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A Framework to Identify Priority Areas for Restoration: Integrating Human Demand and Ecosystem Services in Dongting Lake Eco-Economic Zone, China

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Abstract: The identification of priority restoration areas (PRAs) for ecosystems is a critical step in establishing restoration programs. Because the majority of existing studies focused on improving the ecosystem supply, the PRAs selected are likely to be remote from human demand, and the restoration benefits will not flow to humans. To fill this gap, we constructed an improved framework integrating the ecological restoration projects' cost and benefits as indicators for choosing PRAs. Then, we identified PRAs for each ecosystem service (ES) with Marxan, and ranked the restoration priority grades according to the superimposed value of PRAs for each ES. Finally, we adjusted the restoration priority grades based on human demand and the concentration of those areas, and chose PRAs with a high ES supply and demand. This framework was applied to the Dongting Lake Eco-Economic Zone, one of China's most significant ecological restoration project sites. The results indicated that the areas with "high"-, "sub-high"-, and "low"-grade PRAs, based only on the increase in the ES supply, were equal to 82, 410, and 1696 km^2, respectively. After considering human demand, the PRAs moved continuously towards places with a high human demand; high-priority areas grew to reach 144 km^2, while low-priority areas decreased to 1498 km^2. The upgrade of the proposed framework for the identification of PRAs can contribute to increasing human well-being, while also serving as a support tool for environmental restoration management.

Keywords: priority restoration areas; restoration priority grade; human demand; ES importance; Dongting Lake Eco-Economic Zone

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1. Introduction

Ecological issues such as biodiversity loss and land degradation have recently emerged under the double pressure of global climate change and human activities, seriously threatening human well-being and sustainable development [1–3]. China is one of the countries that have been suffering from serious ecological degradation. In order to ensure the sustainable supply of ecosystem services (ESs), the restoration of ecologically degraded areas has become an important objective of ecosystem management [4–6]. Nevertheless, inadequate financing constrains the large-scale implementation of ecological restoration [7,8]. For the sake of improving the efficiency of restoration and achieving the related goals as soon as possible, it is particularly important to scientifically delineate priority restoration areas (PRAs) [9,10].

Potential restoration areas (PoRAs) need to be identified before prioritizing restoration areas. To this purpose, current research mainly applied the criteria of site suitability [11,12], ecosystem pattern [13,14], and quality [15–17]. Suitability-based studies typically apply land-use rationalization methods, such as converting space that is unsuitable for cropland to other land-use types (e.g., forests or grassland) [18]. Ecosystem-pattern-based studies prioritize the preservation of an ecosystem's natural pattern, such as the restoration of forest that has been converted to grassland [19]. Finally, quality-based studies, which are the most commonly performed, include both narrow and broad spatial scales. At narrow scales, integrated indicators (e.g., tree attributes, plant species diversity, and forest biological productivity) are typically used, including detailed information on the forest ecosystem structure [20], biodiversity composition [21], and function [22,23]. At broad spatial scales, ecological restoration aggregation indicators are frequently gathered through field surveys or long-term monitoring [24,25]; as such, it is difficult to adopt them, due to the time-consuming data-collection process. Therefore, some scientists developed complicated ecological models to estimate the native forest community biomass at the pixel scale as a quality-assessment standard for broad spatial scales [26,27]. Although these approaches improve the accuracy of the ecosystem quality assessment, they need a vast volume of data.

The primary aim of ecological restoration is to enhance the ES supply [22]. Therefore, several researchers, from the perspective of the ES supply, identified areas with a low ES supply but are critical for the development of ecological security patterns as PRAs [22,28,29]. Although this approach improves the structural integrity of the ecosystem and ensures ecological benefits, it fails to account for human demand. In fact, the mismatch between the ESs' supply and demand usually occurs when ESs are provided in places where there is no human demand, or when ESs are not insufficient for human demand [30]. Therefore, a focus solely on the ESs' supply without considering human demand may not provide direct restoration benefits to human society, which will result in a loss of ESs. [31]. Furthermore, as ESs are a vital source of livelihoods for those in impoverished areas, ecological restoration neglecting human demand will destroy human well-being [32,33]. Hence, works of research integrating ESs and human demand into ecological restoration have gained much attention, such as establishing key protection areas in regions with a low ES supply and high human demand [34], considering the ESs' supply–demand balance to optimize the ecosystem configuration [35], integrating the ESs' supply–demand with the relevance of ecosystem protection and restoration to support regional sustainable management [36], etc. These studies have enriched the practice of ecological restoration by applying the exploration of the relationship between ESs and human demand to ecological restoration and protection. However, the cost-effectiveness of restoration has not been emphasized in these works of research. As restoration projects have spread over an increasing number of regions and countries, a planning solution that balances the restoration costs and benefits must be urgently developed. In order to solve these problems, several optimization strategies have been proposed and are rapidly becoming a hot topic of current research; these include the use of linear-programming techniques to optimize the biodiversity or ES in protection areas [37], and the use of heuristic algorithms to identify unknown optimal conservation solutions for protected areas, which, however, faces the problem where large data volumes are required [38]. Marxan, as a system-protection-planning model, can minimize computing effort by applying it to the identification of PRAs, employing a simulated annealing approach to obtain the ideal solution after numerous iterations based on the weighting of multiple indicators [39,40].

To address these issues, we developed an optimized framework to prioritize ecological restoration areas. According to this framework, PoRAs were defined as the area where the ESs' potential supply declines above the mean value. Moreover, Marxan was used to define low-cost, high-supply areas as PRAs for individual ESs. PRAs were then classified based on the overlap of those for the individual ESs, and revised based on human demand and aggregation. This framework was applied to the case-study area of the Dongting Lake Eco-Economic Zone, which is one of China's major ecological restoration project sites and an important ecological barrier in Hunan Province. The objectives of this study were to develop an optimized ES-based framework to identify PRAs, and include the intensity of human demand for ESs as an indicator to determine the grade of the PRAs, in order to provide a theoretical basis for ecosystem restoration practices.

2. Materials and Methods

2.1. The Study Area

The Dongting Lake Eco-Economic Zone (27°58′–31°37′ N, 110°21′–114°09′ E) includes 4 cities and 1 district. It is located in the north of Hunan Province, and has a total area of 61,000 km^2 [41] (Figure 1). This area is characterized by a subtropical monsoon climate, abundant annual precipitations, and a well-developed water system; as such, it is a fundamental water storage ecological zone in the middle and lower reaches of the Yangtze River, as well as an important grain- and cotton-producing area [42]. The diverse topography and favorable climate have resulted in an abundance of biological resources, concentrated at the node where the conjugate and divergent Yangtze River systems coexist, thereby entailing a high ecosystem sensitivity and vulnerability. In recent years, climate change and intense human activities have damaged the Zone's ecosystem, resulting in a series of ecological issues such as environmental pollution, biodiversity reduction, and the shrinking of lakes [43].

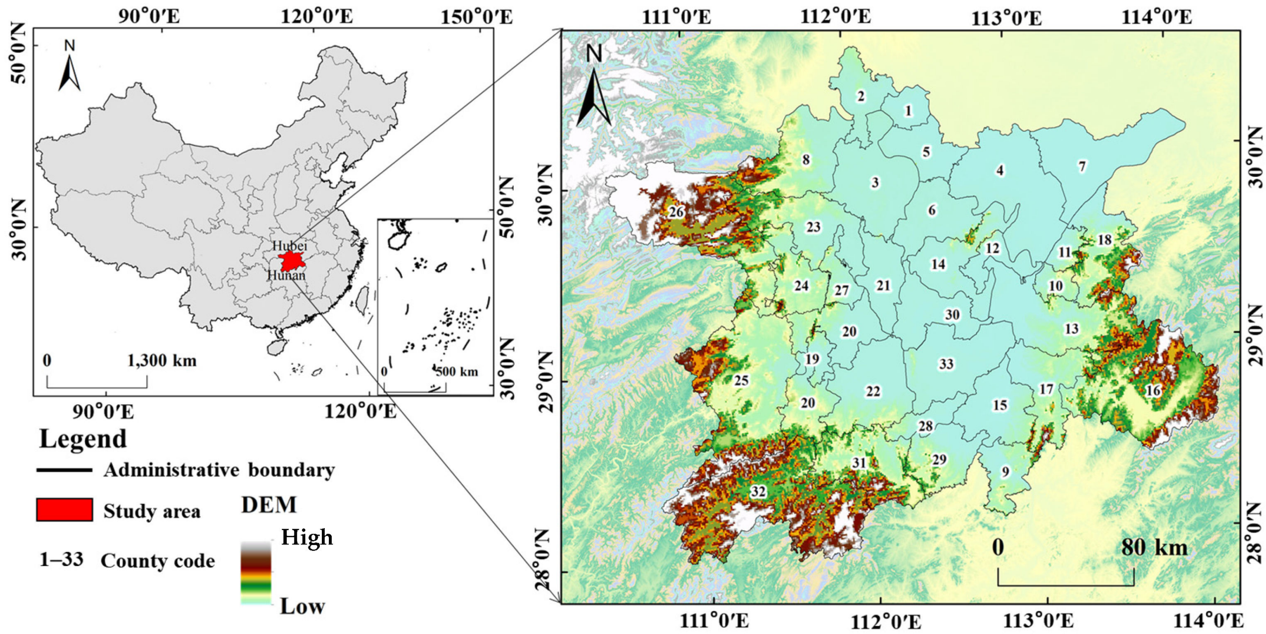

Figure 1. Map and location of the study area.

2.2. Datasets

The data used in this study were obtained from the sources given below, and the access dates for all data are 15 April 2021.

- The land-use maps for 2000, 2005, 2010, 2015, and 2020 (30 m resolution) were obtained from the Resource Environment and Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 13 March 2023). Based on the characteristics of the ecosystem composition of the study area, land-use types were reclassified into six categories: cropland, forest, grassland, water bodies, artificial land, and unused land.
- Average annual rainfall, evaporation, and temperature data were downloaded from the China Meteorological Data Service Center (http://data.cma.cn/, accessed on 13 March 2023).
- The net output productivity (NPP, 100 m resolution) data were retrieved from the website of National Aeronautics and Space Administration (NASA) (https://www.nasa.gov/, accessed on 13 March 2023).
- The Digital Elevation Model (DEM, 90 m resolution) was taken from the Geo-spatial Data Cloud (https://www.gscloud.cn/, accessed on 13 March 2023).

- Soil classification and data on associated soil attributes were obtained from the 1:1 million digital soil map of China and the Second National Soil Survey of China (http://www.ncdc.ac.cn/portal/, accessed on 13 March 2023).
- Socioeconomic, population density (1000 m resolution), and road, river, and settlement data were obtained from the Resource and Environment Science and Data Center (https://www.resdc.cn/, accessed on 13 March 2023).

All raster data were modified to a spatial resolution of 100 m using the ArcGIS resampling tool.

2.3. Methods

We selected the year 2000 as the starting point for our study, considering the significant milestone achieved by China's economic growth and rapid urbanization, as well as the implementation of ecological policies during that time. In addition, we employed a research timeframe of 20 years, spanning from 2000 to 2020. Figure 2 illustrates the methodological framework employed in this study for the identification of PRAs and ranking of restoration priority grades, which is comprehensively articulated into six steps. The initial step entailed leveraging pre-compiled foundational data to calculate the potential supply and demand of ESs. Afterwards, PoRAs were determined based on the dynamic changes of ES potential supply from 2000 to 2020. Subsequently, it was essential to collate the requisite data for Marxan to establish the foundation for the identification of PRAs of individual ES. A critical component of this step was the development of a comprehensive restoration cost index. In addition, Marxan was used to facilitate the identification of the PRAs for each ES that incorporated both restoration costs and benefits among the PoRAs. In the fourth step, the restoration priority grade, considering only ESs' importance, was ranked based on the spatial overlap analysis of the three PRAs maps. The basic settings were as follows: planning units with PRAs for all three ESs were assigned the highest restoration priority grade, while those with PRAs for any two ESs were assigned a sub-high priority grade, and those with PRAs for any single ES conferred the lowest priority grade. The fifth step was to revise the restoration priority grades using human demand. Finally, the areas with an aggregation degree of less than 100 km^2 were eliminated from the PRAs.

2.3.1. Accounting for Potential Supply of ES

Comprehensively considering the Chinese government's carbon management goals and the distinct function of the study area within the 'National Ecological Function Zoning', as well as the special environment demand of the research area's industrial characteristics, we ultimately chose three representative ESs in demand, namely, carbon sequestration (CS), habitat support (HS), and water harvesting (WH), for the purpose of research.

(1) Carbon sequestration (CS)

CS is the process through which atmospheric CO_2 is fixed in plants and soil [44]. The amount of CS was calculated using the CS module in the InVEST model [45], as follows:

$$Q_{c=\sum_{i=1}^{n}} Q_i \times S_{i \times F_{NEP}} \times 10^{-9} \quad (1)$$

where Q_c indicates the total CS of the ecosystem (t·yr^{-1}); Q_i indicates the amount of carbon sequestration of land-use type i (Mg·yr^{-1}), including the organic carbon density of above-ground, below-ground, soil, and dead organic matter, respectively (Mg·hm^{-2}·yr^{-1}); S_i indicates that area of land-use type i (hm^2); and F_{NEP} represents the spatial correction factor of net ecosystem productivity (NEP), which was obtained using the affiliated fuzzy method based on the mean value for the study area. NEP was obtained by NPP conversion.

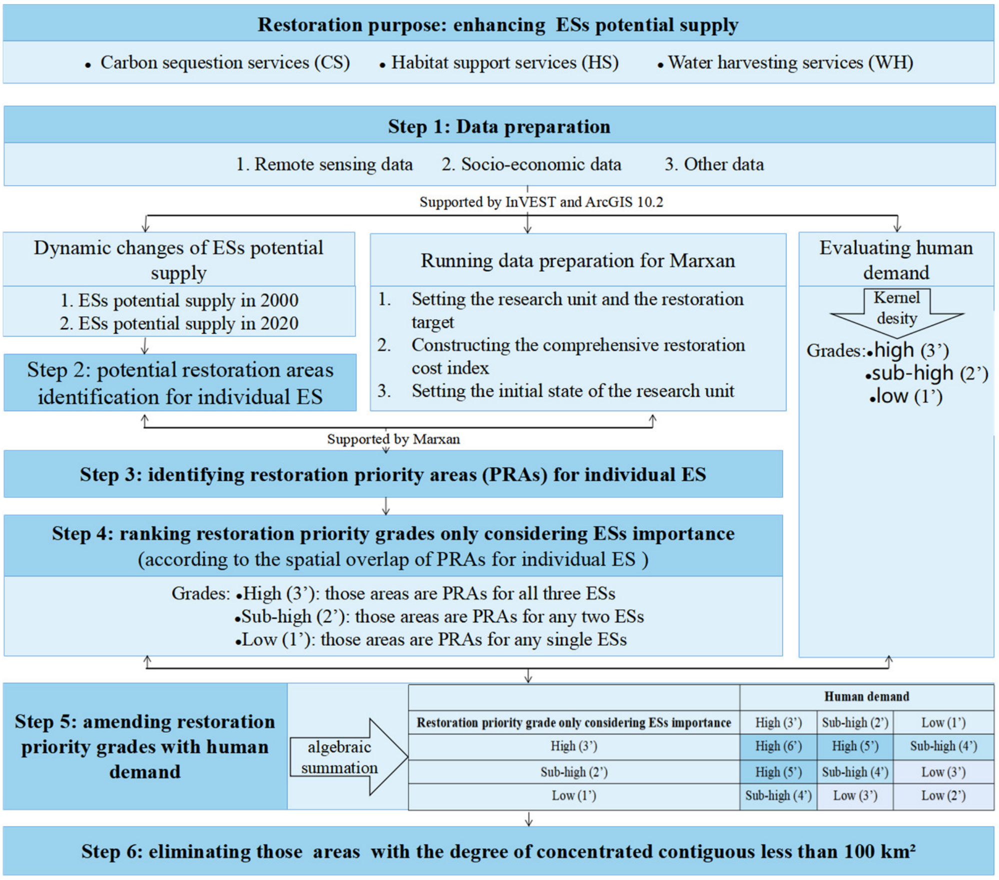

Figure 2. A research framework for the identification of priority restoration areas.

(2) Habitat support (HS)

Habitats are the natural environment that offers living space for a certain species or population within a specific region; as such, they are frequently used as an indication of biodiversity [46]. The Habitat Quality module of the InVEST model was utilized to quantify HS [47], as follows:

$$S_{Q_{ij}} = H_i \times [1 - D_{ij}^z / (D_{ij}^z + K^z)] \quad (2)$$

where S_{Qij} is the habitat quality index in cell i of land-use type j; D_{ij} is the habitat degradation index in cell i of land-use type j; z and k are constants; and H_j is the habitat suitability of landscape j. All parameters are dimensionless.

(3) Water harvesting (WH)

Following the water balance equation [48], WH was calculated as follows:

$$Q_w = \sum_{i=1}^{j} (P_i - R_i - ET_i) \times A_i \times 10^{-3} \quad (3)$$

where Q_W is the amount of WH ($m^3 \cdot yr^{-1}$); P_i represents precipitation (mm); R_i denotes rapid runoff (mm); ET_i indicates evapotranspiration; and A_i represents the area of ecosystem i (m^2).

2.3.2. Accounting for the Importance of ES Demand

Relative inequalities in socioeconomic development and natural resource availability within a certain zone result in disparities in ES demand. The concept of 'point of interest' (POI) refers to the spatial distribution of geographic entities in a city that are closely linked to human activities, including food and beverage services, medical education, and residential and recreational places, reflecting the density of population and socioeconomic activities. In general, the spatial distance between an ecological site and a POI impacts the level of demand for the ecological site. The POI data were treated in ArcGIS 10.2 using the kernel density analysis tool, with a search radius of 30 km. The generated POI kernel density raster map was divided into three classes—high, medium, and low—utilizing geometric intervals to ensure that the ecological demand is positively correlated with the kernel density classes, as follows:

$$f(x) = \sum_{i=1}^{n} \frac{1}{D^2} \times k \times (\frac{x - c_i}{D}) \tag{4}$$

where $f(x)$ is the image element x's kernel density calculation function; k is the spatial weight function; D is the distance decay queue; and c_i is the raster x distance in the search decay range of all POIs. All parameters are dimensionless.

2.3.3. Identifying PoRAs

The potential supply of CS, HS, and WH was standardized using Equation (5). By comparing the potential supply in 2000 with the current situation, the areas where the supply decreased more than the average value were defined as PoRAs for each ES, as follows:

$$ES_x = \frac{ES_{st} - ES_{min}}{ES_{max} - ES_{min}} \tag{5}$$

where ES_x denotes the standardized value of ESs' potential supply; ES_{st} represents the current value of ESs' potential supply; and ES_{min} and ES_{max} indicate the minimum and maximum values of ESs' potential supply.

2.3.4. Marxan

Marxan, a systematic-protection-planning tool, uses simulated annealing methods to provide the most effective protection within specific protection cost restrictions [40]. The basic functions of the model operations are as follows:

$$S_c = cost + boundary + penalty \tag{6}$$

where *Sc* is the total cost of protection; *cost* represents the combined cost of the selected planning unit; *boundary* indicates the sum of the boundary lengths of the selected planning units, whose value represents the strength of connectivity between planning units; and *penalty* indicates the penalty assigned to the planning system for not effectively representing conservation features. It relies on the idea that if the conservation target is not achieved, then the penalty should be an approximation of the cost of raising the conservation feature up to its target representation level.

Before running the model, the study area was first divided into a certain number of planning units. The commonly used planning units were divided into 3 types: grid cells, hexagonal, and catchment cells. Each planning unit contained a specific area of the protected object and had a specific cost of protection. Then, four initial states were assigned to the planning units based on their attributes (Table 1).

2.3.5. Identifying PRAs with Marxan

(1) Setting the research unit and the restoration target

The study area was divided into 61,741 cells of 1000 × 1000 m as the fundamental restoration cells using the "Create Fishing Grid" tool of ArcGIS 10.2. Following the Aichi Biodiversity Convention, which set the target of restoration of 15% of a damaged habitat to significantly improve biodiversity [49], the restoration target was chosen as equal to 15% of the PoRAs.

Table 1. Description of the initial states for planning units.

Initial States	Description
0	The planning units can be excluded or included in the final plan, depending on the proportion of an initial reserve system (Marxan selects a certain number of planning units as the initial protection system at the beginning of the operation and performs iterations based on the initial protection system). Normally, the initial state of remaining planning units other than those with the initial state of 1, 2, and 3 can be set to 0.
1	The planning units belong to the potential protection system, and their inclusion in the final plan depends on the weight of the protection target.
2	The planning units are locked and will definitely appear in the final plan.
3	The planning units will definitely not appear in the final plan.

(2) Constructing the comprehensive restoration cost index

As stated in the "Announcement on the Implementation Plan for the Comprehensive Management Plan of Dongting Lake Water Environment in Hunan Province (2018–2025)", the cost of the Dongting Lake water ecological restoration project was 5.4 million yuan/hm^2. In parallel, in accordance with the "Implementation Standards for Restoration of Vegetation and Forestry Production Conditions in Hunan Province (trial version)", the investments necessary to restore forest and grassland vegetation were 2 and 3 million yuan/hm^2, respectively. Hunan Province is mainly characterized by paddy fields as the main type of cultivated land; according to the available data, the approximate cost for the restoration of paddy fields is 1.5 million yuan/hm^2. As the cost of ecological restoration is influenced by the ecological quality of the restored area, as well as by the difficulty of the restoration project, the cost data were spatially adjusted using the slope, the distance-to-road/settlement/river, and the GDP/population density [50], as follows. Initially, these indicators were reassigned based on the ecological meaning of the aforementioned indicators (Table 2); subsequently, the reassigned indicator values were utilized to modify the ecological restoration project costs of each ecosystem. However, in some parcels of land the costs and benefits of restoration were not comparable; therefore, focusing solely on low prices could result in poor benefits for the PRAs. To address this issue, we quantified restoration benefits as the largest difference on a long-term pixel scale, and integrated the cost of ecological restoration project with the reassigned restoration benefits to calculate the ecological restoration cost. To avoid the magnitude effect, we equalized the ecological restoration project costs and restoration benefits. The formulae employed are as follows:

$$C_i = P_i \times \sum_{j=1}^{n} L_j \tag{7}$$

$$\eta_i = C_i + B_i \tag{8}$$

where C_i indicates the amended cost of the ecological restoration project for planning unit i; P_i represents the cost of the ecological restoration project for planning unit i, which is determined by the land-use type of planning unit i; L_i indicates the revised indicators after reassignment; n is the number of restoration cost indicators; B_i indicates the restoration benefits; and $_i$ is the comprehensive cost index. To avoid a negative "cost" parameter in Marxan, we reassigned the restoration benefits in order of magnitude, and the ecological restoration cost is obtained by adding the restoration project cost to the reassigned restoration benefits.

Table 2. Revised indicators for *C* (*L*) and restoration benefits (*B*).

	Evaluation Index	Reassignment Method	Grading/Distance	Cost Index
L	GDP density, population density, slop	Natural breakpoint method	5	Value assigned from 5 (highest) to 1 (lowest)
	Distance to river	Multi-ring buffer	500 m	1
			500–1000 m	2
			1000–1500 m	3
			1500–2000 m	4
			≥2000 m	5
	Distance to road, settlement	Multi-ring buffer	500 m	5
			500–1000 m	4
			1000–1500 m	3
			1500–2000 m	2
			≥2000 m	1
B	$ESV_{2000–2020}$	Natural breakpoint method	5	Value assigned from 1 (highest) to 5 (lowest)

(3) Setting the initial state of the research unit

According to the description of different initial states for planning units in Table 1, we set the initial state of research units as follows: (i) As the surface of artificial land is irreversible, we assigned the initial status for the planning units with the artificial land as equal to 3, to ensure that those units would definitely not appear in the final plan. (ii) We established a 15% restoration target in this research, which indicates that a portion of the PoRAs will be identified as PRAs. Consequently, the initial state of the planning units for PoRAs was set to 1. (iii) The other remaining units were set to 0.

2.3.6. Classification of the Priority Grade, Only Considering Ecological Importance

We overlapped the spatial distribution maps of PRAs for CS, HS, and WH to obtain the ecological restoration priority grade. By default, Marxan assigned value of 1 to the PRAs, and a value of 0 to other planning units. Then, we used the Raster calculator tool of ArcGIS 10.2 to integrate the spatial distribution maps of the PRAs for three ESs. According to the results, the planning units with a value of 3 had the highest restoration priority grade, followed by the planning units with a value of 2, while those with a value of 1 had the lowest restoration priority grade.

2.3.7. Modifying the Restoration Priority Grades, Considering Human Demand and Aggregation Degree

Based on the importance of ES, both PRAs and the importance of ecological demand were assigned a value from 3 to 1 from highest to lowest. According to the algebraic summation, the ecological restoration priority grade was modified using the importance of ecological demand (Table 3).

Table 3. Revision of priority restoration grades with human demand.

Priority Grade for Ecological Restoration Only Considering Ecological Importance		Human Demand		
		High	**Sub-High**	**Low**
		3	**2**	**1**
High	3	6	5	4
Sub-High	2	5	4	3
Low	1	4	3	2

Long-term ecological restoration activities have demonstrated the need for concentrated and large-scale treatment to produce comprehensive benefits. Based on the characteristics of the study area, we eliminated from the PRAs those image cells with an aggregated area of less than 100 km^2. Then, with the support of the Grid module in ArcGIS 10.2, the "docell" command was used to conditionally select the PRA layers corrected for demand importance with the aggregation layer, resulting in PRAs combining aggregation, demand importance, and ecological importance.

3. Results

3.1. Potential Supply of ES

The ecological function spatial pattern reflects ES spatial heterogeneity. In both 2000 and 2020, the spatial distribution of CS increased from the center to the periphery (Figure 3(a1,a2)). This is mainly attributed to the fact that the level of CS is primarily dependent on the land-use types. The area with a high CS value was located in the northwestern portion of the study area, characterized by forest with a high carbon density and CS capability. The central area, which includes cropland and water bodies, had a low value of CS. The spatial distribution of HS followed those sites characterized by a perfect ecological background and the absence of strong human disturbance. Accordingly, HS was higher in the eastern and western parts of the study area and Dongting Lake, where several national nature reserves are located, guaranteeing high levels of biodiversity. In contrast, those areas with low HS were mainly located in the cropland-dominated central area and other artificial land area (Figure 3(b1,b2)). Finally, WH depends on the water storage capacity of vegetation. WH was higher in the eastern and southwestern parts of the study area, characterized by high annual precipitation (Figure 3(c1,c2)), abundant vegetation, and strong water storage capacity. Areas with low WH were mainly found in the central part of the study area, characterized by low precipitation, mono-vegetation, and rapid evaporation.

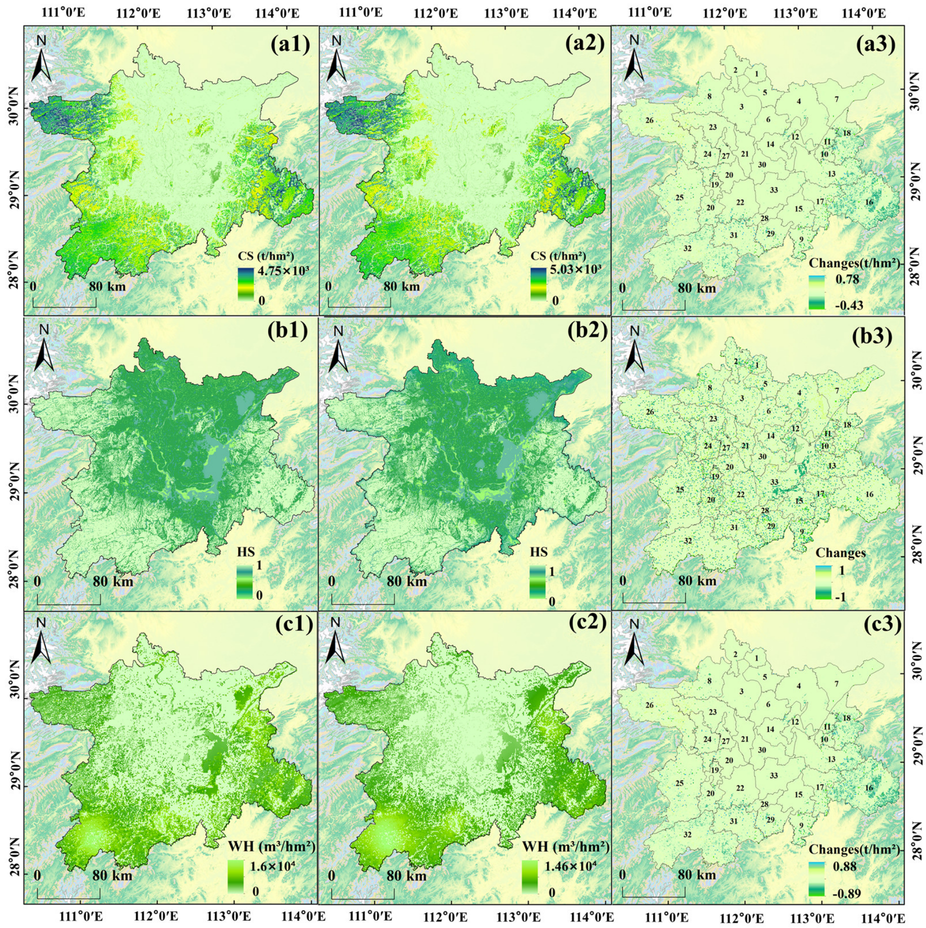

Figure 3. ES potential supply and dynamic changes from 2000 to 2020: (**a1**) CS in 2000; (**b1**) HS in 2000; (**c1**) WH in 2000; (**a2**) CS in 2020; (**b2**) HS in 2020; and (**c2**) WH in 2020. Dynamic changes from 2000 to 2020: (**a3**) for CS; (**b3**) for HS; and (**c3**) for WH.

In terms of the evolution of the spatial pattern from 2000 to 2020, CS recorded a small increase, with the area of the increasing and unaltered parts being 27.3% and 58.1% of the study area, respectively, while the part where CS decreased covered 14.6% of the study area, primarily located in County 16 and County 18 (Figure 3(c1)). In parallel, HS showed a significant decline. In more detail, the area of this decline reached 79.2% of the total area, and was primarily located in areas other than Dongting Lake and Hong Lake (Figure 3(c2)). This is attributable to the growing human disturbance, which has caused habitat stress and the deterioration in habitat quality. The areas where HS increased and remained unchanged were equal to 11.7% and 9.1% of the total area, respectively. Finally, WH also marked a reduction, having decreased in 36.3% of the study area. The counties surrounding Dongting Lake, as well as Counties 15, 13, and 12, saw the greatest declines (Figure 3(c3)), owing to the transfer of water to unutilized land. The areas where WH increased and remained unchanged were 46.3% and 17.4% of the total area, respectively, with Counties 4 and 7 as the areas where the greatest increase occurred.

3.2. Comprehensive Cost Index (η)

Ecological restoration costs were ranked as follows: CS (6.29) > HS (6.22) > WH (6.17), indicating that CS had a higher restoration cost and lower benefits, and vice versa for WH (Figure 4). Overall, the majority of counties had minimal differences in the mean value of η for the three ESs, whereas large differences in the proportion of artificial land and ecological land in Counties 15, 16, 18, and 32 resulted in wide variations in the mean value of η for the three ESs. Specifically, at the county scale, those counties η with the smallest county area, such as Counties 1, 10, 11, 12, 19, 27, and 28, had a lower, while the high degree of human disturbance and economic growth in these counties lead to a high mean value of η.

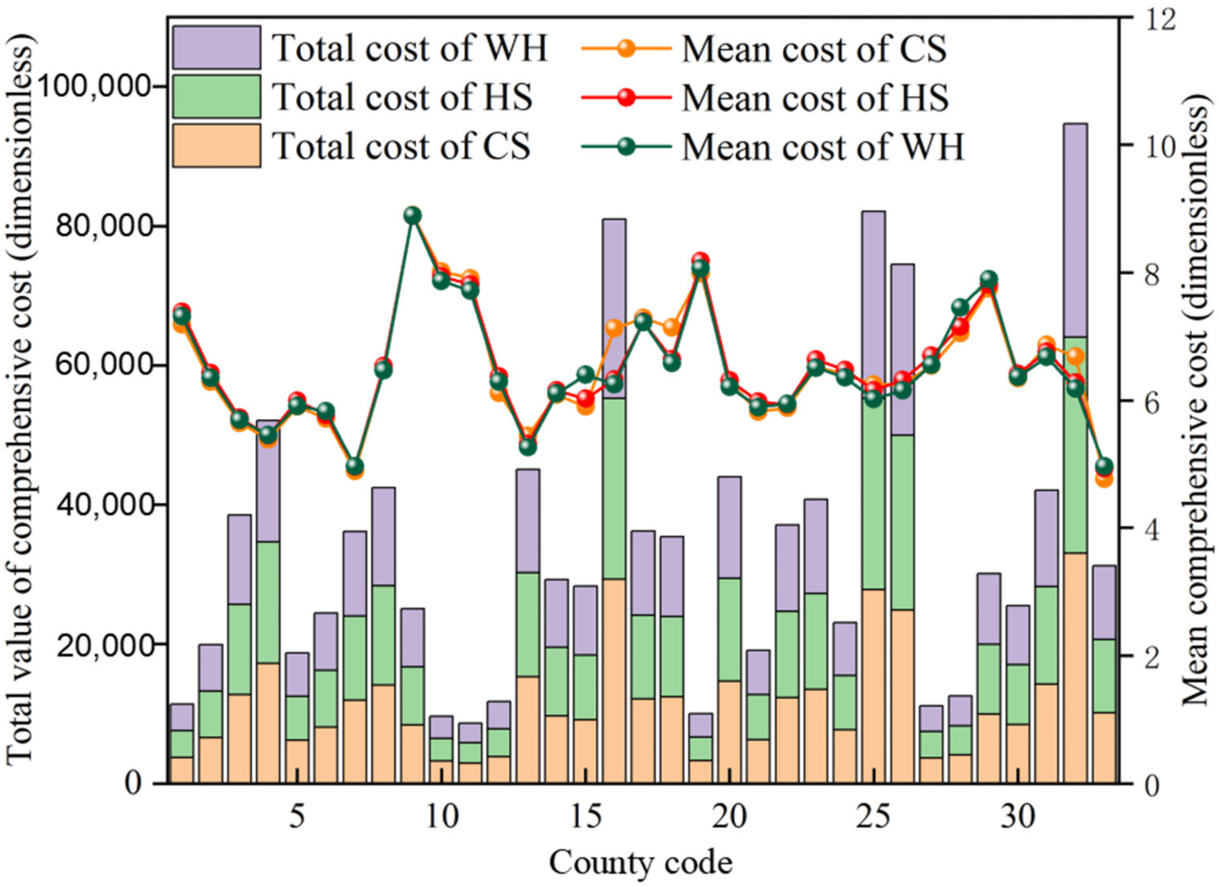

Figure 4. Ecological restoration cost of PRAs.

3.3. Potential Restoration Areas

Those areas where the potential ES supply is severely degraded were considered as PoRAs. According to changes in the potential supply of the three ESs from 2000 to 2020, the area of CS-PoRAs was 6759 km^2, equal to 38.8% of the CS degraded area, and mainly located in Counties 16, 18, 32, and 31 (Figure 5a). The HS-PoRAs distributed in a scattered manner covered 6407 km^2, accounting for 42.9% of the HS degraded area, and were mainly clustered in the counties surrounding the Dongting Lake, the southern part of County 9, and the western part of County 1 (Figure 5b). The spatial distribution of WH-PoRAs was equally scattered, accounting for 12.1% (3887 km^2) of the WH degraded area, and concentrated at the junction of Counties 9, 13, 15, 28, and 29 (Figure 5c). In terms of land-use types, forest was the main land-use type in the CS-PoRAs, with an area of 5242 km^2, corresponding to 77.5% of the total area of CS-PoRAs (Figure 5d). Cropland was the main land-use type in the WH-PoRA, covering an area of 1823 km^2, equal to 46.9% of the total area of WH-PoRA.

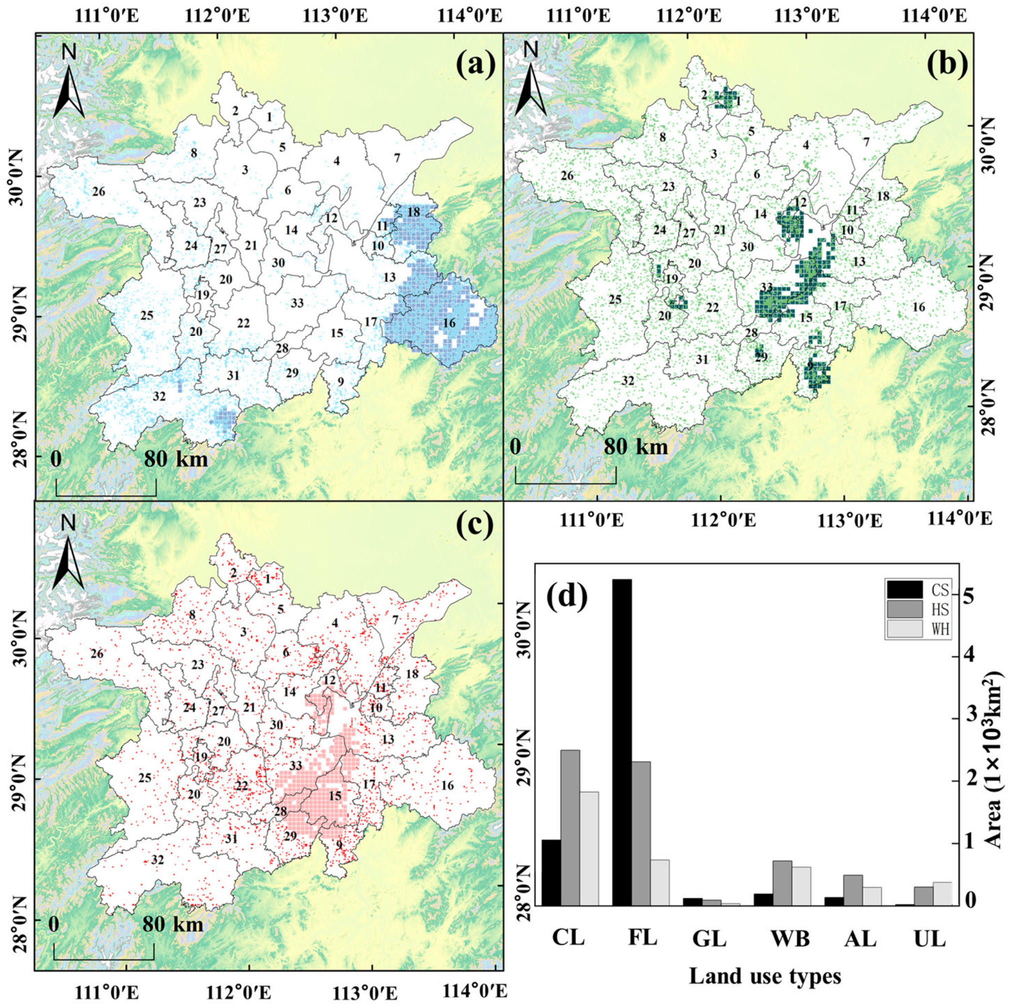

Figure 5. Spatial distribution of PoRAs: (**a**) for CS; (**b**) for HS; and (**c**) for WH. (**d**) Extension of each land-use type for each PoRA.

3.4. PRAs for Single ES

Figure 6 shows the spatial distribution of PRAs across counties. The PRAs in CS, HS, and WH occupied 962, 885, and 538 km^2 and covered 1.61%, 1.43%, and 0.87% of the entire study area, respectively. The detailed breakdown of the area occupied by each county in the PRAs, displayed in Figure 6, reveals that the CS-PRAs were mainly located in Counties 13, 15, and 12, and the land-use type was mainly forest, accounting for 73.49%

of the total area of CS-PRAs. This is mainly due to forest's high biomass, which entails a great CS after restoration, resulting in significant ecological benefits. HS-PRAs were mainly located in Counties 33, 13, and 25, where they extended for 238 km^2, 113 km^2, and 66 km^2 respectively. Water bodies were the main land-use type for HS-PRAs (32.77%), due to the importance of the Dongting Lake wetlands in conserving biodiversity, particularly for bird species. Other land-use types for HS-PRA were unutilized land, forest, and cropland, with 23.16%, 22.15%, and 21.24% of the total area of HS-PRAs, respectively. WH-PRAs were relatively spatially concentrated in County 33 (200 km^2), County 13 (84 km^2), and County 15 (68 km^2). Unutilized land and water bodies were the main land-use types in WH-PRAs, accounting for 38.29% and 35.32% of the total area of WH-PRAs, respectively, followed by cropland with 17.66%. This is because the unutilized land in these areas was practically converted from water bodies, and restoring these areas back to water bodies can enhance their water retention capacity. It is worth noting that PRAs to promote CS, HS, and WH did not include artificial land, while they included only a small amount of grassland. This is because irreversible changes to the surface of artificial land can result in high restoration costs, while the restoration of grassland produces fewer ecological benefits.

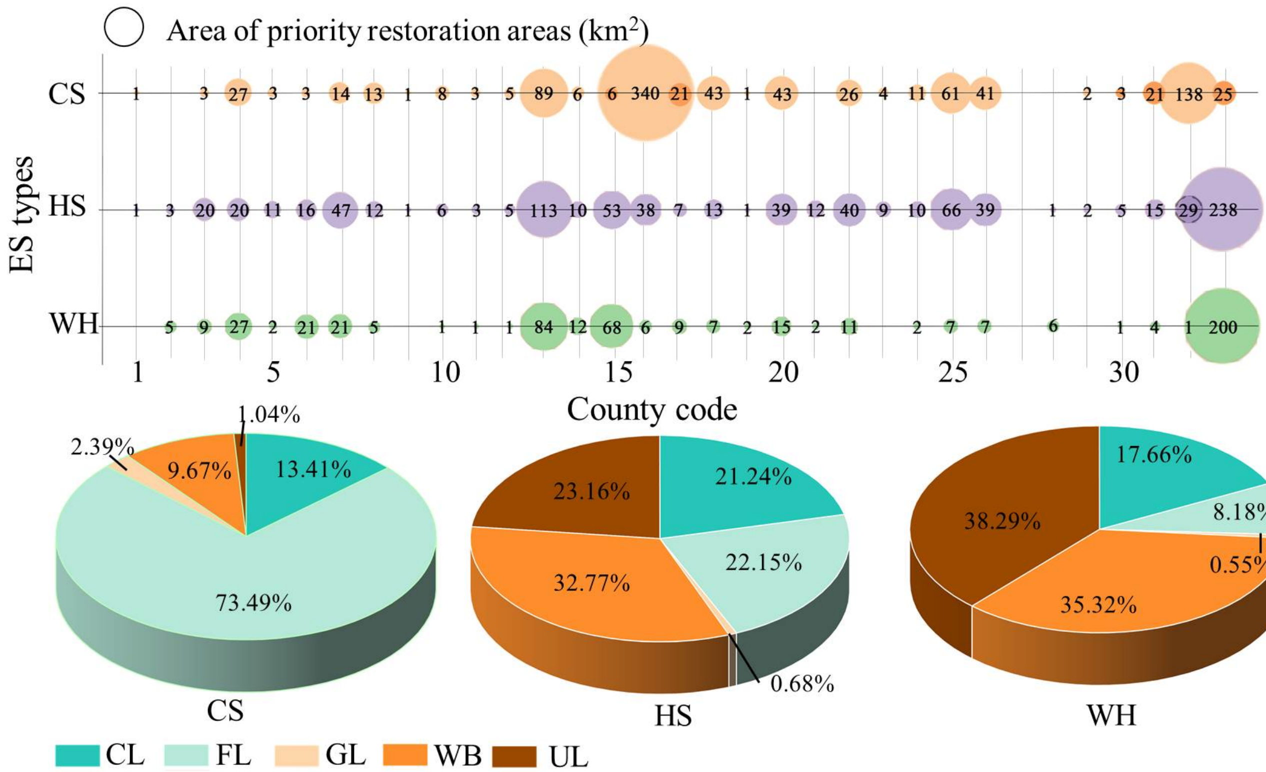

Figure 6. Spatial distribution of PRAs among counties.

3.5. Restoration Priority Grade Based on ES Importance

The area and spatial distribution of PRAs varied greatly across different priority grades. The PRAs with a "high" ranking were relatively concentrated in the northeastern part of County 33 (Figure 7), with an area of 82 km^2 (0.13% of the total study area). The restoration of these areas can promote the synergistic enhancement of CS, HS, and WH. Moreover, these areas were also found to have a low population density, hence resulting in a low restoration cost. Moreover, a large amount of unutilized land degraded from water was included in this area, which could yield significant restoration benefits by converting it into water bodies through ecological measures such as dredging. The area of PRAs with a "sub-high" ranking was 410 km^2, the majority of which was devoted to enhancing HS and WH simultaneously (207 km^2), and was located primarily in the border areas of County 13, 15, 16, and 33. The PRAs to enhance CS and HS covered 150 km^2, scattered in Counties 16, 32, and 3. The area of PRAs to improve CS and WH was only 53 km^2 and had a scattered distribution, mostly located in Counties 16, 18, and 33. All other PRAs with a "low" ranking priority covered an area of up to 1696 km^2, located mainly in Counties 33, 32, 16, 13, and 12.

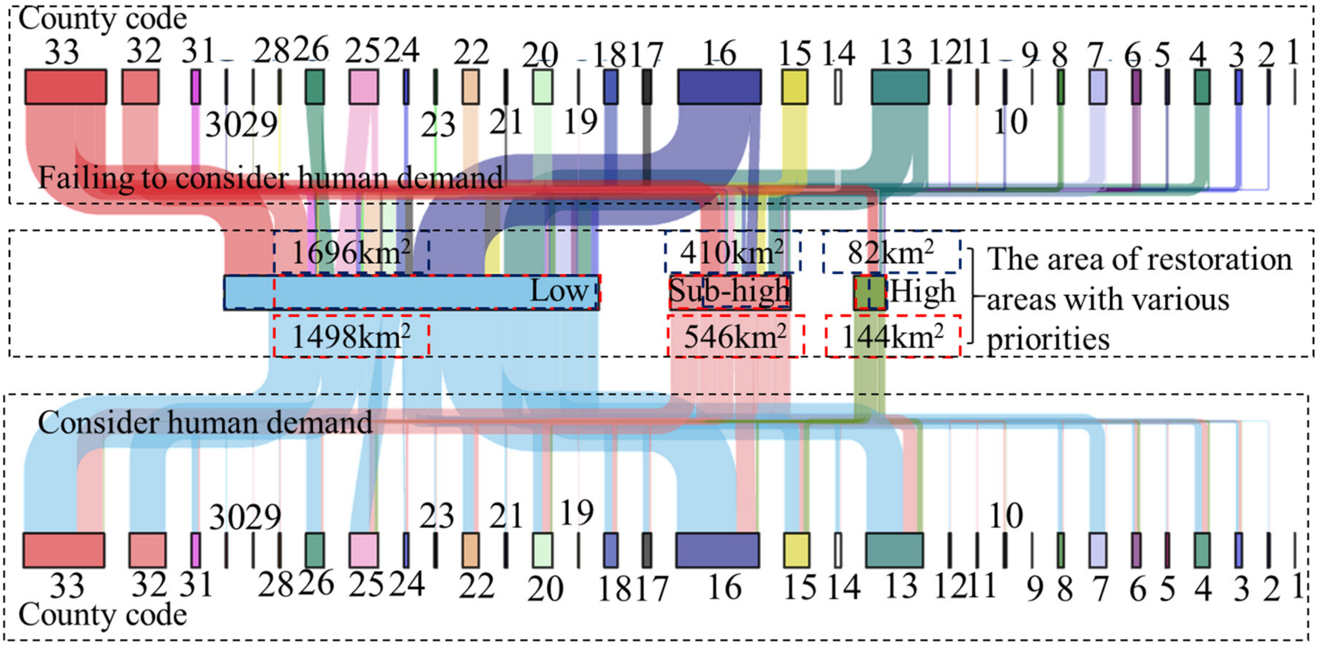

Figure 7. The area of restoration areas with different priority grades in each county.

3.6. Revising Priority Restoration Grades Based on Demand Importance and Aggregation Degree

The extent and spatial distribution of the various PRAs, taking into account human demand, were modified as follows: (1) The "high"-grade PRAs increased by 75.61%, reaching 144 km^2, and began to shift from County 33 to areas with a "high" human demand and "sub-high" ecological importance, such as Counties 13, 15, and 16 (Figure 8c(c1–c3)). After restoration, these areas allowed the related benefits generated to flow directly to human society (Figure 8b(b1–b3)). In contrast, while the high PRAs in County 33 can offer more restoration benefits, they are relatively poor in terms of socioeconomic development; hence, the initial "high" PRAs were reclassified into "sub-high" PRAs, considering human demand. (2) "Sub-high" PRAs shifted from Counties 15, 33, and the eastern part of County 13, to County 16 and the western part of County 13, covering an area of 546 km^2 with an increase of 32.45%. The enlarged portion of sub-high PRAs within County 16 was transformed from low PRAs with significant human demand. (3) "Low" PRAs shrank by 11.36%, with the majority of this reduction occurring in those areas where the original level grade was "high" and "sub-high".

In order to maximize efficiency, the aggregation areas smaller than 100 km^2 were removed from the PRAs, resulting in an improved distribution map of the restoration priority grade. The total area of corrected PRAs shrank by 602 km^2, reaching 1586 km^2. Specifically, the "high" PRAs decreased by 32 km^2 (112 km^2), while the "sub-high" and "low" PRAs decreased to 386 km^2 (160 km^2) and 1088 km^2 (410 km^2), respectively. Moreover, the geographical distribution of PRAs became more clustered, mainly at the junction of Counties 13, 15, and 33 and within Counties 16, 25, and 32.

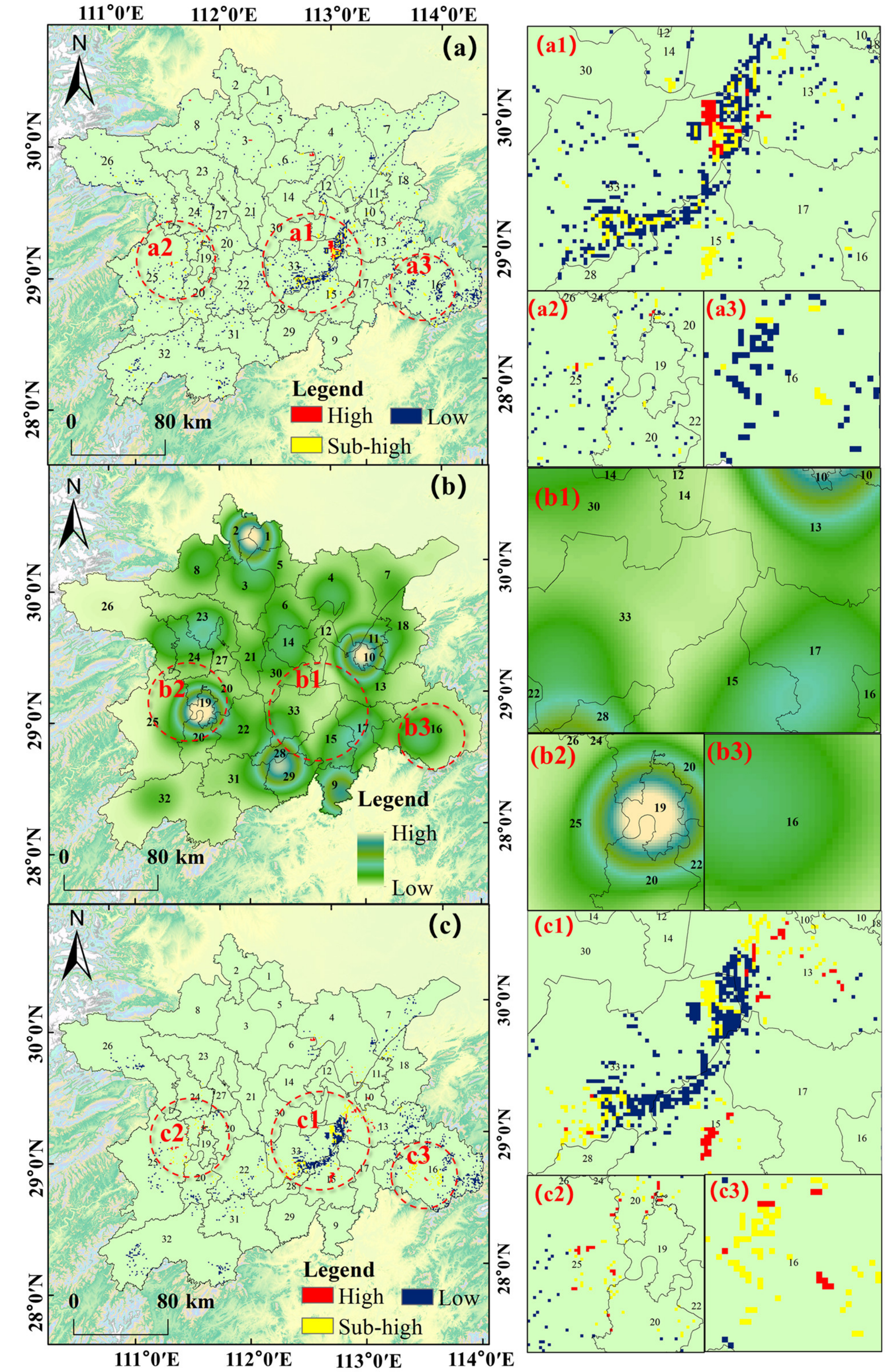

Figure 8. Spatial distribution of priority grades for PRAs and human demand: (**a**) distribution of PRAs only considering ES importance; (**b**) distribution of human demand; and (**c**) distribution of PRAs revised based on human demand and aggregation degree; (**a1**–**a3**), (**b1**–**b3**) and (**c1**–**c3**) are amplified pictures of important nodes in picture (**a**), (**b**), and (**c**) respectively.

4. Discussion

In order to promote the balanced allocation of limited restoration resources among ecologically degraded areas, it is necessary to improve the accuracy of identification for

PRAs. Although the current supply-based identification of PRAs can improve the ecological patterns and, thus, increase their potential supply capacity [51], the widespread imbalance between the ES supply and demand undermines the integrity of ES processes and hinders the realization of social benefits from ecosystems [52]. It is well-known that ESs serve as a bridge between the natural and social systems [53]. In this study, we proposed a framework for the identification of PRAs to boost the ESs supply, which integrates the ecological and socioeconomic benefits of restoration and simplifies the identification process using Marxan.

The identification of PoRAs is the foundation for the selection of ecological PRAs [54]. In this respect, our study provided a novel viewpoint on PoRA identification. Several previous studies concentrated on land-use change, considering the land transformed from natural ecosystems to cropland, pastures, and even artificial land as PoRAs [55]. However, with the increase in the intensity of anthropogenic disturbances, a large extension of degraded land did not experience conversion [56], leading to a variety of global difficulties if the land failed to be restored. Because changes in the ES supply may indicate ecosystem conversion and degradation, this study utilized variations in the ES supply over a long period to identify PoRAs. The findings showed that PoRAs for CS, WH, and HS include not only areas converted from forest and water bodies to cropland, but also a large number of degraded forest and water bodies.

Our framework enables the inclusion of 'low-cost, high-yield supply' areas in PRAs, thereby boosting resource allocation efficiency and increasing the feasibility of restoration projects in the case of limited restoration financing. In previous studies on the identification of PRAs, ecological importance and restoration urgency were considered as the primary determining factors. For instance, the areas with high ecological vulnerability and a sharp decline in the ESs supply were regarded as PRAs [15,57,58]. However, these methods for ecological restoration neglected the feasibility of implementation facing limited restoration resource [39]. In this study, we evaluated the feasibility of restoration according to the ecological restoration cost. Initially, the indicators measuring restoration difficulties such as GDP, population density, and slope were used to modify the cost of ecological restoration projects. Moreover, the maximum ES differential between PoRAs over the study period was used to quantify the restoration benefits, while the ecological restoration cost was obtained by integrating the restoration benefits, the cost of ecological restoration projects, and the difficulties. The ecological restoration cost supported a more direct and accurate evaluation in the feasibility of restoration compared to the indirect indicators such as urbanization level [59]. According to the results of our study, forest and water bodies are the main land-use types in PoRAs for CS, HS, and WH, all of which have a high ES supply. Additionally, the degraded water bodies and forest are mainly distributed around Dongting Lake and the southwest part of the study area, respectively, which are all low-cost and high-yield, making it more feasible and easier for the government to implement.

The proposed framework aims to improve the ESs supply through restoration. Although previous research showed that restoration allows us to successfully increase the ESs supply, restoration activities aiming at improving a specific ES supply may jeopardize other ESs. For example, non-native plants used to alleviate soil erosion in dry areas may decrease native vegetation cover and increase water demand [60]. In this study, these shortcomings were addressed by superimposing maps showing PRAs for HS, CS, and WH, and assigning restoration priority grades based on the degree of the spatial overlap. According to our findings, even if there is little spatial overlap in the PRAs for the three ESs, the cost efficiency will be maximized if restoration funds are directed to locations with high restoration synergy in priority. Furthermore, it has been demonstrated that water bodies and forest play an important role in biodiversity conservation and climate change mitigation [26]. This was confirmed by our study, which showed that the PRAs for CS were dominated by forest, whereas those for HS were dominated by water bodies.

Moreover, the proposed framework balances the demand importance with the ESs supply, as well as the aggregation degree of PRAs, assisting with generating the maximum restorative benefits flowing to human society. The majority of previous studies on ES emphasized a supply-side perspective, i.e., restoring primarily high-supply areas [22]. Nevertheless, the prevalence of supply–demand imbalances in ecosystems prevents the restoration benefits generated by restoring high-supply areas from flowing directly to human society, resulting in a loss of ES. In this study, the demand importance was used to modify the priority restoration grades. After considering human demand, the results showed that the location of "high"-priority PRAs began to move away from County 33 and toward those areas with dense POI such as Counties 13, 15, and 16, characterized by a heavy supply and demand (Figure 9). Furthermore, the scattered restoration patches were removed from the PRAs after employing the aggregation correction, to ensure comprehensive restoration benefits. The proposed framework also serves as a useful tool for the rapid identification of PRAs. Conventional methods for identifying PRAs using pixels as research units encounter significant computation challenges due to the vast amount of required data [30,57,61] On the contrary, the usage of Marxan considerably simplified the computational effort based on a simulated annealing algorithm. Moreover, when multiple comparative scenarios are required to be established, Marxan can swiftly compute an alternative solution tailored to the target by self-adjusting the parameters, thus considerably improving the generalization of the method adopted.

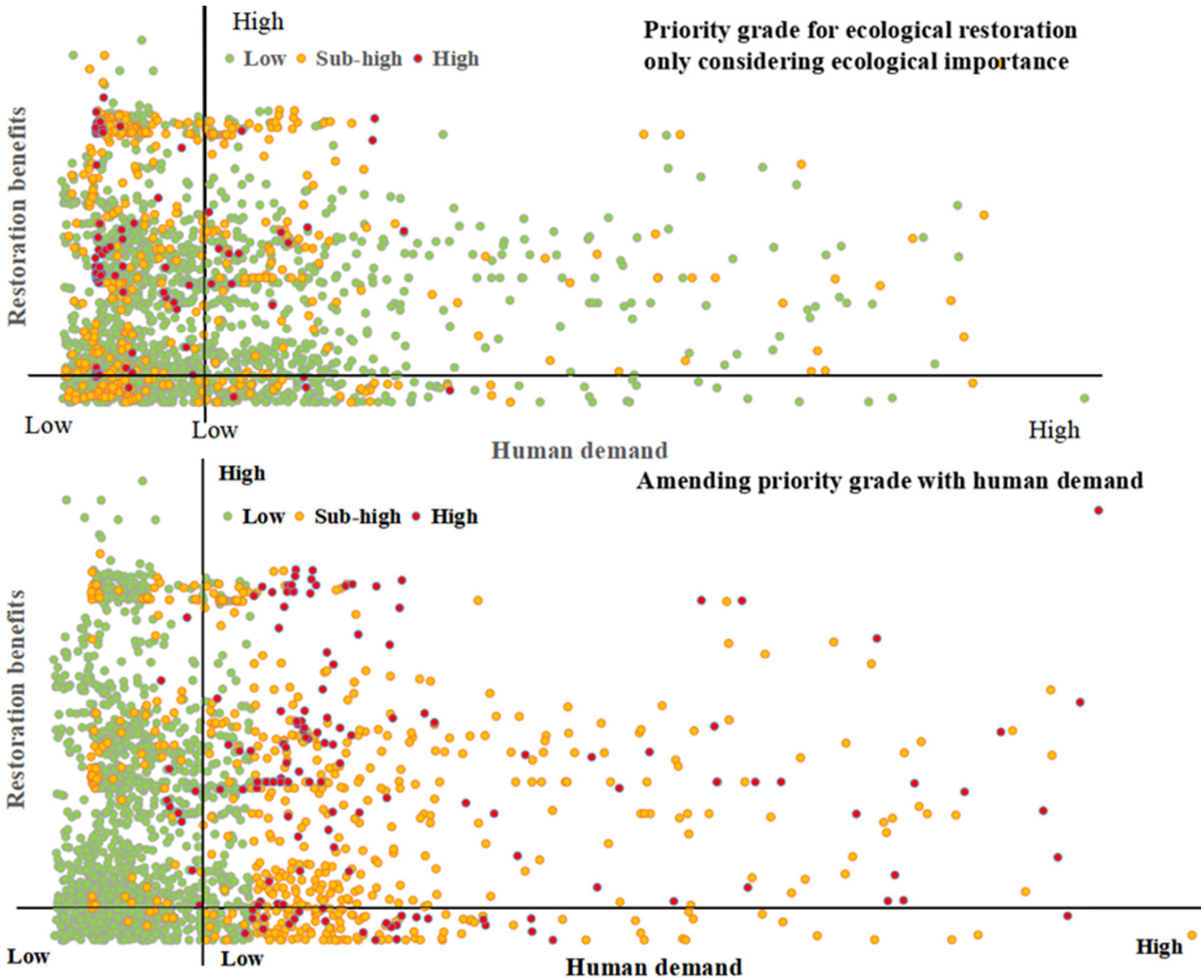

Figure 9. Relationship between priority grades and restoration benefits, and human demand.

The proposed framework allows us to generate maps of PRAs based on a trade-off between the social and ecological benefits of ecosystems, and enables government agencies to manage ecosystems more effectively. For example, the PRAs for forest should be restored primarily by enhancing forest quality. In terms of restoration areas dominated by cropland, the first choice would be the selective restoration of cropland to forest and water bodies, on the premise of guaranteeing regional food security, targeting, for example, cropland with slopes greater than 15° or poor yields. Furthermore, the increase of plant diversity towards the ending-stage of reforestation would dramatically favor the improvement of CS [62].

This study successfully identified PRAs for improving ES by considering the costs, benefits, and human demand. Moreover, its findings are also critical for the sustainable management of ES and the increase of human well-being. However, there is still potential for improvement. First, this study was affected by uncertainty in the relevant data, such as land-use maps and economic data. Second, the kernel density value of the POI data was used to characterize human demand when determining the demand importance; however, the value preference for the beneficiary subjects of social benefits varies widely, and this method does not reflect the choice and preference of stakeholders for ES well. Hence, future research should place a greater emphasis on incorporating stakeholder value into decision making. Finally, our framework has identified PRAs based on the current state of ecosystems and human demand, neglecting that ecosystems and social systems are dynamic processes. Therefore, integrating regional development planning to identify PRAs can lead to a more accurate identification of PRAs.

5. Conclusions

This study proposed a well-established framework for the identification of PRAs to improve ES that integrates both the ecological and demand importance. The comparison of changes in the potential supply of long-term ES facilitates the identification not only of areas where ecosystem conversion has occurred, but also of unconverted areas where ecological quality is being degraded, thus allowing us to perform a more comprehensive selection of PoRAs. Furthermore, the ecological restoration cost integrated the ecological restoration projects' cost and restoration benefits, allowing the PRAs identified through Marxan to be characterized by both a low cost and high ES supply. Finally, the correction of the restoration priority grades based on the demand importance and aggregation degree enabled "high" PRAs to maximize the comprehensive restoration benefits, i.e., to generate a huge ES supply while meeting human demands. Applied into practice, the improved framework allowed us to exactly define the restoration priority grade for CS, HS, and WH in the Dongting Lake Eco-Economic Zone. These findings are critical for the efficient implementation of ecological restoration in the region, as well as for supporting the effective management of the ecosystem and improving human well-being.

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