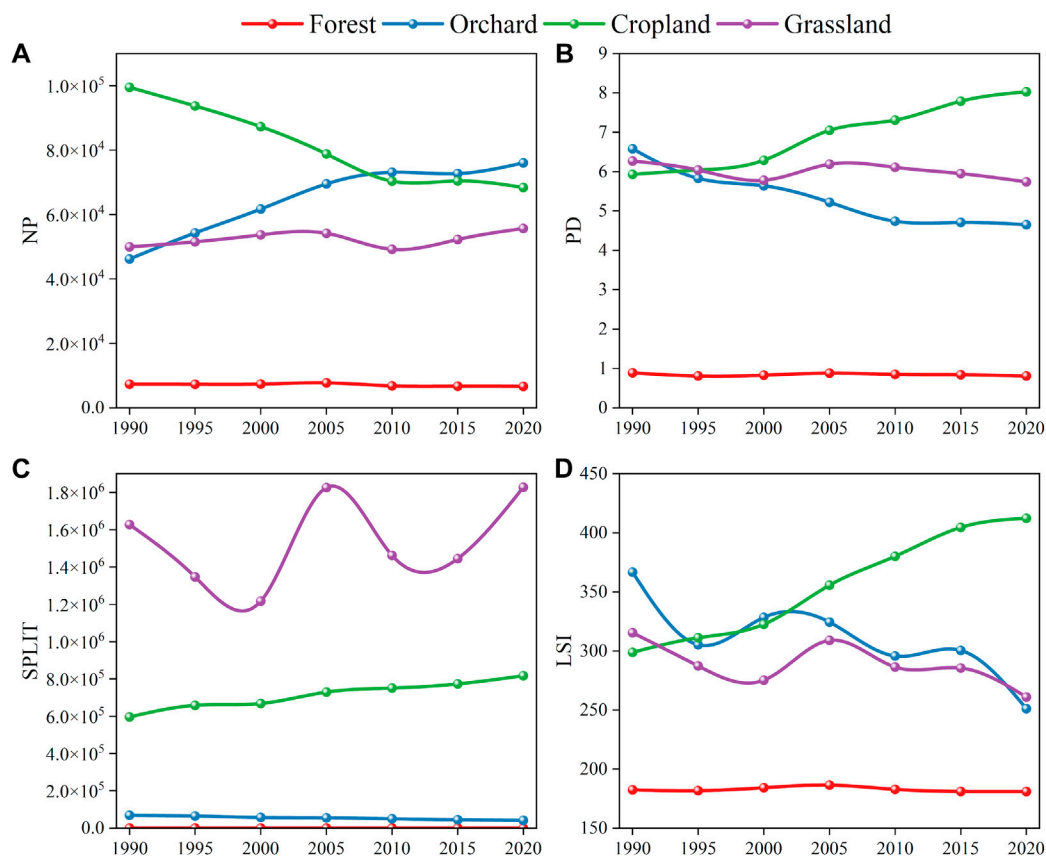
FIGURE 9
Evolution landscape metrics of different land use. Four landscape metrics were selected, including NP, PD, SPLIT and LSI. **(A–D)** Shows the evolution results of four land use types, including forest, orchard, cropland and grassland.

For the three counties, Figure 10 shows the dynamics of orchard distribution in different suitability zones during the period 1990–2020. In the high suitability zone, Luochuan increased its orchard area by 16,431 ha, surpassing Fuxian and Huangling. Although the overall plantation suitability of the study area is good, orchard expansion is nevertheless concentrated in the most suitable regions, implying their inherent strong connection. In recent years, orchard expansion has gradually slowed down and the highly suitable areas of orchards are already at capacity.

3.3 Driving forces analysis

3.3.1 Feature importance

Among all the 17 factors, the slope, proportion of adjacent farmland, agricultural output, aspect, distance from main road and standard deviation of elevation made a great contribution to orchard expansion, with the sum of their feature importance up to 70% (Figure 11A). In particular, slope, aspect and standard

deviation of elevation are all topographic factors and their total feature importance is up to 50%. These findings demonstrated that topographical factors are the primary motivator for orchard expansion, of which slope is the most notable attribute due to its highest feature importance. The feature importance of soil pH, distance from urban area, soil texture type, distance from water source and the proportion of adjacent forest are less than 5%. For the remaining factors, we detected few contributions to orchard expansion.

3.3.2 Partial dependence

Figure 11B presents the quantitative relationship between the orchard expansion and the first six influencing factors. When the slope is larger than 10°, the orchard expansion significantly slowed down, implying the orchard expansion is mainly concentrated in the area with slope below 10°. Due to the policy of arable land protection, the magnitude of orchard expansion gradually decreases with the increase of the proportion of adjacent farmland. At present, the orchard expansion mainly occurs in those regions where neighboring
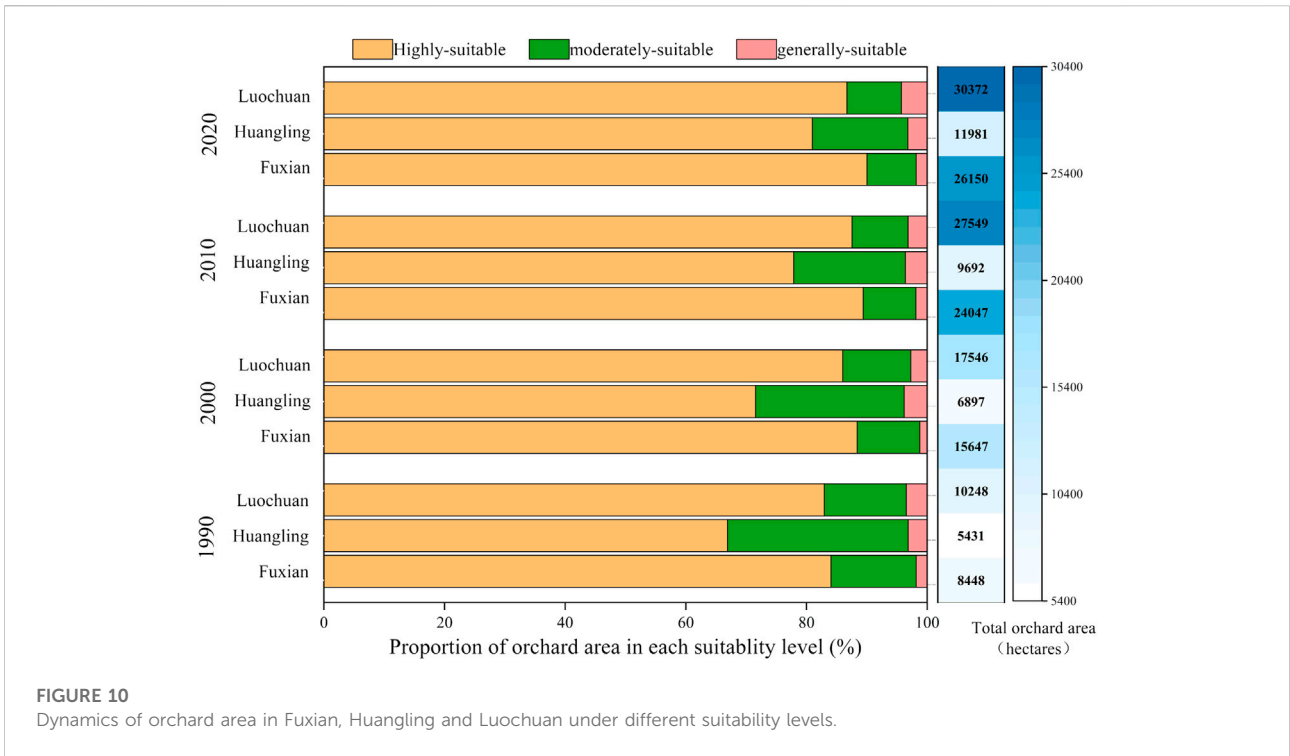
FIGURE 10
Dynamics of orchard area in Fuxian, Huangling and Luochuan under different suitability levels.
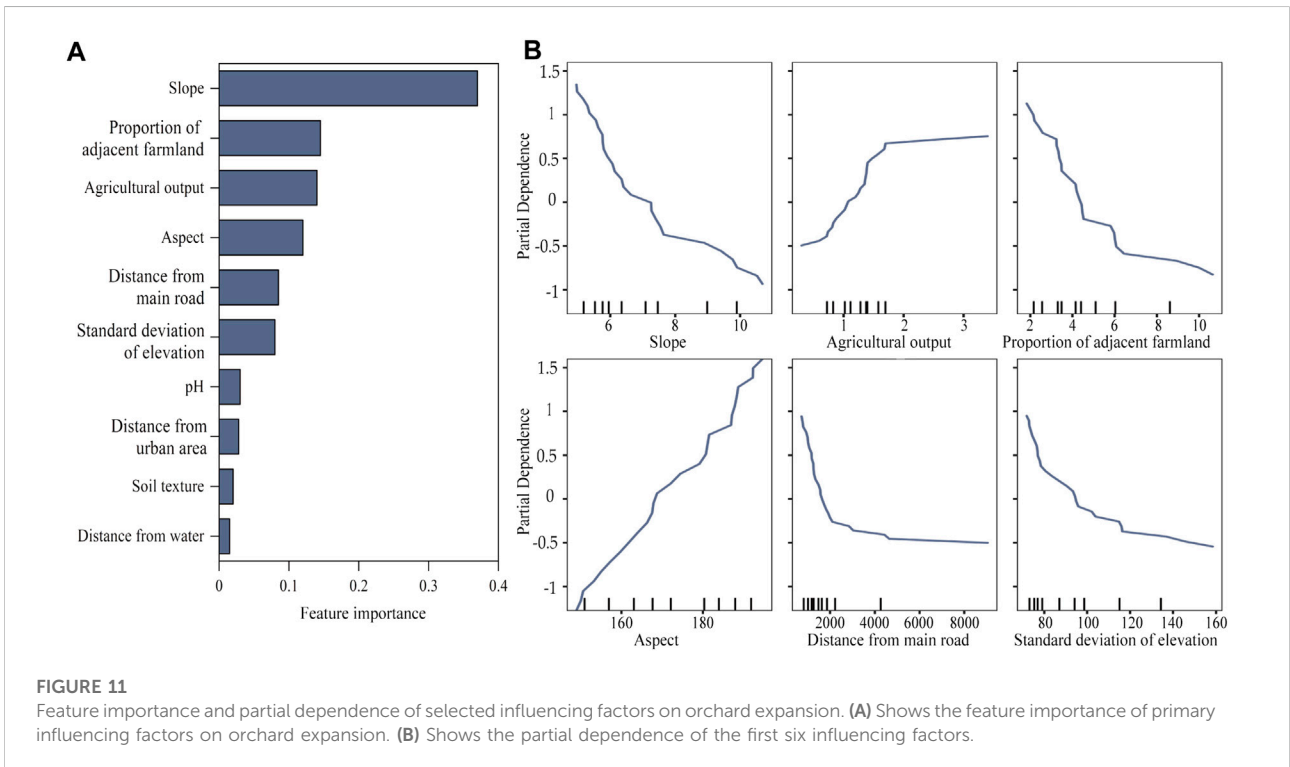
FIGURE 11
Feature importance and partial dependence of selected influencing factors on orchard expansion. **(A)** Shows the feature importance of primary influencing factors on orchard expansion. **(B)** Shows the partial dependence of the first six influencing factors.

cultivated land is below 6%. The relationship between the orchard expansion and aspect tends to be a fixed straight line, but there is no clear expansion pattern. With the increase of the

distance from the main road, we observed a downward and then flat trend. In other words, the larger the distance from the road, the less likely the orchard will expand under a threshold of 2 km.

When the distance exceeds 2 km, the orchard area tends to stabilize and transportation will no longer influence orchard expansion under such circumstances. On the contrary, an upward and then flat trend was observed with the increase of the local agricultural output. When the value is between 0 and 160 million-yuan, orchard area will increase rapidly due to the development of social economic development. The orchard expansion changes in two stages with the increase of the standard deviation of elevation of the township. Before the standard deviation of elevation of the township grows to 120 m, the orchard expansion decreases rapidly. After reaching 120 m, the expansion decreases at a slower rate. This is mainly due to the fact that the township with relatively large elevation standard deviation distributed many mountainous areas with large slope, which are not suitable for orchard planting.

4 Discussion

4.1 Orchard expansion and suitability evaluation

Assessing the suitability of orchard plantation can provide valuable instruction for the sustainable expansion of orchards (Pimenta et al., 2021; Arab and Ahamed, 2022). At present, with the rapid development of society, along with land use conflicts, the implementation of the scientific assessment of planting suitability not only helps to improve the efficiency of land use but also enables a rational land allocation. As people's diets change, the demand for fruit is increasing. In order to promote economic development, the local government has adopted different policies to motivate fruit farmers.

In this study, the suitability evaluation results confirm that over 80% regions were highly suitable. It is unsurprisingly to find that the majority of orchards (84.5%) were located in highly suitable areas in 2020. Our findings demonstrate a robust positive relationship between farmers' land-use decisions and local environment condition. Land suitability has been proved to be the crucial factor driving the expansion of local orchards, especially slope. Thus, regional policy guidelines are supposed to focus on improving land suitability. Besides, more social factors, such as infrastructure development and regional incentive strategies, need to be taken into account. Those measures are of tremendous help in places where slope is relatively higher.

In addition, areas with highly suitable orchards are facing the problem of aging orchards, which need to be renewed (Hou et al., 2021). Identifying aging orchards and improving orchard yields are other issues that need to be further addressed. Blind orchard expansion is not the only solution to enhancing economic performance, but the renewal of aging orchards in highly suitable areas deserves more attention. Not only will this raise farmers' incomes and orchard yields, but it will also help rationalize the use of land resources and strike a balance between economic development and ecological conservation.

4.2 Policy recommendations for orchard expansion

The orchard expansion in LP is hugely affected by topographical circumstances. Cultivating apples on the suitable slope will guarantee their yield and quality. Based on the analysis of suitability evaluation, the most suitable slope for apple plantation in the region is 3–10°. To boost the profitability of apple production, local authorities should encourage farmers to grow apples in optimal locations and increase access to agricultural expertise.

In addition, our findings revealed the distance of the orchard from water sources, major roads and urban areas were also key factors influencing the orchard expansion. The cultivation, harvest, and transportation of apples are profoundly influenced by the transportation accessibility. In order to reduce the apples losses during long-distance transit, the government is obligated to improve public infrastructure development in various locations. Besides transportation can be centralized, and apple purchasing markets should be established within an appropriate distance from orchard locations. At the same time, the government should organize the purchase in the fields or in households during the harvest season.

Soil conditions are another essential consideration for apple growth. With the large expansion of orchards, the biological environment of soil was greatly impacted by the excessive intake of pesticides and fertilizers. Emphasis on the application of organic fertilizers can promote the circular ecological agriculture. The government should formulate policy standard for pesticides control and apply scientific fertilization in conjunction with tree growth. This can be a potential external incentive factors driving the orchard expansion. However, such policy related impact factors were not included in this study. In the future, relevant policy projects, poverty alleviation funds and other associated policies should be considered, which can provide more valuable insights for orchard planting in the future.

5 Conclusion

In this study, the land use/cover classification of three typical orchard planting counties on the Loess Plateau from 1990 to 2020 was mapped based on the combination of the LSMA model and the decision tree method. According to the standard deviation ellipse analysis, landscape metrics, physical

geographic features and planting suitability assessment, we analyzed the spatiotemporal dynamics of the orchard expansion over the past three decades. From the perspective of environment and socioeconomic, we then developed an evaluation indicator system of potential determinants on orchard expansion. The random forest regression was carried out to quantify the feature importance and partial dependence of those factors. Furthermore, we investigated the evaluation of orchard planting suitability in order to put forward favorable policy suggestions. Our study aims at providing empirical references for the sustainable and synergistic development of agricultural land and economic boom in the ecological fragile region.

The results demonstrate that the orchard has expanded rapidly over the past 30 years, especially between 1990 and 2005. The orchards continued to spread out towards the northwest, and their spatial geometry center migrated from the southeast to the north central area, with decreased fragmentation. In the last 30 years, orchards mainly expanded to highly suitable areas, which totally reached up to 37,839 ha, with a growth rate up to 197%. The natural conditions served as the chief factor to orchard expansion, among which slope contributed the most. Our results revealed the most suitable slope for orchard planting in the study area is 3–10. Therefore, for areas with more hilly and mountainous terrain, gentler slope should be preferred for orchard planting. At the same time, the transportation convenience and the policy support for agriculture also provide a "non-negligible" reference basis for future orchard planting.

Compared with previous studies, this study focused on the ecologically fragile areas of the Loess Plateau from the view of natural geographic characteristics, landscape pattern and orchard planting suitability. Our study provided novel approach for identifying cash crop expansion in ecologically fragile areas. Besides, this study explored the driving factors of orchard expansion from multiple scales by applying machine learning regression, which was innovative compared with previous studies. However, policy related impact factors were not included in this study. In the future, relevant policy projects, poverty alleviation funds and other associated policies should be considered, which can provide more valuable insights for orchard planting in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization ZL; Data curation, ZL, QH, and XG; Formal analysis, ZL, QH, XG, and SW; Funding acquisition, ZL and FL; Methodology, ZL, QH, XG, SW, and QW; Software, QH and XG; Supervision, ZL and FL; Validation, YQ and WZ; Writing—original draft, ZL, QH, XG, SW, and QW; Writing—review and editing, ZL, QH, XG, SW, QW, YQ, and WZ. All authors have read and agreed to the published version of the manuscript.

Funding

Acknowledgments

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1097236/full#supplementary-material

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