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Achieving sustainable crop management: A holistic approach to crop competitiveness assessment and structure optimization with dual natural-social environmental impacts

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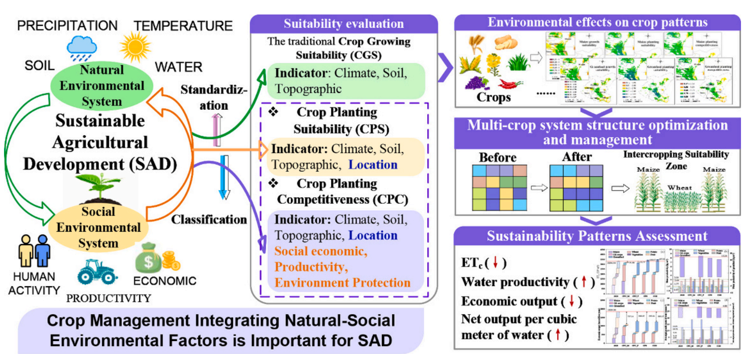
HIGHLIGHTS

- Human activities and social environment have not received sufficient attention for their impacts on agricultural patterns.
- Proposed a novel approach to crop suitability assessment and structural optimization integrating natural and social systems.
- Optimized patterns under the CPC scenario reduced water consumption and improved water productivity and net water benefits.
- Findings emphasize the importance of considering human activities and social environmental drivers in agricultural planning.
- Crop management based on dual environmental assessments provides a practical solution to promote sustainable agriculture.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Improving the spatial pattern of agricultural systems has become a promising approach for enhancing agricultural productivity and sustainability. However, previous studies have often focused on the influence of natural factors on crop distribution, ignoring factors such as human activities, socio-economic level and ecological environment.
OBJECTIVES: This study aims to investigate the influence of natural factors and social environmental drivers on the optimal pattern of multiple crops and evaluate the potential of optimal patterns to enhance agricultural productivity and sustainability.
METHODS: Here, we present a multi-criteria approach integrating natural and social environment system factors and set up three assessment scenarios: crop growth suitability (CGS), crop planting suitability (CPS), and crop planting competitiveness (CPC). Applying this approach to the Shiyang River basin in China as a case study, we

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assessed the suitability and competitiveness of single crops. To maximize agriculture competitiveness, we optimized the structure of the multi-crop system, and a method was proposed to identify highly suitable intercropping areas using crop competitiveness conflicts. Regional crop water consumption, water productivity, and economic benefits were calculated to analyze the potential for agricultural intensification under different optimization patterns.

RESULTS AND CONCLUSIONS: We found that the weights of four categories factors of location, socio-economic conditions, productivity, and environment protection accounted for 26.9%, 7.5%, 13.7%, and 4.5%, respectively, and the weight of social environmental influence indicators had accounted for about 43.5%, which cannot be ignored. The distribution area above moderate suitability (L2) in the CPS and CPC scenarios was about 7.92% - 30.03% and 6.14% - 26.4% higher than the CGS scenario, respectively. Social environmental factors are important to consider in assessing the suitability of crops. From the spatial structure, three optimization patterns all suggested increasing the planting proportion of wheat and potato in the future. The optimization patterns in CPC scenario could reduce total crop water demand by 91.86 to 175.77 million cubic meters compared with 2020 while showing great potential to improve crop water productivity and net output per cubic meter of water. Furthermore, we offered recommendations for the layouts of common intercropping systems in Northwest China based on the proposed method for identifying high suitability zones.

SIGNIFICANCE: This study emphasizes the importance of considering multiple environments to accurately assess crop suitability and achieve sustainable agricultural. The results could provide useful insights for managing and optimizing diverse planting systems, addressing growing concerns surrounding food and water security in resource-constrained regions.

1. Introduction

Achieving the sustainable development goal of “zero hunger” by 2030 remains a challenge, with growing global food demand, climate change, and urbanization posing significant threats to food security and agricultural sustainability (Tilman et al., 2002; Di Lorenzo et al., 2020; Hanjra and Qureshi, 2010; Fanzo et al., 2018). The COVID-19 pandemic has further exposed dangerous flaws in the food system, with 820 million people going hungry in 2021, despite the fact that we are producing more food than ever before. To address these challenges, it is crucial to transform existing agricultural systems in order to enhance sustainability and competitiveness (Egli et al., 2020), particularly in response to environmental and climate change crises.

Understanding the suitability of crops to their environments and how agriculture adapts to the environment is crucial for ensuring food security (Beddow and Pardey, 2015; Costinot et al., 2016; Gil et al., 2019). Climate change has a direct and significant impact on crop growth and yield (Almaraz et al., 2008), particularly temperature (Lobell et al., 2011; Challinor et al., 2014; Moore et al., 2017) and precipitation (Rhebergena et al., 2016). Moreover, the distribution of some crops and the suitable areas for cultivation are also expected to change as the climate changes (Izrael et al., 2007; Hannah et al., 2013; Moriondo et al., 2013; Fujimori et al., 2019). According to He et al. (2019), global warming drove the advantaged summer maize growing area in China to shift northeast, while the center of gravity for unsuitable areas moved southeast. A key strategy for agricultural adaptation to environmental change is crop switching, where matching crops to the most suitable cultivated land can optimize agricultural production (Dessai et al., 2007). It has been predicted that under RCP 8.5, total agricultural profits in the United States will decline by 31% in 2070, half of which could be avoided if cultivated land is reallocated to restructure planting systems (Rising and Devineni, 2020). Richter et al. (2023) also demonstrated that crop mix optimization could result in additional water savings of 21–59% in the study area. Therefore, exploring the potential of changing crops and their spatial distribution in reducing agricultural water use and improving economic efficiency is necessary for sustainable agricultural development.

Crop distribution is the result of complex interactions between topography, soils, climate and management practices (Kravchenko et al., 2005; Juhos et al., 2019; Akbari et al., 2019; Lombardo et al., 2020). Accurate assessment of crop suitability for growth in multiple environments can provide a scientific basis for cropland layout. Previous research extensively explored the impacts of climate change, soil, and topography on crop suitability. (Ye et al., 2015; He and Zhou, 2016; Feng et al., 2021). However, the spatial arrangement of crops not only depends on natural factors, but also shaped by human activities (Yang et al., 2022). The effects of human activities, social environment and ecological environment have not been given sufficient attention in previous studies. Additionally, studies often focus on single crops without considering the competition and trade-offs of multiple crop layout on resources.

Various methods have been used to assess crop suitability, including climate classification methods (Araya et al., 2010; Lai et al., 2011), correlation analysis (Wu et al., 2022), and multi-criteria decision-making (MCDM) (Tuan et al., 2011; Nguyen et al., 2015; Zolekar and Bhagat, 2015), among others. With the development of 3S technologies (RS, GIS, and GPS), the integration of GIS and Analytical Hierarchy Process (AHP) has become common (Akıncı et al., 2013; Yalew et al., 2016; Jayanthi et al., 2020). Nevertheless, the AHP is prone to individual subjectivity. Methods that integrate subjective and objective weighting, such as the AHP combined with the entropy weight method (EWM) (Tao et al., 2017) and the object element method (Seyedmohammadi et al., 2019), overcoming the limitation have gained widespread acceptance. It is less frequently involved in the assessment of crop suitability of complex agricultural systems.

Sudden crop diversification or planting pattern changes carried out without assessing environmental uncertainties can pose a significant risk. This is particularly important in the north-west of China, where irrigated agriculture is predominantly practiced, with fragile ecosystems and wasted resources. Taking this typical region as an example, this study aims to integrate various resources such as land, climate, and social environment, to explore regional highly competitiveness, resource-environment coordinated and sustainable agricultural patterns. Our objectives are 1) Integrate factors of crop habitat, location, social economic conditions, productivity and environment protection into the natural-social environmental factor pool of planting systems, and to construct evaluation systems for crop growth suitability, planting suitability and planting competitiveness scenarios. 2) Construct multi-level evaluation models based on multi-criteria decision-making methods, and to elucidate the effects and contributions of location, social economic conditions, productivity and environment protection drivers on crop suitability. 3) Optimize the multi-crop planting pattern and assess the potential of different crop switching patterns in improving agricultural production and resource use efficiency. This study can provide valuable recommendations for intercropping system design and sustainable management of planting systems based on highly competitiveness crop patterns.

2. Materials and methods

2.1. Study region

The study region, Shiyang River basin is located in in Gansu Province, Northwest China, between 100°57 ′ E - 104°12′ E and 37° 02 ′ N - 39°17 ′ N, as shown in Fig. 1. The total area of the basin is about 40,852 km^2. The cultivated land area is 5445.2 km^2. The region has continental temperate arid climates. The average annual precipitation is about 164.4 mm and the average temperature is about 7.8 °C. The main soil types in this region are sandy and loamy. The soil nutrient content is low, and the average soil organic matter (SOM) content is around 2%. Underground water depths in Minqin are within 30 m from the surface, in Jinchang and Wuwei is within 50 m, and in some local areas within 50–100 m. The region has abundant light resources, with an annual sunshine duration of up to 3028 h. Due to the scarcity of precipitation, agricultural water mainly comes from the river or groundwater. The total water consumption in the region in 2020 was 2.423 billion cubic meters, of which the water consumption for agricultural irrigation accounted for 77.9%. The special climatic conditions combined with the unreasonable utilization of water resources make the current water shortage in the basin very serious, with a total water shortage of 520 million cubic meters in 2020. The deteriorating ecological environment has severely restricted the agriculture and ecology sustainable development of the Shiyang River Basin.

2.2. Data source and processing

The meteorological data (precipitation and effective accumulated temperature (EAT) used for this study came from the China Meteorological Data Network (1989–2020) (http://data.cma.cn/). The spatial grid data was interpolated by ArcGIS tool, and the spatial resolution was 200 × 200 m. Soil data originated from the national Qinghai Tibet Plateau data center (http://data.tpdc.ac.cn/zh-hans/). Spatial geographic location data, such as highway, rail, river, lake, and settlement, are from the national catalog service for geographic information (https://www.webmap.cn/main.do?method=index). The data on forbidden underground water areas and mechanical wells are from the water resources department of the Gansu Province. Using Euclidean distance analysis, the distance from rivers, lakes, roads, wells, etc. was determined, and the spatial resolution was uniformly resampled to 200 × 200 m. The data on social economy and agricultural productivity come from the statistical yearbook and survey yearbook of the study region. The data on ecological function protection area (EPA), cultivated land production potential (PP), and ecological service value were collected from the resource and environment data center of the Chinese Academy of Sciences (https://www.resdc.cn/Default.aspx). Based on ENVI and GEE platforms, the planting structure in 2020 was extracted from Landsat 8 remote sensing images by using a decision tree and random forest, with a spatial resolution of 30 × 30 m and resampling to 200 × 200 m. The crop price and unit output were obtained through the

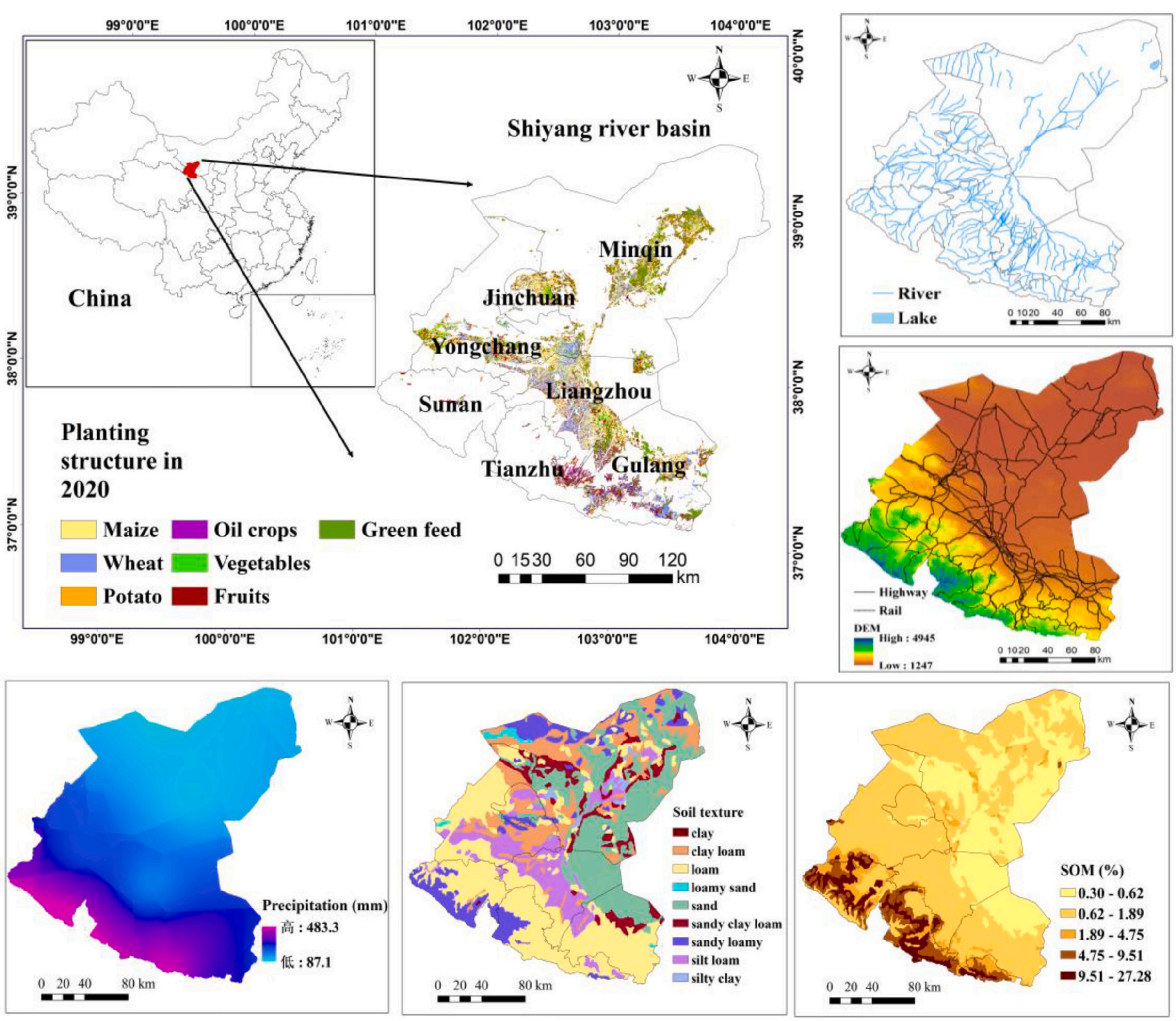

Fig. 1. Geographical location, agriculture, climate, and basic soil conditions of the study region.

Gansu Rural Yearbook and the national agricultural product price survey Yearbook. Excel, Origin, MATLAB, ArcGIS, and other software were used for data calculation and mapping.

2.3. Model construction

2.3.1. Construction of evaluation indicator system

This study screened the influencing factors from the natural environment and social environment systems to construct the evaluation indicator systems, and three assessment scenarios, crop growth suitability (CGS), crop planting suitability (CPS), and crop planting competitiveness (CPC), were designed. The factors were categorized in terms of the roles and impacts they produced. The CGS scenario is based on a set of natural environmental indicators, collectively referred to here as crop habitat factors, including climate (precipitation, effective accumulated temperature (EAT ≥0 °C)), soil properties (texture, organic matter (SOM), bulk density (BD), pH, total nitrogen (TN), total phosphorus (TP), and total potassium (TK)), as well as topographic features (DEM, slope, and aspect). For the CPS assessment scenario, six location indicators were added based on the CGS evaluation indicator system. Among them, two indicators, distance to river (To_river), distance to lake (To_lake) were selected from the natural environment system, and four indicators, distance to highway (To_highway), distance to railway (To_rail), distance to settlement (To_settlement), and distance to motor-pumped well (MPW) were selected from the social environment system. To more comprehensively explore the impact of social environmental drivers on the assessment results, the CPC scenario has three additional dimensional social environmental factors: socio-economic conditions (including number of employees in agriculture (NEA), cultivated land subsidies (CLS), degree of continuity of cultivated land (DCCL), and total value of agricultural production(TVAP)), agricultural productivity level (including operation level of agricultural machinery (OPAM), potential productivity (PP), and effective irrigation area ratio (EIAR)), and environment protection (including ecological protection area (EPA), ecological service value including water supply services (WSS), clean environment services (CES), and climate regulation services (CRS), and groundwater forbidden area (CFA)), compared to the CPS scenario. “DCCL” refers to the degree of connectivity between different plots, with higher connectivity indicating smaller distance between them. “CLS” refers to the economic subsidies provided by the government to farmers who have contracted cultivated land and protected the quality of cultivated land. “EIAR” is the ratio of the cultivated land area that can be irrigated normally to the actual cultivated land area. The evaluation unit is 200 m × 200 m grid.

2.3.2. Standardization and classification of evaluation indicators

In order to eliminate the influence of the scale between indicators, the evaluation indicators were standardized in the study, so that the suitability of each indicator was taken in the range of 0.1–1. When 1 is taken, it indicates that the indicator had the highest suitability. Qualitative indicators such as soil texture, pH, EPA, and CFA are classified with reference to classification criteria developed by the Second National Soil Census. Score 0.1–1 were separated into 6 grades, as shown in Table 1.

This study used fuzzy mathematical principles to quantify the quantitative evaluation indicators. The affiliation function has been divided into discrete and S-type (including positive-type and reverse-type) (Hermann, 1967; Page et al., 1997). The positive indicators (such as SOM, TN, TP, TK, etc.), within the constraint range, the larger the better. The reverse type indicators (e.g., To_river, To_lake, and MPW, etc) should be as small as possible within the constraints. The standardized affiliation functions are shown in Formula 1, 2, respectively. Discrete indicators (e.g., pH, SD, etc.) determined the affiliation value according to the classification standard.

$$f(x)=\begin{cases}0.1 & x<a_1\\ 0.1+0.9^{*}\dfrac{x-a_1}{a_2-a_1} & a_1<x\le a_2\\ 1.0 & x>a_2\end{cases} \tag{1}$$

$$f(x)=\begin{cases}1.0 & x\le a_1\\ 0.1+0.9^{*}\dfrac{a_2-x}{a_2-a_1} & a_1<x\le a_2\\ 0.1 & x>a_2\end{cases} \tag{2}$$

Where, *f(x)* is the standard value of the suitability of each evaluation indicator, a_1 and a_2 are the critical values of the suitability range of the evaluation indicator.

2.3.3. Determination of evaluation indicator weight

As shown in Fig. 2, a three-level structural model with objective level (I), criteria level (II), and indicator level (III) was built based on the Analytical Hierarchy Process (AHP). The three objectives of crop growth suitability, crop planting suitability and crop planting competitiveness in the objective level were uniformly represented by the competitiveness assessment for agricultural development (ADCA), and different scenarios selected the required criterion level and indicator level in the structural model. The ratio method was used to compare the relative importance of each element in the criteria level. The weighted contribution of each indicator in the indicator level to the upper-level indicators (II) was calculated using improved AHP and the entropy weight method (EWM), respectively. The combined weights were obtained based on the minimum information entropy. Then, according to the hierarchical structure and the weight of II, the combined weight of each indicator to the higher objective level was calculated. Finally, the comprehensive ranking of the contribution of all indicators to the highest level was determined.

(1) Weight calculation based on improved AHP

This study used the improved AHP proposed by Zhang et al. (2006) for weight calculation. This method uses the sample standard deviation $S(i)$ ($i = 1 \sim n$) of each evaluation indicator to reflect the degree of influence of each evaluation indicator on the comprehensive evaluation and is used to construct the judgment matrix $D_{n\times n}$. The calculation of the internal element values of the judgment matrix is shown in Formulas 3 and 4.

$$b_{ij}=\begin{cases}\dfrac{S(i)-S(j)}{S_{\max}-S_{\min}}(b_m-1)+1 & S(i)\ge S(j)\\ 1\Big/\left[\dfrac{S(j)-S(i)}{S_{\max}-S_{\min}}(b_m-1)+1\right] & S(i)<S(j)\end{cases} \tag{3}$$

$$b_m=min\{9, int[S_{\max}/S_{\min}+0.5]\} \tag{4}$$

Where S_{max} and S_{min} represent the maximum and minimum standard deviation of the sample of each evaluation indicator, respectively. b_m is the relative importance parameter of each indicator.

The characteristic vector corresponding to the maximum characteristic root of matrix $D_{n\times n}$ is the importance ranking of each evaluation factor. First, the product of each row element is calculated in Formula 5.

$$M_i=\prod\nolimits_{j=1}^{n} b_{ij} \tag{5}$$

Where M_i is the product of the elements of each row.

Calculate the n-power root $\overline{W}_i$ of $M_i$and normalize the vector $\overline{W} = (\overline{W_1}\ \ \overline{W_2}\ \ \overline{W_3}\cdots\overline{W_n})^T$, then the weight of indicator *i* is:

Table 1
Suitability ratings and scores for indicators.

Classification	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Standard score	1	0.9	0.7–0.8	0.5–0.6	0.3	0.1

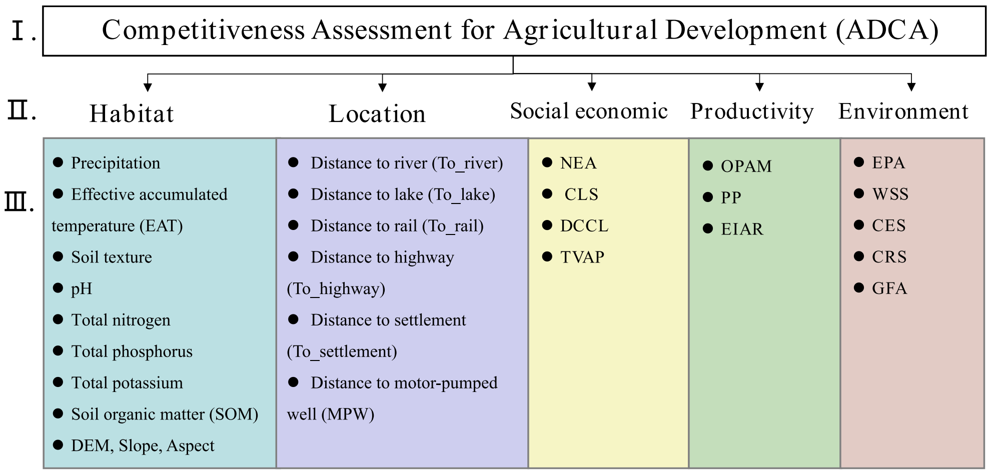

Fig. 2. Structure of multi-level evaluation model and system of evaluation indicators.
Note: In the figure, I, II and III represent the objective level, the criteria level and the indicator level, respectively. The meaning of the abbreviations “NEA, CLS, DCCL, TVAP, OPAM, PP, EIAR, EPA, WSS, CES, CRS, GFA” is given in the description found in Section 2.3.1.

$$W_{1i} = \overline{W_i} \Big/ \left(\sum_{i=1}^{n} \overline{W_i} \right) \tag{6}$$

Then, $W = (W_1, W_2, W_3, \cdots, W_n)^T$ is the required eigenvector.

Theoretically, the judgment matrix $D_{n\times n}$ needs to satisfy unity, reciprocity, and consistency (Zai and Zhang, 1994). The consistency check formula for matrices is:

$$CR = CI/RI \tag{7}$$

$$CI = (\lambda_{\max} - n)/(n-1) \tag{8}$$

$$\lambda_{\max} = \sum\nolimits_{i=1}^{n} \frac{(B\omega)_i}{nW_{1i}} \tag{9}$$

Where CI is the consistency indicator and RI is the average random consistency indicator, λ_{max} is the largest characteristic root and CR is the proportion of consistency. When $CR < 0.10$, the judgment matrix is considered to satisfy the consistency test. $(B\omega)_i$ is the ith element of the vector, which is the product of the judgment matrix $D_{n\times n}$ and the weight matrix. The value of RI depends on the order of the matrix. The judgment matrix and the weights of the criterion level elements are shown in Table 2.

(2) Weight calculation based on the EWM

The smaller the entropy value, the greater the dispersion of the indicator, the greater the influence (i.e. weight) of the indicator on the overall evaluation (Liu et al., 2010). In the evaluation problem with m evaluation indicators and n evaluation objects, the entropy of the ith evaluation indicator is defined as:

$$E_i = -ln(n)^{-1} \sum_{j=1}^{n} p_{ij} ln p_{ij} \tag{10}$$

$$p_{ij} = Y_{ij} \Big/ \sum_{j=1}^{n} Y_{ij}, \quad i = 1, 2, \cdots, m, \ \ j = 1, 2, \cdots, n \tag{11}$$

Where$0 \le p_{ij} \le 1$, when$p_{ij} = 0$, $p_{ij} ln p_{ij} = 0$.

p_{ij} is the proportion of the ith indicator and the jth evaluation object to the indicator. Y_{ij} is the evaluation indicator.

After defining the entropies of the ith indicator, the weight of the ith indicator is calculated as follows:

$$W_{2i} = \frac{1 - E_i}{m - \sum_{i=1}^{m} E_i} \tag{12}$$

Where $0 \le W_{2i} \le 1$, $\sum_{i=1}^{m} W_{2i} = 1$.

(3) Calculation of combination weights

The subjective weight W_{1i} and objective weight W_{2i} of the comprehensive indicator should be as close as possible. Therefore, this study calculated the combination weight of indicator level based on the minimum relative information entropy and obtains the calculation formula of combination weight using the Lagrange multiplier method (Woodbury and Ulrych, 1993):

$$\begin{aligned} minf &= \sum_{i=1}^{m} W_{ij}\left(lnW_{ij} - lnW_{1i}\right) + \sum_{i=1}^{m} W_{ij}\left(lnW_{ij} - lnW_{2i}\right) \\ &\sum_{i=1}^{m} W_{ij} = 1, \quad 0 \le W_{ij} \le 1, \quad i = 1, 2, \cdots, m \end{aligned} \tag{13}$$

$$W_{ij} = \frac{(W_{1i}W_{2i})^{0.5}}{\sum_{i=1}^{m} (W_{1i}W_{2i})^{0.5}} \tag{14}$$

The weighting of all indicators to the highest level is:

Table 2
Judgment matrix and weights of each element of the criterion level.

Criteria level	Habitat	Location	Social economic	Productivity	Environment	Weight	CI	CR
Habitat	1	3	5	4	7	0.475	0.0744	0.0664
Location	1/3	1	3	4	5	0.269		
Social economic	1/5	1/3	1	1/3	2	0.075		
Productivity	1/4	1/4	3	1	4	0.137		
Environment	1/7	1/5	1/2	1/4	1	0.45		

$$W_i = W_k W_{ij} \quad k = 1, 2, \cdots, 5 \tag{15}$$

Where W_k is the weight of each indicator in the criteria level. W_{ij} is the combination weight of indicator level.

2.3.4. Crop pattern optimization and intercropping high suitability zone identification

The suitability (competitiveness) spatial scores of different crops were obtained based on the assessment model and classified into four grades: high, moderate, marginal and unsuitability (or uncompetitive) (Table 3), with the higher the score, the higher the grade. The crop types with the highest suitability (competitiveness) scores at the same raster point were screened using the raster calculation tool in ArcGIS. Based on three assessment scenarios, three optimal regional multi-crop planting patterns were obtained, including the growth suitability pattern, the planting suitability pattern, and the planting competitiveness pattern. The existing planting pattern in the region (2020 for example) was divided into stable and potentially suitable zones using ArcGIS. The area where the existing planting structure coincides with the optimal planting pattern is defined as the stable suitability area, and the rest is the potential suitability area.

When multiple crops are spatially optimized, two or more crops with very close suitability (competitiveness) scores may appear in the computational cell, which we consider as areas with competitiveness conflicts between crops. These areas are considered highly suitable for intercropping. Four common intercrops in the study area: maize-wheat, maize-potato, maize-vegetables and wheat-vegetables were selected for analysis in this study. Taking the C1-C2 intercropping system as an example, crop C1 distribution zones were extracted from the planting competitiveness pattern map. In these areas, grid cells with C2 crop competitiveness scores higher than the moderate suitability level (L2) are screened, and these grid cells are the high suitability areas of C1-C2 intercropping.

2.4. Assessment of productivity and economic benefits of agriculture

The annual reference evapotranspiration of different crops was calculated based on the Penman-Monteith formula recommended by FAO-56 using the daily data of regional meteorological stations from 1989 to 2020. The water demand of different crops was calculated based on the crop coefficient method and the spatial distribution was obtained using the ArcGIS spatial interpolation tool. We located different crops, calculated their grid number N_{ki} and corresponding water demand ET_{cki} in ArcGIS, and obtained their total water demand ET_{ck}. The total water demand (ET_c) and crop water productivity (WP_k) were calculated using the following formulas:

$$ET_c = \sum ET_{ck} \quad k = 1, 2, 3, 4, 5, 6, 7 \tag{16}$$

$$WP_k = \frac{Y_k}{(ET_{ck})} \tag{17}$$

Where Y is total yield, and k is the crop type.

The economic benefits of different crops are calculated as follows:

$$E_k = y_k \times c_k \times a_k \times 10^{-4} \quad k = 1, 2, 3, 4, 5, 6, 7 \tag{18}$$

$$E = \sum_{k=1}^{7} E_k \tag{19}$$

Where E_k is the economic benefit of the kth crop, ten million yuan. y_k is the unit area yield of the kth crop, t/hm^2. c_k is the market unit price for the kth crop, $yuan/kg$. $a_k$is the planting area of the kth crop, hm^2. E is the total economic agricultural output, ten million yuan.

The net output per cubic meter of water is calculated using the following formula:

$$EW_k = \frac{E_k}{ET_{ck}} \quad k = 1, 2, 3, 4, 5, 6, 7 \tag{20}$$

EW_k is the net output per cubic meter of water of the kth crop, $yuan/m^3$.

3. Results

3.1. Weight contribution of different indicators to the evaluation model

Indicator scores in crop suitability and competitiveness assessments were subject to significant influence from a complex array of natural and social environment factors, which can vary greatly depending on the particular crop in question. As shown in Fig. 3, in the CGS scenario, the EAT, DEM, soil texture, and SD indicators hold higher weight, with their combined scores accounting for 38.9%–47.8% of all factors. DEM holds a high weight in the evaluation results of different crops, especially maize, vegetables, and fruits. This is primarily due to the DEM's simultaneous impact on light, temperature, and air pressure, making it highly correlated with the spatial distribution of crops. For oil and greenfeed crops, EAT and soil texture obtained a higher weight proportion. In contrast, soil texture and SD hold higher weight scores among the indicators for wheat and potato. We attribute this to the scarce precipitation in the study region, where agriculture mainly relies on irrigation and light and heat resources are abundant. Consequently, the soil requirements for wheat and potato are higher, resulting in a higher weighting of soil spatial differences on crop distribution than climate.

Location indicators were incorporated into the CPS scenario, with the weight allocation of all location indicators reaching 30%. Notably, the distance to settlement (To_settlement) ranked among the top five weight indicators for different crops. This finding underscores the significant correlation between crop distribution and the distance from residential areas. In the CPC scenario, the categories of socio-economic, productivity, and environment protection factors hold a weight of 7.5%, 13.7%, and 4.5%, respectively, amounting to a total of 25.7%, which is a result that should not be disregarded. In contrast, crop habitat indicators and location indicators have a higher weight of 47.5% and 26.9%, respectively. While natural environmental factors are typically the key determinants of crop suitability, our assessment results highlight that the indicators of distance to settlement (To_settlement) and distance to railway (To_rail) have high weight. This suggests that agricultural cropping activities are closely linked to social environment factors such as distance and transport accessibility.

Table 3
Suitability and competitiveness rating criteria.

Score	$0.85 \le S \le 1$	$0.60 \le S < 0.85$	$0.40 \le S < 0.60$	$0 \le S < 0.40$
GSR/PSR	High suitability	Moderate suitability	Marginal suitability	Unsuitability
PCR	High competitiveness	Moderate competitiveness	Marginal competitiveness	Uncompetitive
Category	L3	L2	L1	N

Note: GSR, PSR, and PCR are abbreviations for growth suitability rating, planting suitability rating, and planting competitiveness rating, respectively.

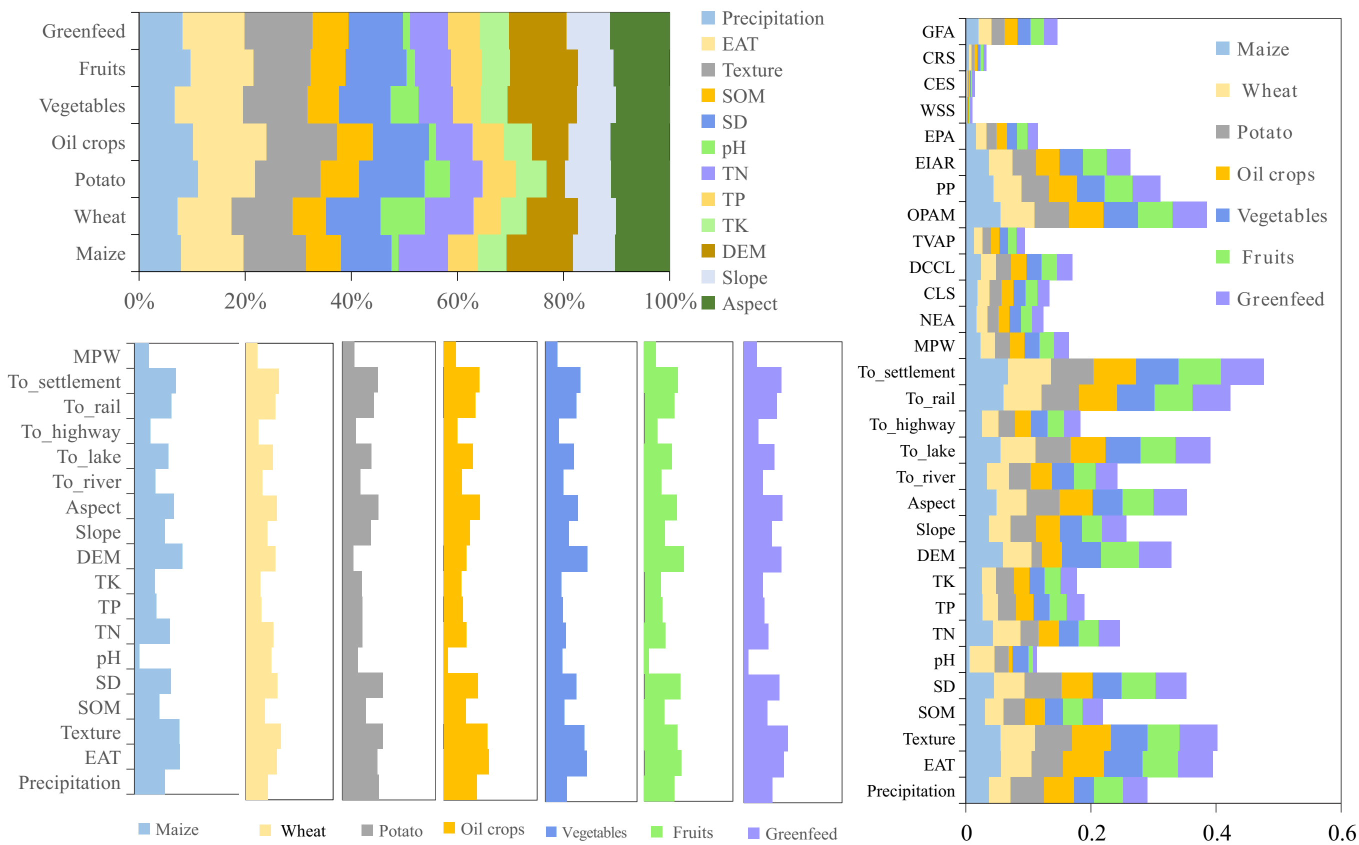

Fig. 3. The contribution of indicators to the weights of different crops in different assessment scenarios.

3.2. Impact of multiple environmental drivers on crop suitability

The distribution of crop suitability considering only natural environmental factors is clearly different from that incorporating both natural and social environmental factors, and the influence of social environmental factors needs to be emphasized. As illustrated in Fig. 4, the distribution of crop suitability across three assessment scenarios exhibited marked variability, with suitability (competitiveness) classes predominantly concentrated within the L1 and L2, which collectively represented over 85% of the overall area. Importantly, the minimal suitability scores for diverse crops in the other two scenarios demonstrated an increase compared to the CGS scenario, with the percentage of crop area in the L1 rating decreased substantially, while the L2 rating witnessed a noticeable increase. In the CPS scenario, the distribution area of crops above the L2 rating increased by 7.92%–30.03% relative to the CGS scenario. This discovery underscores the efficient exploitation of location factors, such as water sources, roads, and settlements, within the existing agricultural spatial pattern. In the CPC scenario, the highest competitiveness values for certain crops, such as maize, wheat, potato, and greenfeed, decreased to varying degrees in comparison to the other two scenarios. Moreover, the crop area with suitability above the L2 rating increased by 6.14%–26.4% relative to the CGS scenario, but exhibited a decline in varying degrees compared to the CPS scenario. The results indicate that crop suitability considering only natural environmental factors may be underestimated compared to considering social environmental factors.

3.3. Multi-crop spatial pattern optimization

Based on the assessment scores for a single crop, the optimal spatial patterns of multiple crops under three scenarios were determined, as illustrated in Fig. 5. In Fig. 5 (a), (b) and (c), the main distribution areas of different crops are relatively consistent, but differently distributed on some fragmented and scattered croplands. Maize, wheat, and greenfeed are more widely distributed in the study region and showed higher competitiveness compared to other crops in all three scenarios. Specifically, maize and greenfeed exhibit a marked competitiveness in the Minqin and Liangzhou areas, while wheat is more suitable for planting in Yongchang, Liangzhou, and Gulang regions. In comparison to the regional crop structure of 2020, the proportion of wheat in the optimization pattern is 10.34%–32.72% higher, while the share of potato is 5.74%–6.19% higher. The findings suggest that wheat and potato cultivation could be considered for expansion in the future. In the CPC assessment scenario, no clear distinction was made between maize and greenfeed due to their similar scores. The planting decision can be determined by the farmer's will. In the CPC scenario, the percentage of stable suitable areas for cultivated land is reduced to 12.87%. This result highlights that there is still significant potential to adjust the crop structure of potentially suitable areas to enhance the efficiency of agricultural resource use. The stable suitable areas in the Fig. 5(c) are mainly located in Wuwei, Jinchang, and Minqin in the central and northern parts of the study area, where the population and cultivated land are more concentrated and agricultural production conditions are more convenient. This finding also reflects the relevance of human activities and social environment to agricultural cultivation activities.

3.4. Assessment of water saving and economic benefits in agriculture

The crop growth suitability pattern and planting suitability pattern showed a considerable increase in the total regional crop water demand (ET_c), whereas the optimization patterns under the CPC scenario substantially reduced the total regional ET_c. Compared to the year 2020, the CPC_F pattern and CPC_M pattern reduced the total ET_c by 175.77 million cubic meters and 91.86 million cubic meters, respectively, while

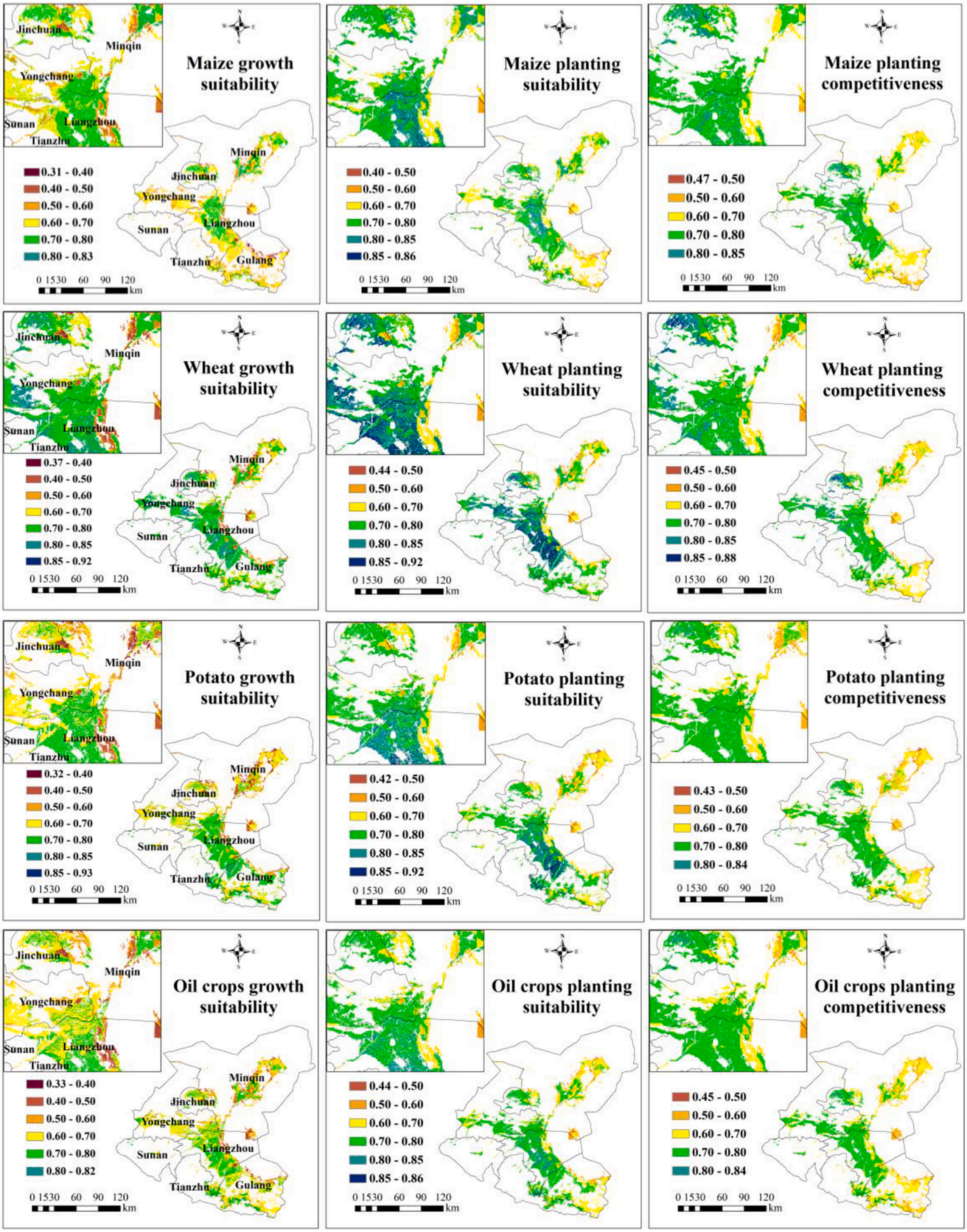

Fig. 4. Spatial distribution of single crop suitability and competitiveness and the percentage of each grading based on three assessment scenarios.
Note: The higher the value in the raster map, the higher the suitability or competitiveness. "N, L1, L2, L3" represent four ratings of suitability (competitiveness): unsuitability (uncompetitive), marginal, moderate, and high, respectively. "Gi (i=0,1,2,3), Si (i=0,1,2,3), Ci (i=0,1,2,3) " represent the area of crops corresponding to different ratings in the three scenarios, respectively.

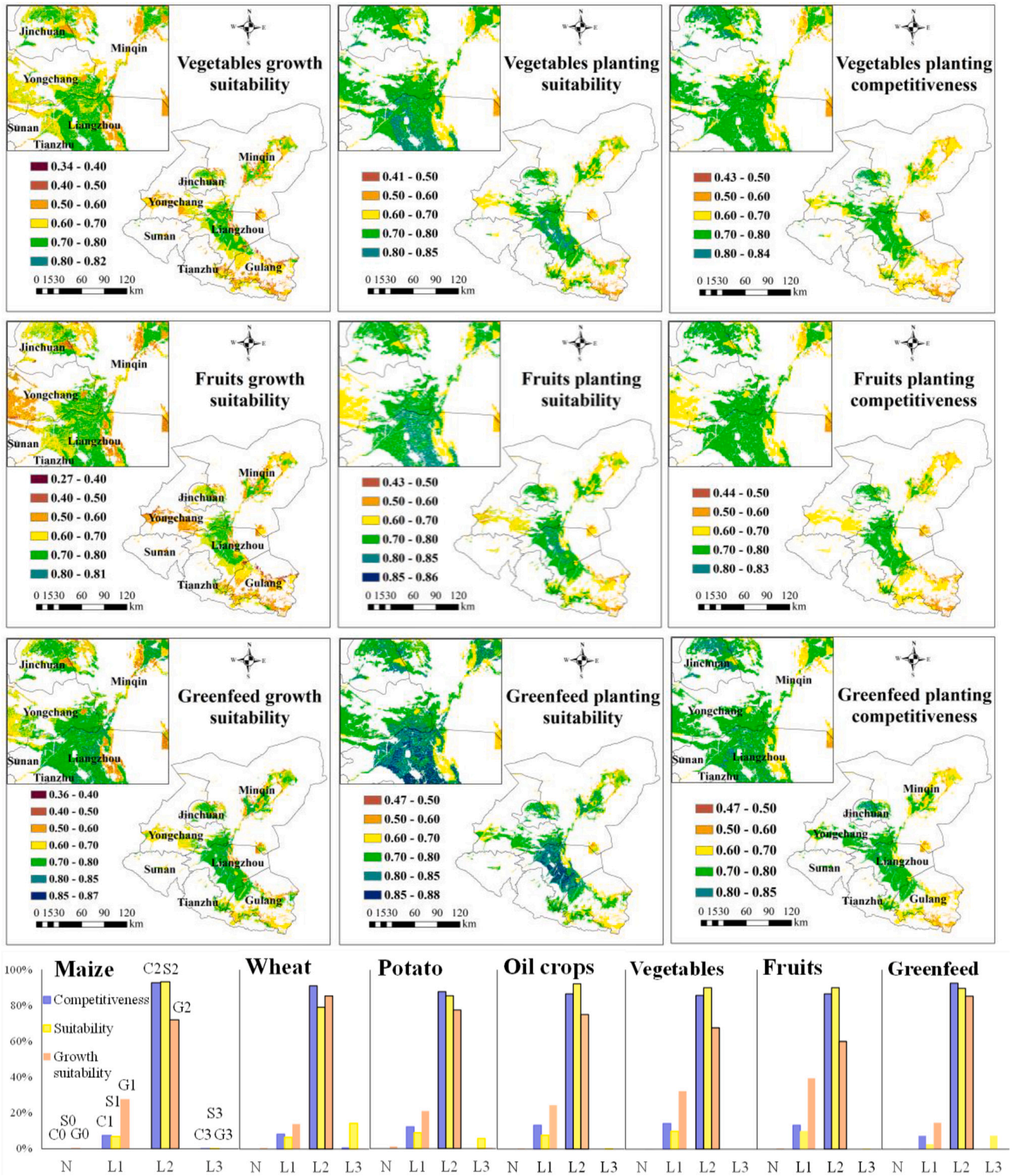

Fig. 4. (*continued*).

the optimization patterns in the CPS and CGS scenarios increased the total ET_c by 130.17 million cubic meters and 187.33 million cubic meters, respectively (Fig. 6(a)). The water productivity (WP) of different crops in both the CPC_M and CPC_F pattern obtained higher values, exceeding the other two scenarios evaluated and the year 2020. However, in the CPS and CGS scenarios, potato, oil crops, and vegetables showed an increase in WP, while others showed a decrease (Fig. 6(b)). We observed disparate outcomes in the analysis of agricultural economic output. The CPC_M resulted in the lowest agricultural economic output value among the four optimization patterns, while the CPC_F pattern yielded the highest agricultural economic output value (Fig. 6(c)). Nevertheless, in either optimization scenario, the agricultural economic output was lower than that of the 2020 planting pattern, indicating that the current crop layout, while potentially generating higher economic gains, increased water consumption and ecological pressures. Additionally, our calculations revealed that the different crops under both CPC_M and CPC_F patterns had a greater net output per cubic meter of water than in 2020 (Fig. 6(d)). Remarkably, potato, oil crops, and

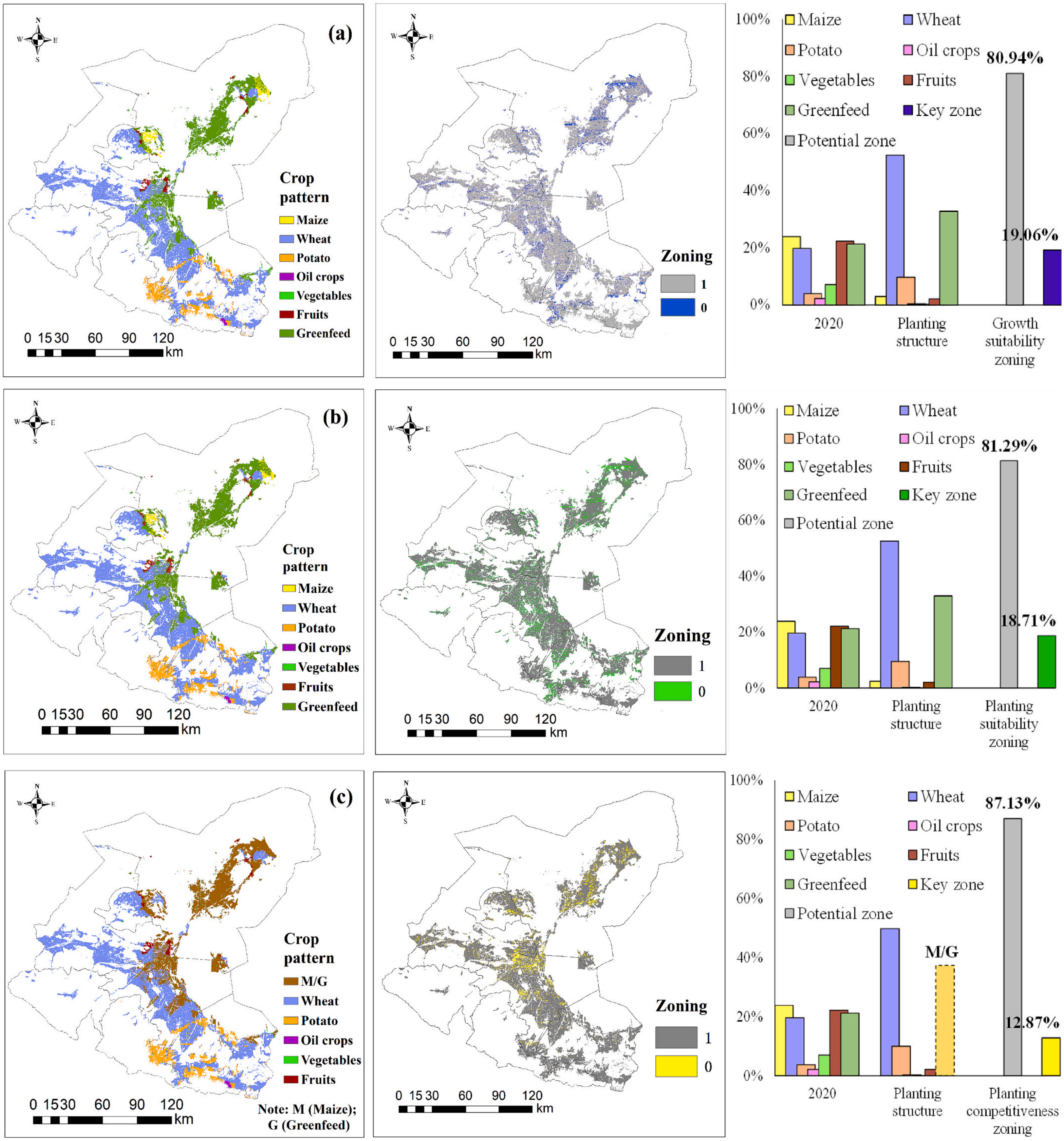

Fig. 5. Optimal patterns of multiple crops under different scenarios: crop growth suitability pattern (a), planting suitability pattern (b), planting competitiveness pattern (c), and the distribution and proportion of stable and potentially suitable areas of cultivated land in different patterns.
Note:"1″ represents potentially suitable areas. "0 "represents stable suitable areas. In the multi-crop optimal pattern map based on planting competitiveness (Fig. 5 (c)), M/G indicates that maize and greenfeed can be planted in the same area on the map.

vegetables showed marked improvements in net output per cubic meter of water, rising by 33.36%, 34.71%, and 48.20%, respectively. It indicates that crop optimization patterns based on the CPC scenario have immense potential to enhance WP and net output per cubic meter of water.

3.5. Intercropping suitable areas and agricultural sustainable management

The study considers the identification of intercropping high suitability zones based on crop competitiveness conflict zones to be a promising approach for improving resource utilization and promoting sustainable agriculture. We obtained highly suitable zones for

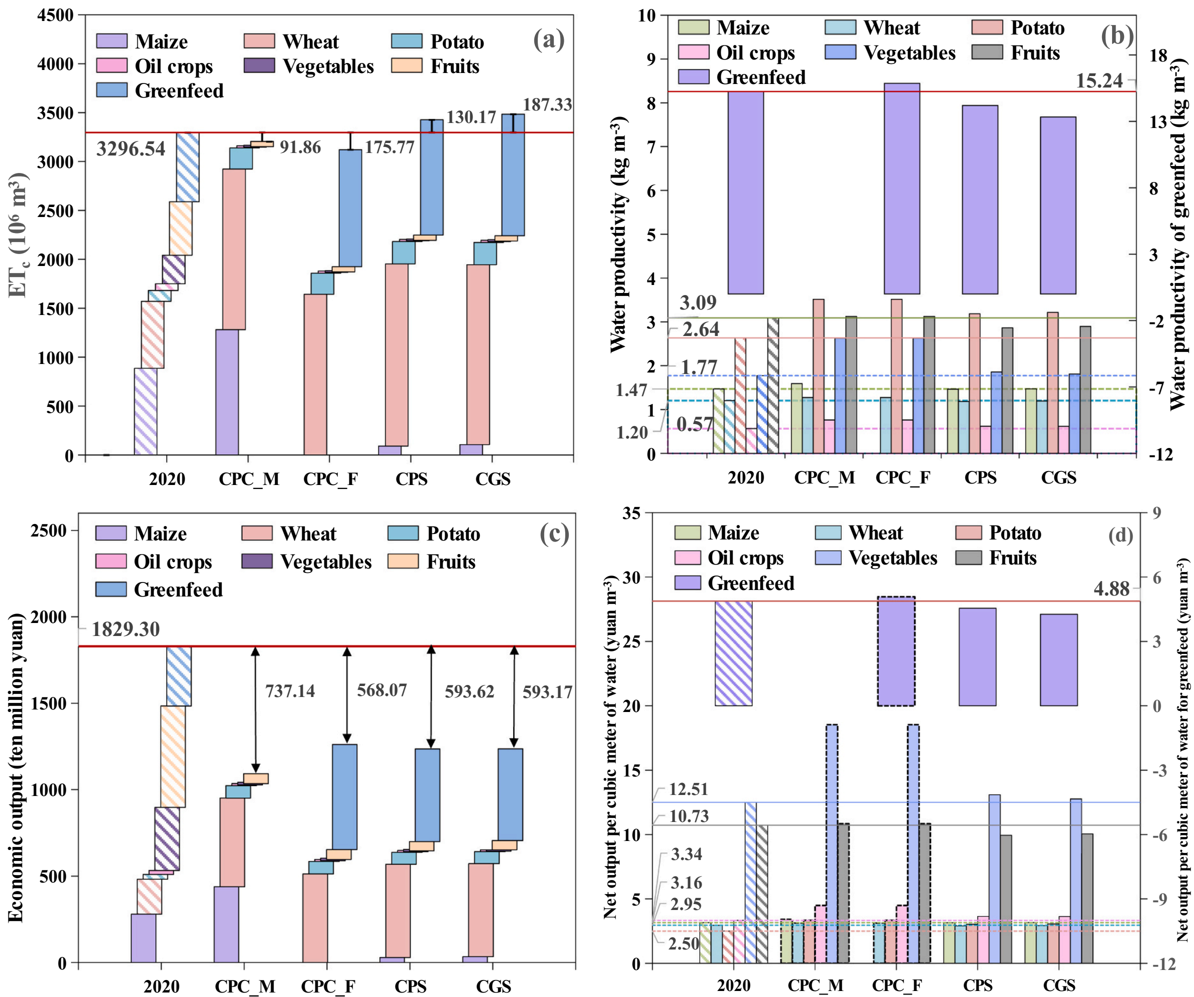

Fig. 6. Comparison of crop water demand and water productivity, agricultural economic output, and net output per cubic meter of water in 2020 with three multi-crop optimization patterns.

Note: In the horizontal headings, 2020 represents under the regional crop structure in 2020, "CPC_M" represents the pattern that all maize-greenfeed conflict areas are planted with maize in the crop planting competitiveness scenario, and "CPC_F" represents the pattern that all maize-greenfeed conflict areas are planted with greenfeed in the crop planting competitiveness scenario. "CPS" represents the crop planting suitability scenario, and "CGS" represents the crop growth suitability scenario.

intercropping with four intercropping types, maize-wheat, maize-potato, maize-vegetables, and wheat-vegetables, as shown in Fig. 7. The high suitability zones for maize-wheat intercropping were widely dispersed, with approximately 80.83% of the basin's cultivated land being conducive to maize-wheat intercropping. About 21.11% of the cultivated land in the basin was deemed appropriate for maize and potato intercropping, with the majority of the high suitability zones located in Minqin, Liangzhou, and Gulang, where sandy and loamy soils are better suited for potato growth. Additionally, approximately 32.94% and 45.77% of the cultivated land was found to be suitable for maize-vegetables and wheat-vegetables intercropping, respectively. The high suitability zones for maize-vegetables intercropping mainly distributed in Minqin and Liangzhou, and those for wheat-vegetables intercropping primarily located in Yongchang, Liangzhou, and Gulang. Attention is required that specific planting decisions need to take full account of the land and market conditions at the time of actual production.

4. Discussion

Our findings support the importance of planting suitability assessments considering not only the natural environment in which crops are grown, but also human activities and social environment factors, which have often not been given sufficient attention in previous studies (Mao et al., 2016; Zhang et al., 2016). Although the crop optimization schemes derived from such studies focusing on natural environmental factors are capable of producing the maximum potential yield, they do not take into account the costs and benefits of growing a specific crop in actual production. For farmers, factors such as transportation proximity and ease of crop management are essential considerations in planting decisions. It is also corroborated in our results. Therefore, it is not necessarily optimal if the costs are high, even though maximum yields can be achieved. Our study found that factors such as EAT, soil texture, DEM, and SD occupied a high weight in the assessment results (Fig. 3), consistent with previous studies emphasizing the importance of factors such as climate, soil texture, and topography in determining crop growth and productivity (Tian et al., 2019; Zhang et al., 2021). The combined weight of the social environment indicators among all indicators is about 43.5% (Fig. 3), which suggests that the influence of social environmental factors is highly important in crop suitability assessment. As evidenced by the clear increase in the distribution area of crops above medium suitability (L2) in both CPS and CPC assessment scenarios compared to the CGS scenario (Fig. 4), this indicates that there is considerable uncertainty in the assessment results considering only natural environmental factors. Interestingly, we observed a slightly

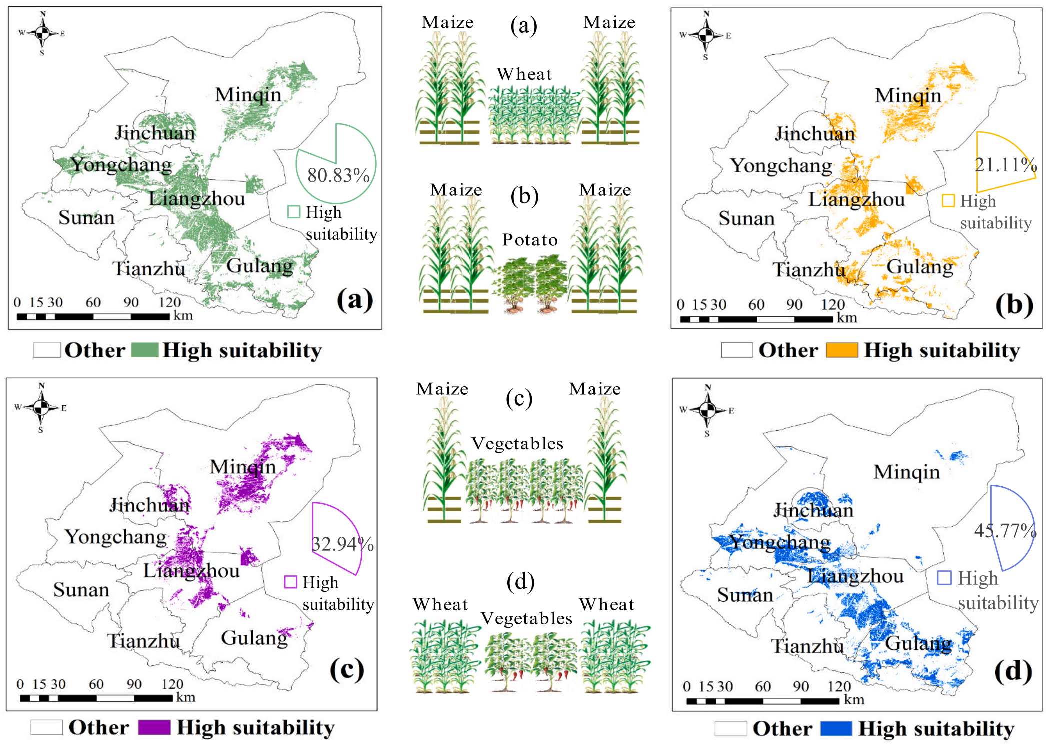

Fig. 7. Distribution of high suitability areas for crop intercropping based on planting competitiveness pattern.
Note: (a), (b), (c), and (d) indicate that intercropping is suitable for the distribution of maize-wheat, maize-potato, maize-vegetables, and wheat-vegetables, respectively.

lower of crop area above L2 rating in the CPC scenario compared to the CPS scenario, which also confirmed the importance of incorporating social environmental drivers in the assessment of crop competitiveness as well. Our findings are consistent with a recent study (Yang et al., 2022).

The results of this study indicate that optimizing the spatial pattern of multi-crop systems can improve agricultural productivity and sustainability. Comparing the optimized planting pattern with the existing planting pattern, all three optimized crop patterns increased the planting area of wheat and potato (Fig. 5), which suggests that increasing the planting proportion of wheat and potato could be appropriate in the future study region. Additionally, we found that the proportion of stable suitable areas of the existing planting pattern in the three scenarios was below 20%, which implies the existing planting structure is not conducive to the healthy development of agriculture. In the CPC scenario, it was lower, indicating that the existing planting pattern is not fully matched with social and environmental resources, and new policies for adjusting planting patterns are urgently needed. Despite the economic output value of agriculture in the optimal patterns being lower than that in 2020, both optimization patterns of the CPC scenarios reduced the total ET_c and improved the WP of crops and the net output per cubic meter of water. This indicates that the CPC scenario has great potential in improving agricultural productivity and resource utilization efficiency. On the other hand, optimization patterns in CGS and CPS scenarios increased the total ET_c, which proves the superiority of the CPC scenario compared to the other two optimization scenarios.

Previous studies have demonstrated the potential of crop intercropping systems to optimize the use of resources such as water and land, increase crop productivity, and improve agricultural sustainability (Midega et al., 2014; Ngwira et al., 2012; Liu et al., 2020; Xu et al., 2020). This study proposed recommendations for developing intercropping practices in areas where spatial competitiveness conflicts exist. The intercropping of wheat and maize (Sun et al., 2007), wheat - beans and maize - beans (Li et al., 2007) are common planting modes in northwest China. Using four common intercropping systems as examples we provide a methodology for identifying intercropping highly suitable zones and give recommendations based on the study region. The approach can provide valuable guidance for the design and management of diverse and resilient cropping systems. However, our assessment model is based on a predetermined set of indicators and weights, which may not fully reflect the complexity of multi-crop farming systems. Thus, future research could explore the development of more comprehensive assessment models that take into account other factors such as market demand, labor supply, and technology adoption.

5. Conclusion

In this study, a multi-level evaluation model was constructed to investigate the effects of natural and social environmental factors on the spatial distribution of crop suitability and competitiveness. The potential benefits of optimal multi-crop layouts in reducing agricultural water use and enhancing efficiency were analyzed. Our findings revealed that the crop habitat category of indicators held the highest weight (47.5%) in assessing crop competitiveness, particularly factors such as EAT, soil texture, DEM, and SD. Moreover, the weights of the categories of location, social economic, productivity and environment protection factors account for 26.9%, 7.5%, 13.7%, and 4.5%, respectively. The proportion of social environmental impact indicators among all indicators reaches about 43.5%, and it's influence cannot be ignored. The crop suitability distributions in the CPS and CPC scenarios revealed a higher proportion of crop areas above L2 rating compared to CGS scenario. Notably, the current 2020 planting structure lacks stable suitable areas with comprising <20%, and only 12.87% in the CPC scenario. The optimized patterns in the CPC scenario performed the best, reducing the total crop ET_c by 91.86–175.77 million cubic meters compared to 2020. It also demonstrated that the WP and net output per cubic meter of water of different crops outperformed the other two scenarios and the year 2020. The study proposed an intercropping scheme based on high planting competitiveness, and offered an effective method to identify highly suitable intercropping areas. Approximately 80.83% of cultivated land in the study region is suitable for maize-wheat intercropping, with 21.11% suitable for maize-potato, 32.94% for maize-vegetables, and 45.77% for wheat-vegetables. These findings can offer valuable insights for optimizing multi-crop agricultural systems' spatial structure and promoting agricultural sustainability.

CRediT authorship contribution statement

Shimeng Ma: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Coen J. Ritsema:** Writing – review & editing, Supervision. **Sufen Wang:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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