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Conservation Strategies for Xishuangbanna: Assessing Habitat Quality Using the InVEST Model and Human–Elephant Conflict Risk with Geographic Information System

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Abstract: Xishuangbanna, located in southern Yunnan, China, is a vital tropical rainforest reserve supporting rich biodiversity, including the endangered Asian elephant (*Elephas maximus*). Increasing human activities, such as urbanization and agricultural expansion, have degraded habitats and intensified human–elephant conflicts, adding to the challenges of conservation. This study integrates habitat quality assessment and conflict risk analysis using the InVEST model across 2128 villages, considering land use and habitat threats like cropland and roads. The model reveals significant overlap between high-conflict zones and low-quality habitats near key reserves, underscoring the need for targeted conservation strategies. We propose establishing Ecological Source Areas (ESAs) to protect high-quality habitats and Ecological Restoration Zones (ERZs) to improve ecological conditions in low-quality, high-conflict zones. ESAs are essential for providing continuous ecosystem services and ensuring ecological security, while ERZs focus resources on areas with high conflict risk that urgently need restoration. Additionally, we recommend creating ecological corridors to connect fragmented habitats, enhance connectivity, support herd interactions, and reduce conflicts by expanding elephants' safe roaming range. This integrated framework emphasizes habitat protection, ecological restoration, and conflict mitigation while accounting for human dynamics to support sustainable conservation. Reducing overlap between human and elephant activities remains a key objective. Future research should refine these models with more detailed data and extend their application to other regions, focusing on adaptive management and monitoring to address evolving ecological and human dynamics.

Keywords: Xishuangbanna; Asian elephant; human–elephant conflict; habitat quality; InVEST model; conservation planning

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Citation: Tang, H.; Li, L.; Pang, C.; Slate, T.J.; Giraudoux, P.; Afonso, E.; Guo, H.; Wu, G.; Zhang, L. Conservation Strategies for Xishuangbanna: Assessing Habitat Quality Using the InVEST Model and Human–Elephant Conflict Risk with Geographic Information System. *Diversity* **2024**, *16*, 761. https://doi.org/10.3390/d16120761

Academic Editor: Corrado Battisti

Received: 15 October 2024
Revised: 9 December 2024
Accepted: 11 December 2024
Published: 13 December 2024

1. Introduction

The Asian elephant (*Elephas maximus*), a keystone species vital to the ecological balance of Asian tropical forests, faces increasing threats from habitat fragmentation and human–elephant conflicts, particularly in the Xishuangbanna region of southern Yunnan, China [1,2]. Since 1976, the Asian elephant population in Xishuangbanna has fluctuated

(Table 1), impacted significantly by human activities, including extensive deforestation for rubber plantation development [3–5]. Recent enhanced conservation measures have brought the population to about double what it was in 2005–2006 [6]. However, the species remains critically endangered. Habitat degradation and expanding human activity are leading to increases in both the frequency and severity of conflicts [7–9]. This habitat degradation and increased conflict put the recent elephant population gains and sustainable practices at risk, underscoring the urgent need for effective conservation strategies that address both ecological and social dimensions [10,11]. There is not currently a target elephant population value for Xishuangbanna. This is a gap that needs to be addressed soon to further guide conservation measures and protect against human–elephant conflict.

Table 1. Estimated Asian elephant populations in Xishuangbanna from 1976 to 2014.

Year	Population (Approx.)
1976	101
1983	213
1997	165 to 197
2003	187 to 217
2005–2006	132 to 149
2014	228 to 279

Habitat quality is a fundamental determinant of an ecosystem's capacity to support wildlife and maintain biodiversity [11,12]. Understanding how habitat quality is influenced by various disturbances, both natural and anthropogenic, is important in planning and prioritizing conservation strategies. Disturbances, whether natural or anthropogenic, play a critical role in shaping ecosystems. Disturbances such as urbanization, agricultural expansion, and infrastructure development can degrade habitats and fragment ecosystems [13]. Moderate disturbances can sometimes enhance biodiversity and species coexistence by creating habitat mosaics and promoting ecological succession. However, excessive or frequent disturbances often result in irreversible degradation [14].

In Xishuangbanna, rapid urbanization, agricultural expansion, and infrastructure development have significantly transformed land use and land cover, resulting in habitat loss and degradation [15]. Although substantial research has been conducted on habitat fragmentation and human–wildlife conflicts, integrated assessments evaluating both habitat quality and conflict risks are urgently needed in regions experiencing these rapid environmental changes [16,17]. Innovative approaches combining spatial analysis, ecological modeling, and conflict data provide avenues for developing targeted conservation strategies that address both ecological and human dimensions [18].

There are currently many methods for evaluating habitat quality, but it is essential to consider the influence of ecological disturbances in this process. Drawing on the theoretical framework of disturbance ecology, this study integrates multiple threat factors, such as cropland, roads, and villages, to assess their spatial impacts on habitat quality. These insights align with the work of Salafsky et al. and Wohlgemuth et al., highlighting the dynamic role of disturbances in shaping ecosystem resilience and biodiversity [13,14].

One commonly used method is conducting field surveys to construct habitat quality assessment indicators. This method requires a large amount of human and material resources and is time-consuming and labor-intensive. As such, it is only suitable for small-scale research. It is too difficult to use in large-scale habitat quality assessments [19]. Another commonly used method is to use models to evaluate habitat quality. This method involves using various modern technological means, such as remote sensing technology and GIS technology, to establish mathematical models to evaluate habitat quality [20,21]. The advantage of this method is that it can quickly obtain large-scale habitat ecosystem quality information and can be evaluated at different scales according to needs. Among these habitat quality models, the widely used InVEST model has the advantages of easy parameter acquisition, the visualization of results, etc. [22,23]. Moran's I spatial autocorrelation analysis is used to identify clusters of high and low habitat quality, providing spatial pattern insights to further guide priority conservation [24].

In addition, a GIS-based human–elephant conflict risk model was developed as part of this study using insurance claim data to simulate the human–elephant conflict risk level of the entire study area. The claim data included the location and extent of damage, making it a good method for measuring conflict risk and impact. This integrated approach can identify high-risk areas and provide a detailed understanding of the dynamics of conflict space, which is crucial for developing targeted conservation strategies.

Through the innovative integration of NDVI, GIS, and the InVEST model, this study's aim is to improve the accuracy of habitat quality evaluation, providing valuable guidance for regional conservation planning. These findings have broader implications for similar conservation challenges worldwide, emphasizing the need for multifaceted approaches to protect wildlife in rapidly changing landscapes.

This is not a study of the elephants themselves; it is a study of the elephant's habitat and of human–elephant conflict risks. The primary goal of this study is to assess habitat quality and human–elephant conflict risk for Asian elephants in order to develop effective conservation strategies that support the long-term survival of the species. While calculating human–elephant conflict risk, we focused on incident data, specifically insurance claims data, as these directly reflect human–elephant conflict occurrences. However, in constructing the model, we also included relevant variables such as cropland distribution, open woodland areas adjacent to cropland, and slope. These factors have been validated by previous studies as key areas where human–elephant conflicts are likely to occur [25]. Additionally, when assessing habitat quality for Asian elephants, we carefully considered habitat suitability specific to this species. Parameter selection was guided by published research on Asian elephant habitats in Xishuangbanna, incorporating primary threat factors such as cropland, village roads, settlements, and orchards to evaluate habitat quality [26,27]. This ensures that the model accounts for environmental factors directly relevant to Asian elephants and their habitat needs, rather than solely focusing on conflict-related variables.

2. Study Area

The Xishuangbanna Dai Autonomous Prefecture in the southern part of Yunnan, China, is situated in the Hengduan Mountains (Figure 1). The geographic coordinates range from 21°08′ to 22°36′ N latitude and 99°56′ to 101°50′ E longitude, encompassing an area of approximately 19,100 km^2. The topography of Xishuangbanna is characterized by high elevations surrounding a lower central basin, creating significant terrain variations across the region [28].

The region experiences a tropical monsoon climate with an average annual temperature exceeding 20 °C and annual precipitation reaching 2491 mm. These humid climatic conditions are conducive to the growth of tropical rainforests. However, the rapid increase in human population and the expansion of economic crops such as rubber, coffee, and tea have substantially altered land use patterns, which in turn has led to the significant fragmentation of the elephants' original habitat areas [29].

The intensification of human activities, particularly agricultural expansion and infrastructure development, has directly impacted the range and distribution of the Asian elephant, exacerbating human–elephant conflicts in the region. In response to these ecological challenges, the Yunnan Xishuangbanna National Nature Reserve was established in 1958 to protect this critical ecosystem [30]. The reserve spans Menghai County, Jinghong City, and Mengla County, comprising five geographically distinct sub-reserves: Mangao, Mengla, Menglun, Mengyang, and Shangyong. These sub-reserves encompass extensive areas of tropical rainforests and host the largest and most concentrated populations of Asian elephants. Despite these conservation efforts, ongoing human encroachment and land use changes continue to pose significant threats to habitat integrity and have intensified human–elephant conflicts within and around the reserve [31].

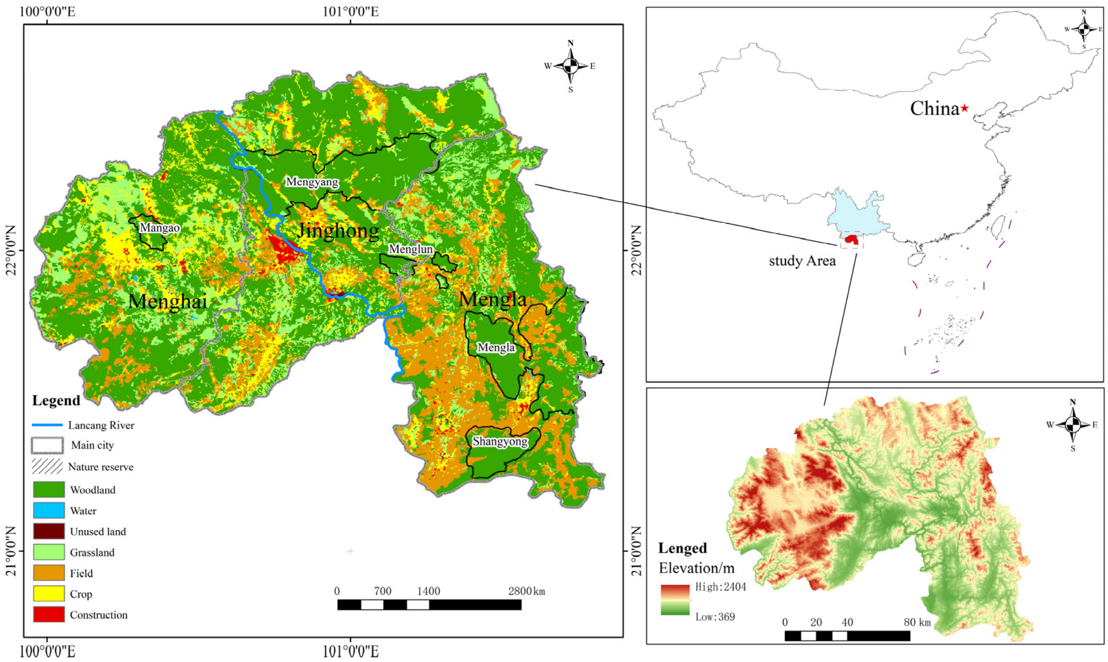

Figure 1. Location, terrain types, geopolitical boundaries, and elevations of the study area.

3. Data Sources and Research Methods

3.1. Data Sources

This study utilizes a diverse range of data sources, as detailed below. All raster data were processed using ArcGIS 10.8, projected uniformly to the WGS_1984_UTM_Zone_48N coordinate system and reclassified into a 1 km × 1 km grid format to ensure data consistency and comparability.

Land Use Data: The land use data for the study area for the year 2020 were sourced from the Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn, accessed 27 February 2023), with a resolution of 1 km × 1 km.

Normalized Difference Vegetation Index (NDVI) Data: NDVI data were sourced from the Earthdata platform (https://earthdata.nasa.gov, accessed 16 April 2023) and used to assess habitat quality.

Road Network Data: Road network information was derived from OpenStreetMap (OSM) (https://www.openstreetmap.org, accessed 4 July 2023), covering all roads within the study area.

Socioeconomic Data: The socioeconomic data of 2128 natural villages were sourced from the Yunnan Digital Rural Network (http://www.ynszxc.gov.cn, accessed 6 May 2018), including information on population and economic activities. Natural villages are settlements that form organically over a long period, with residents living close together within a specific natural environment. Typically, villagers share the same surname and lineage, descending from a common ancestor. Village point data were sourced from the National Catalogue of Geographical Information Resources (https://www.webmap.cn, accessed 10 May 2023). Administrative village boundaries were sourced from the National Geographic Information Public Service Platform, Tianditu (http://www.tianditu.gov.cn, accessed 10 May 2023). Administrative villages are the lowest level of governmental body and often comprise multiple natural villages.

Human–Elephant Conflict Compensation Data: Data on compensation for damages caused by human–elephant conflicts were provided by the Xishuangbanna Branch of China Pacific Property Insurance Co., Ltd., Xishuangbanna, China, and were used to analyze the impacts of such conflicts.

3.2. Research Methods

Habitat Quality Assessment Model

This study employed the Habitat Quality module of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model to evaluate habitat quality in the study area. The InVEST model integrates land use and land cover data, the spatial distribution of threat factors, their respective weights, and the maximum impact distances of threat factors to calculate habitat degradation [32]. The primary threat factors selected for the model were cropland, construction land, orchards, roads, and village development levels due to their significant impacts on habitat quality [26,27].

(1) Evaluation of Village Impact on Habitat Quality through Development Indicators

To evaluate the impact of villages on habitat quality, data were collected from 2128 villages in the study area using 28 development-related indicators across five indicator groups: resources, population, economy, infrastructure, and energy (Table 2). Indicators were standardized to ensure comparability and eliminate dimensional differences. The Entropy Weight Method was subsequently used to calculate the weight of each indicator.

Table 2. Hierarchical structure of indicators for evaluating economic development and its impact on habitat quality.

Indicator Group	Indicator	Indicator Code
Resource Indicators	Common cultivated land area	X11
	Paddy field area	X12
	Dry land area	X13
	Per capita cultivated land area	X14
	Forest area	X15
	Economic forest and orchard area	X16
	Per capital economic forest and orchard area	X17
Population Indicators	Rural population	X21
	Agricultural population	X22
	Labor force	X23
	Number of people engaged in primary industry	X24
	Population with college degree or above	X25
	Population with secondary education	X26
	Population with primary education	X27
Economic Indicators	Total rural economic income (per CNY 10,000 per year)	X31
	Income from cash (per CNY 10,000 per year)	X32
	Income from planting industry (per CNY 10,000 per year)	X33
	Income from animal husbandry (per CNY 10,000 per year)	X34
	Income from Secondary and Tertiary Industries (per CNY 10,000 per year)	X35
	Per capita net income of farmers (per CNY 1 per year)	X36
Infrastructure Indicators	Distance to nearest station (km)	X41
	Distance to nearest market (km)	X42
	Number of cars	X43
	Number of agricultural transport vehicles	X44
	Number of motorcycles	X45
	Number of tractors	X46
Energy Indicators	Number of households with biogas pools	X51
	Number of households with solar energy	X52

The specific steps performed are described below.

Data Normalization: The raw data were normalized to standardize all indicator values to a comparable range.

Entropy Calculation: The entropy value e_j for each indicator was calculated based on the normalized data: $e_j = -\frac{1}{lnm}\sum_{i=1}^{m} P_{ij} lnP_{ij}$, where P_{ij} represents the normalized value of village i for indicator j, and m = 2128 is the total number of villages.

Weight Calculation: Using the entropy values, the weight W_j of each indicator j was computed: $W_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)}$, where m is the total number of indicators [33,34].

Indicator Standardization: Two different formulas were used to standardize the indicators. z_{ij} represents the standardized value for indicator j in village i. For positive indicators, the formula $z_{ij} = \frac{a_{ij}-min(a_{ij})}{max(a_{ij})-min(a_{ij})}$ was used. For negative indicators, the formula $z_{ij} = \frac{max(a_{ij})-a_{ij}}{max(a_{ij})-min(a_{ij})}$ was used. In both formulas for z_{ij}, $min(a_{ij})$ is the minimum value for a given indicator (j) across all villages, and $max(a_{ij})$ is the maximum value for a given indicator (j) across all villages.

Using these weights, the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) was applied to calculate a comprehensive score for each village, determining their relative impact on habitat quality. A higher score indicates a greater negative impact on habitat quality. Each village was assigned to one of five village groups (Village I through Village V) based on this comprehensive score using the natural breaks classification method. The villages with the lowest comprehensive scores were assigned to Village I and the villages with the highest comprehensive scores were assigned to Village V.

(2) Determination of Maximum Impact Distances

Each threat factor, such as cropland or roads, impacts the habitat quality of the area around it. This impact is felt not only in the immediate vicinity of the threat, but also further way from the threat into the habitat area, though at diminishing magnitudes. A road has a very significant impact on habitat quality a few meters from its side. An impact on habitat quality is still felt 1 km away from the side of the road, though the magnitude of this impact is less. A threat factor's impact on habitat quality decreases either linearly or exponentially with respect to distance. The maximum impact distance of a threat is the distance at which the threat factor's impact reaches its first inflection point.

To accurately estimate the maximum impact distances of various threat factors, the Normalized Difference Vegetation Index (NDVI) was used as a proxy indicator for habitat quality [35]. ArcGIS distance analysis tools were applied to examine the trend of NDVI values in relation to increasing distances from the identified threat factors. The analysis revealed that the maximum impact distances for different threat factors varied between two and four kilometers (Figure 2) [36,37]. These calculated maximum impact distances were incorporated into the model to capture the spatial influence of each threat factor on habitat quality.

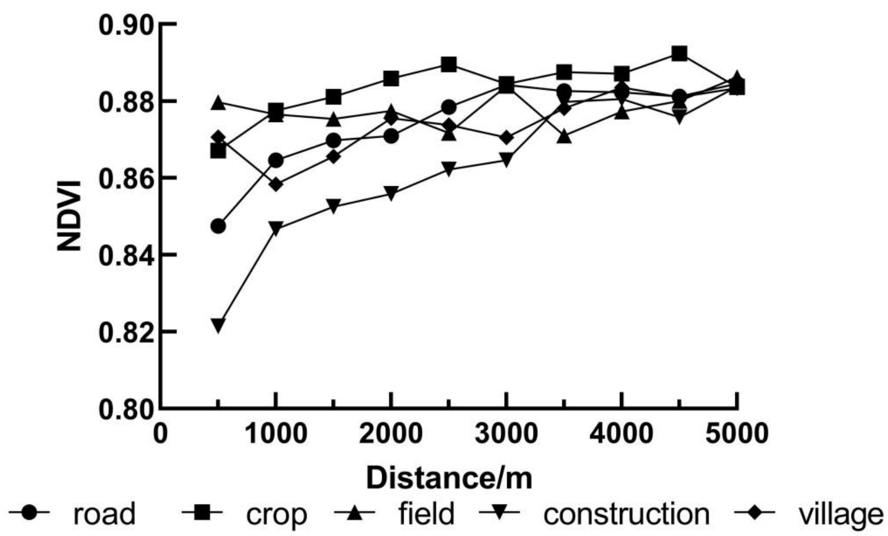

Figure 2. Assessment of impact distance of threat factors based on NDVI.

The data for this calculation were based on previous research on Xishuangbanna habitats conducted by our research group. To determine the maximum impact distance of threat factors, the NDVI values for the habitat types (forest land, sparse forest land, shrubland, grassland) were used. Using ArcGIS's nearest neighbor analysis tool in the distance analysis module, the shortest distance from each habitat point to a nearby threat factor was calculated. Then, in Excel, the average NDVI values were calculated at intervals of 500 m. These data were organized and summarized to create a trend graph showing how NDVI changes with increasing distance from threat factors. According to the trend graph, the maximum impact distance of a threat factor based on NDVI is determined by identifying the first inflection point where NDVI begins to level off after showing a rising trend with increased distance. Beyond this maximum impact distance, NDVI no longer increases significantly, indicating that the influence of the threat factor on vegetation cover in the habitat becomes negligible.

(3) Calculation of Habitat Degradation and Quality

Based on the analysis results, the weights and spatial decay types for each threat factor were determined (Table 3). These weights were determined by referring to published studies on Xishuangbanna habitats, from which an average weight was calculated [38,39]. The classification was tailored to the specific conditions of Xishuangbanna, with sensitivity parameters established for each threat factor based on local conditions and relevant literature (Table 4). The sensitivity of the threat factors was based on related published research on Xishuangbanna habitats [26,38–40].

Table 3. Maximum impact distance and weight of threat factors.

Threat Factors	Maximum Impact Distance (km)	Weight	Spatial Decay Type
Road	3	0.6	Linear
Crop	2.5	0.4	Exponential
Field	3	0.7	Exponential
Construction	4	0.9	Exponential
Village I	2	0.4	Exponential
Village II	2	0.5	Exponential
Village III	2	0.6	Exponential
Village IV	2	0.7	Exponential
Village V	2	0.8	Exponential

Table 4. Sensitivity of land use types to threat factors.

Land Cover	Habitat Suitability	Threat Sensitivity								
		Rd	Crp	Fld	Cnstrct	V-I	V-II	V-III	V-IV	V-V
Crop	0.3	0.6	0	0.4	0.6	0.6	0.6	0.75	0.8	0.9
Woodland	0.9	0.65	0.6	0.9	0.75	0.5	0.55	0.65	0.7	0.8
Shrub	1	0.6	0.5	0.6	0.8	0.5	0.5	0.55	0.6	0.7
Spares Woodland	0.8	0.7	0.6	0.7	0.8	0.6	0.6	0.75	0.8	0.9
Field	0.3	0.5	0.4	0	0.7	0.5	0.55	0.6	0.65	0.7
Grassland	0.6	0.5	0.6	0.5	0.65	0.6	0.6	0.75	0.8	0.9
Water	0.7	0.4	0.45	0.45	0.7	0.45	0.45	0.55	0.6	0.7
Construction	0	0	0	0	0	0	0	0	0	0
Unused Land	0.35	0.2	0.15	0.3	0.3	0.2	0.2	0.35	0.4	0.5

Note: The habitat suitability values indicate the relative suitability of each land cover type for supporting high-quality habitat, while the threat sensitivity values denote the degree to which each land cover type is affected by specific threats. (Rd = road, Crp = crop, Fld = field, Cntrct = construction, V-I = Village I, V-II = Village II, V-III = Village III, V-IV = Village IV, V-V = Village V).

(4) Calculation of the habitat quality index

The habitat quality index was calculated using the following formula [41,42]:

$$Q_x = \frac{H_x}{H_x + D_x + k}$$

where Q_x is the habitat quality index for a specific location, H_x is the habitat suitability score (indicating the inherent ability of a location to support habitat quality), D_x is the habitat degradation index (reflecting the cumulative impact of all threat factors on habitat quality), and k is the half-saturation constant (controlling the smoothness of the transition of quality values between zero (poor habitat quality) and one (high habitat quality)).

The habitat suitability score (H_x) was derived from the sensitivity of different land use types to various threat factors (Table 3). The habitat degradation index (D_x) was computed by integrating the weights and spatial decay types of the identified threat factors, using the maximum impact distances obtained from the analysis. These maximum impact distances were crucial in determining how far the effects of each threat factor extended spatially, thereby influencing the calculation of degradation.

To classify habitat quality into different levels, the equidistance method was employed. This method categorized the habitat quality index (Q_x) into five distinct levels: lowest (<0.2), low ($\geq$0.2 and <0.4), medium ($\geq$0.4 and <0.6), high ($\geq$0.6 and <0.8), and highest ($\geq$0.8) [43].

After calculating the habitat quality index (Q_x) and identifying areas with varying habitat suitability and degradation levels, the next step involved assessing the spatial patterns of habitat quality across the landscape.

3.3. Spatial Autocorrelation Analysis

To further analyze the spatial distribution of habitat quality, Moran's I statistic was employed to identify clustering patterns [44,45]. Both Global Moran's I and Local Moran's I were utilized to provide a comprehensive analysis of spatial dependencies across the landscape. Global Moran's I was applied to measure the overall spatial autocorrelation of habitat quality throughout the study area. This global measure assesses whether habitat quality values are randomly distributed or exhibit a pattern of spatial clustering. A statistically significant Global Moran's I value indicates a non-random spatial distribution, suggesting that similar habitat quality values tend to cluster together [43]. Local Moran's I was used to identify specific clusters and spatial outliers, such as high–high clusters (areas of high habitat quality surrounded by similar areas of high habitat quality) and low–low clusters (areas of low habitat quality surrounded by similar areas of low habitat quality). This local indicator of spatial association (LISA) allows for the detection of localized patterns of spatial clustering or dispersion that may not be apparent from the global analysis alone.

The spatial autocorrelation analysis was conducted using a 1 km $\times$ 1 km grid across the study area in ArcGIS 10.8 [46]. The 1 km grid size was chosen to balance the resolution of the analysis with computational efficiency, providing sufficient detail to capture spatial patterns while maintaining manageable data processing requirements, as well as to maintain consistency in reporting the results. A finer grid could offer more precise local patterns but would significantly increase computational load, whereas a coarser grid might overlook important spatial details.

To create the spatial weights matrix required for Moran's I calculations, an inverse distance weighting approach was used, assigning higher weights to closer habitat patches to reflect stronger spatial interactions. This approach ensured that the analysis adequately captured local spatial dependencies, which are critical for understanding the distribution of habitat quality throughout the landscape. By applying both Global and Local Moran's I, this study aimed to identify the presence of spatial autocorrelation in habitat quality and detect specific clusters to inform targeted conservation strategies. The identification of high-quality clusters highlights areas where conservation efforts should be prioritized, and the identification of low-quality clusters highlights areas where restoration efforts should be prioritized.

3.4. Establishment of Risk Assessment Model for Human–Elephant Conflicts

Building on the spatial analyses of habitat quality, this section focuses on developing a risk assessment model for human–elephant conflicts. Understanding how these conflicts correlate with habitat conditions and land use patterns is critical for effective conservation planning and conflict mitigation.

3.4.1. Data Collection and Sources

To develop a comprehensive risk assessment model, this study utilized data collected from two primary sources spanning different time periods. For the period from 2010 to 2016, data were obtained from insurance claim records provided by insurance companies. These records detailed incidents involving Asian elephants, including the locations of impacted households, dates of incidents, and types of losses (e.g., damaged crop areas, tree species affected, livestock losses, casualties, and property damage) [29,47]. This dataset was instrumental in understanding the spatial and temporal distribution of human–elephant conflicts during this timeframe. For the period from 2016 to 2022, additional data were extracted from the published literature, focusing on studies documenting human–elephant conflict incidents and their impacts. This dataset provided insights into the proportion of different land types affected by conflicts, such as cropland, forest areas, and other land use categories. By combining these two data sources, we were able to conduct a detailed analysis of how human–elephant conflicts impacted various land use types over different periods.

3.4.2. Identification and Spatial Analysis of Conflict Points

The collected conflict data were georeferenced to specific villages, leading to the identification of 339 human–elephant conflict points across the study area. These spatial data points were essential for pinpointing the areas most affected by Asian elephants and for analyzing the spatial patterns of conflicts over time. The distribution of these conflict points provided critical insights into the areas most vulnerable to human–elephant conflicts, aiding in targeting conservation efforts.

3.4.3. Risk Assessment Model Development

To assess the risk of human–elephant conflicts, the analysis drew on previous research findings indicating that conflicts predominantly occur in croplands, low-slope areas, and sparsely wooded regions adjacent to croplands [29]. A 1 km $\times$ 1 km fishnet grid was created in ArcGIS 10.8, serving as the foundational unit for analysis [46]. The model incorporated cropland data from 2020, applying the natural breaks (Jenks) classification method to categorize the proportion of cropland and establish thresholds for different levels of conflict risk. These were grouped into four risk grades: no risk [0–0.1094), low risk [0.1094–0.3336), medium risk [0.3336–0.6362), and high risk [0.6362–1] [48].

Additional spatial layers, such as sparsely wooded areas adjacent to high-risk zones and slope data, were integrated to refine risk area definitions [29,49]. Areas with a higher likelihood of conflicts were identified based on their proximity to cropland and lower slope gradients. The spatial join tool in ArcGIS linked conflict records to grid units, enabling the calculation of conflict points within each risk area.

3.4.4. Model Validation and Accuracy

The risk assessment model was validated using spatial overlay analysis to evaluate its accuracy. The validation compared model-predicted high-risk areas with actual conflict points from field data. The spatial join tool in ArcGIS was used to calculate the percentage of actual conflict points that fell within the predicted high-risk zones. Further, the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) metrics were employed to assess the model's predictive power and accuracy [50]. The ROC curve visually represented the model's ability to differentiate between high-risk and low-risk areas, while the AUC metric quantified the overall accuracy of the model's predictions.

3.5. Development of Conservation Planning Strategies

Based on the findings from habitat quality assessments and human–elephant conflict risk analyses, this study developed conservation strategies to mitigate conflicts and enhance habitat connectivity in Xishuangbanna. The study area was divided into three zones: Ecological Source Areas, which are high-quality habitats prioritized for protection; Ecological Restoration Zones, which require habitat restoration to improve ecological conditions; and Ecological Transition Zones, which serve as buffers to reduce conflicts between high-quality habitats and human settlements. To enhance landscape connectivity and facilitate the safe movement of Asian elephants, ecological corridors were strategically planned using GIS tools to connect fragmented habitats while avoiding high-conflict and low-quality zones. These corridors were designed to minimize disturbances and promote connectivity among key conservation areas, including the Mengyang, Mengla, and Shangyong reserves. Restoration zones were identified near conflict hotspots and targeted for reforestation and habitat enhancement to improve degraded areas. Conservation strategies aim to optimize habitat quality, enhance landscape connectivity, and mitigate human–elephant conflicts, supporting the long-term survival of Asian elephants and maintaining the ecological integrity of the region.

4. Result

4.1. Assessing Habitat Degradation and Human–Elephant Conflict Risk Using InVEST and GIS-Based Models

Using the InVEST model, this study integrates land use and land cover data, spatial distributions of threat factors, and their respective weights and maximum impact distances to calculate habitat degradation [22]. Key threat factors, including cropland, construction land, orchards, roads, and village development levels, were identified for their significant impact on habitat quality [26,27]. The Normalized Difference Vegetation Index (NDVI) was employed to refine the maximum impact distances for these factors, providing a more precise analysis of their spatial influence on habitat conditions [23,51]. Furthermore, Moran's I spatial autocorrelation analysis was applied to identify clusters of high habitat and low habitat quality, offering insights into the spatial patterns that can guide conservation priorities [24].

Additionally, a GIS-based conflict risk model was developed using insurance claim data to simulate human–elephant conflict risk levels across the study area. The claim data include the location and extent of damage and hence are a good measure of conflict risk and impact.

4.2. Habitat Quality Assessment

The spatial distribution of habitat degradation and scarcity across the study area shows a heterogeneous pattern, with both high and low degradation levels observed (Figure 3). Establishing habitat degradation in the InVEST model involves mapping the impact of threats (roads, cropland, etc.) on the existing landcover; it is not a reflection of the change in habitat over two points in time. Higher degradation is predominantly found in the central and southern regions, where intensive land use and human activities are concentrated, particularly around high-grade administrative villages, croplands, and orchards. These areas exhibit degradation levels reaching up to 0.164, suggesting significant ecological stress. In contrast, the northern region generally displays lower degradation levels, indicating less impact from anthropogenic activities.

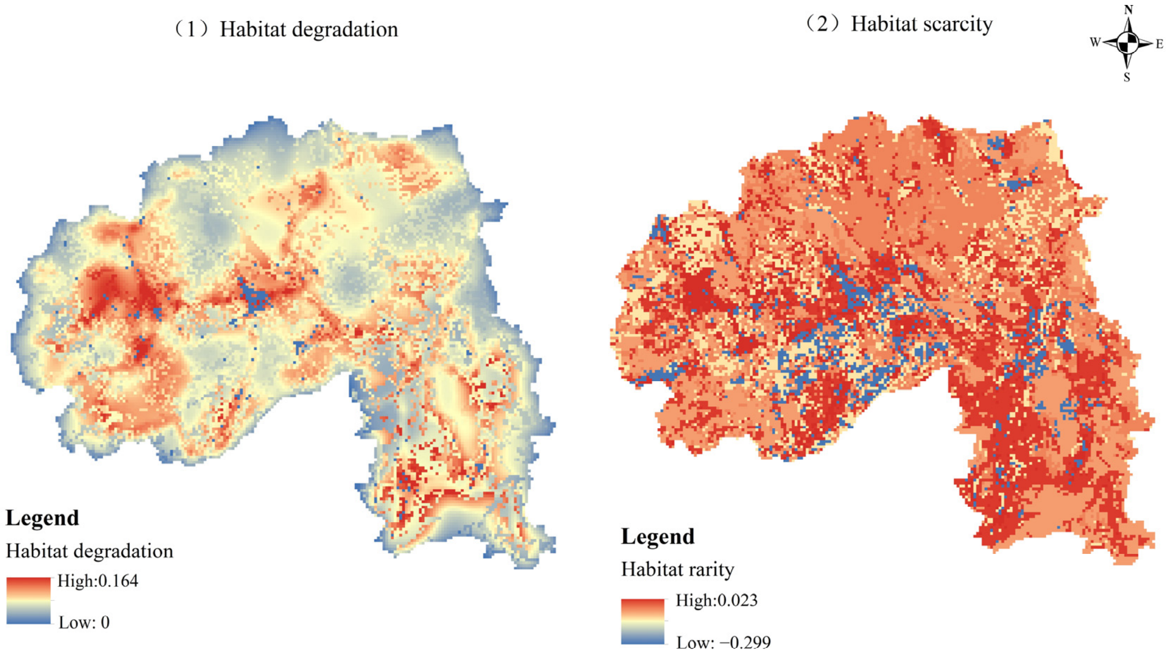

Figure 3. Spatial distribution of habitat degradation and habitat scarcity in Xishuangbanna.

Habitat scarcity is also notably high throughout the study area, particularly in the western and southern regions. These regions are characterized by both high degradation and high scarcity, identifying them as vulnerable areas that might require urgent ecological protection measures. The central region shows lower habitat scarcity but is adjacent to high degradation zones, suggesting a potential risk for further ecological decline.

The analysis of habitat quality indicates an average habitat quality index of 0.4191 across the study area, reflecting a moderate level of overall habitat quality. The spatial distribution of habitat quality (Figure 4) reveals that low-grade habitats (quality scores below 0.4) dominate the landscape, accounting for 51.58% of the total area. The lowest quality class (scores below 0.2) spans 3427 km^2, or 17.90% of the study area, while the highest quality class (scores above 0.8) is limited to 992 km^2, representing 5.18% of the area (Table 5).

Table 5. Area and proportion of different habitat quality classes (year 2020).

Habitat Quality Status	Score Range	Area (km^2)	% of Total Area
Lowest	<0.2	3427	17.90
Low	≥0.2, <0.4	6447	33.68
Medium	≥0.4, <0.6	4513	23.58
High	≥0.6, <0.8	3763	19.66
Highest	≥0.8	992	5.18

Higher habitat quality is generally observed in the northern region, whereas the southern and central regions exhibit lower-quality habitats. The lowest-quality areas are primarily found along major roads, particularly in the southeastern and southwestern parts of the study area. These regions are in close proximity to orchards, high-grade administrative villages, and croplands, indicating a clear correlation between intensive land use and reduced habitat quality.

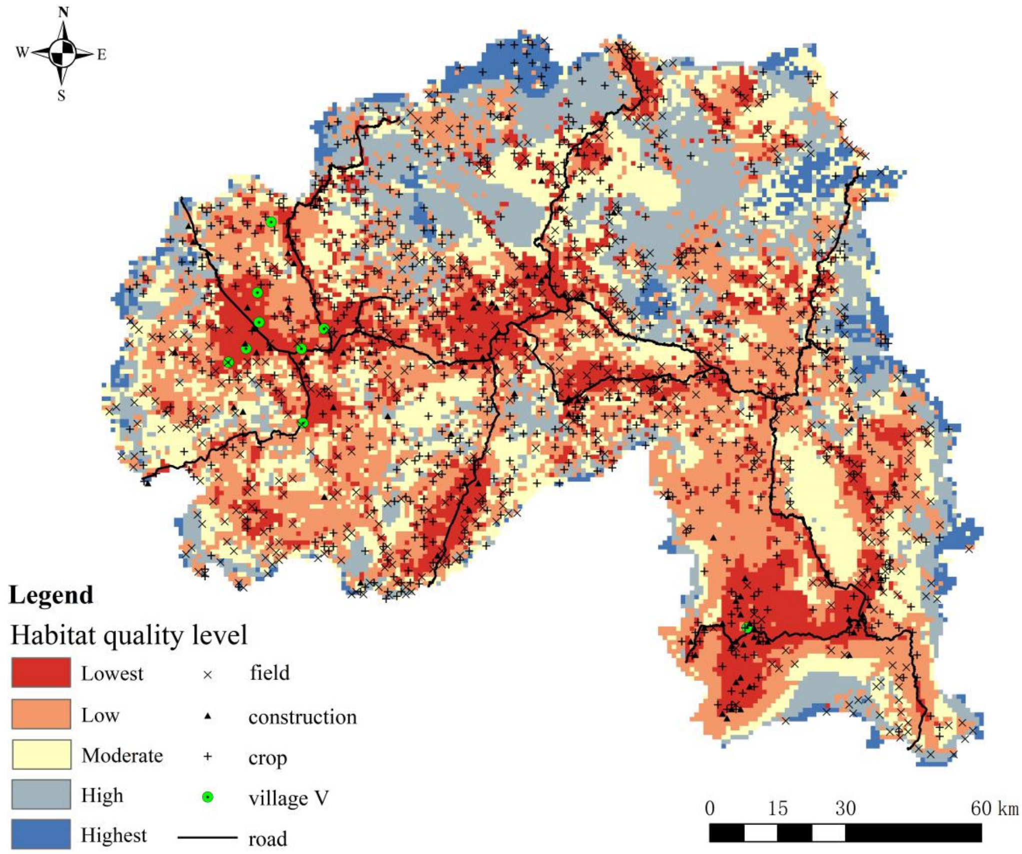

Figure 4. Spatial distribution of habitat quality in Xishuangbanna.

4.3. Risk Assessment of Human–Elephant Conflicts

The risk assessment of human–elephant conflicts (HEC) across Xishuangbanna identified significant spatial patterns in the distribution of conflict points, derived from insurance claim data and the literature as described earlier, and analyzed using spatial methods. The spatial distribution map (Figure 5) shows that conflicts are predominantly concentrated around key protected areas, including Mengyang (MY), Mengla (MLa), and Shangyong (SY), as well as along major roads and in regions with high levels of human activity. Areas with no risk account for 68.35% of the total study area (13,084 km^2), while low-risk areas account for 17.40% (3330 km^2), medium-risk areas for 10.46% (2003 km^2), and high-risk areas for 3.79% (725 km^2) (Table 6). Although high-risk areas are relatively small in size, they exhibit a high frequency of conflicts and generally lower habitat quality. Zones with a high frequency of conflict were identified in the western, southeastern, central, and northern regions of Xishuangbanna, with these areas characterized by proximity to agricultural lands (particularly croplands) and densely populated human settlements. The data indicate that conflicts are more prevalent where natural habitats intersect with agricultural and developed lands, with areas near croplands and adjacent to protected areas reporting higher conflict rates due to elephants moving into these regions, resulting in crop damage and other human–elephant interactions.

The risk assessment model demonstrated strong predictive accuracy, correctly identifying approximately 87% of high-risk zones and achieving a Receiver Operating Characteristic-Area Under Curve (ROC-AUC) score of 0.9, which indicates excellent model performance [52]. The sensitivity analysis further validated the model's robustness, showing consistent results under varying parameter settings. These results confirm the model's capability to accurately identify areas at high risk for human–elephant conflicts, providing a reliable foundation for future conflict mitigation strategies.

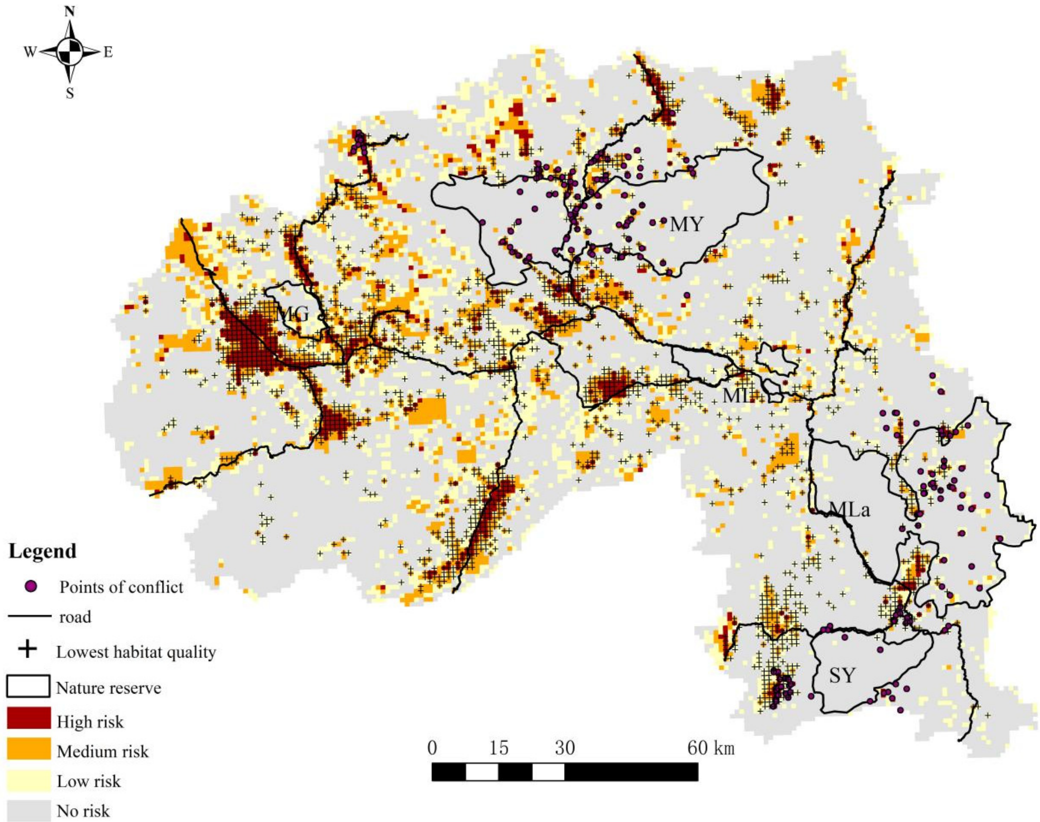

Figure 5. Spatial distribution of human–elephant conflict (HEC) risk in Xishuangbanna (MG = Mangao, MY = Mengyang, ML = Menglun, MLa = Mengla, SY = Shangyong).

Table 6. Area and proportion of different human–elephant conflict (HEC) levels (year 2020).

Risk Class	Area (km^2)	% of Total Area
No risk	13,084	68.35
Low risk	3330	17.40
Medium risk	2003	10.46
High risk	725	3.79

4.4. Integration of Habitat Quality and Conflict Risk Models for Conservation Planning

The integration of habitat quality and human–elephant conflict (HEC) risk models offers a robust foundation for conservation planning in Xishuangbanna, pinpointing areas where interventions are most urgently needed. Spatial analysis reveals a notable overlap between high-risk HEC zones and regions of low habitat quality, particularly in the western, southeastern, central, and some northern parts of the study area. These high-risk zones are primarily located around key protected areas, such as the Mengyang (MY), Mengla (MLa), and Shangyong (SY) reserves, where there is a significant intersection between human activities and elephant habitats. The HEC risk map indicates that approximately 90% of conflict points are situated within designated risk zones, highlighting the need for targeted management strategies in these areas (Figure 5).

Further spatial analysis using Moran's I reveals that high-quality habitats which form high–high spatial clusters are predominantly located in the northern and peripheral regions near protected areas such as Mengyang (MY). These areas, identified as Ecological Source Areas, are prioritized for strict protection to maintain ecological integrity (Figure 6). In contrast, areas categorized as low–low spatial clusters, which indicate substantial habitat degradation, are concentrated around Shangyong (SY), Mangao (MG), and Menglun (ML). These zones, characterized by low habitat quality and high conflict risk, are designated as

Ecological Restoration Zones, necessitating focused restoration efforts to enhance habitat conditions and mitigate human–elephant conflicts (Table 7, Figure 6). High–high clusters are areas of high habitat quality surrounded by similar areas of high habitat quality. Low–low clusters are areas of low habitat quality surrounded by similar areas of low habitat quality. High–low outliers are areas of high habitat quality surrounded by contradictory areas of low habitat quality. Low–high outliers are areas of low habitat quality surrounded by contradictory areas of high habitat quality.

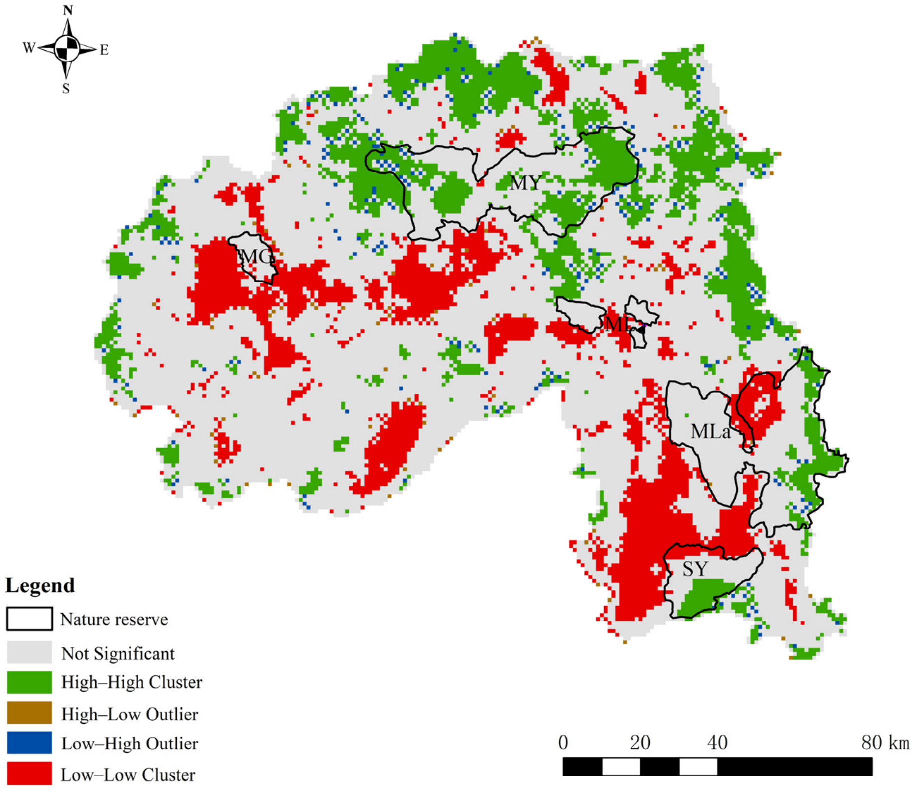

Figure 6. The spatial clustering of different habitat quality levels, highlighting the locations of high–high clusters near the Mengyang protected areas and low–low clusters in the western and south-eastern regions. (MG = Mangao, MY = Mengyang, ML = Menglun, MLa = Mengla, SY = Shangyong).

Table 7. Area and proportion of local spatial autocorrelation of habitat quality (year 2020).

Local Spatial Autocorrelation	Area (km^2)	% of Total Area
Not Significant	12,607	65.86
High–High Cluster	3144	16.42
Low–Low Cluster	3058	15.98
High–Low Outlier	81	0.42
Low–High Outlier	252	1.32

Additionally, integrating habitat quality and conflict risk data is instrumental in planning ecological corridors to enhance habitat connectivity while minimizing conflict risk (Figure 7). These corridors are strategically mapped to connect high-quality habitats, such as those in Mengyang (MY), Mengla (MLa), and Shangyong (SY), while avoiding the high-risk zones identified in the conflict risk model. This strategic placement supports the safe movement of elephants and reduces landscape fragmentation, aligning with conservation goals to protect biodiversity, improve habitat connectivity, and minimize human–elephant conflicts.

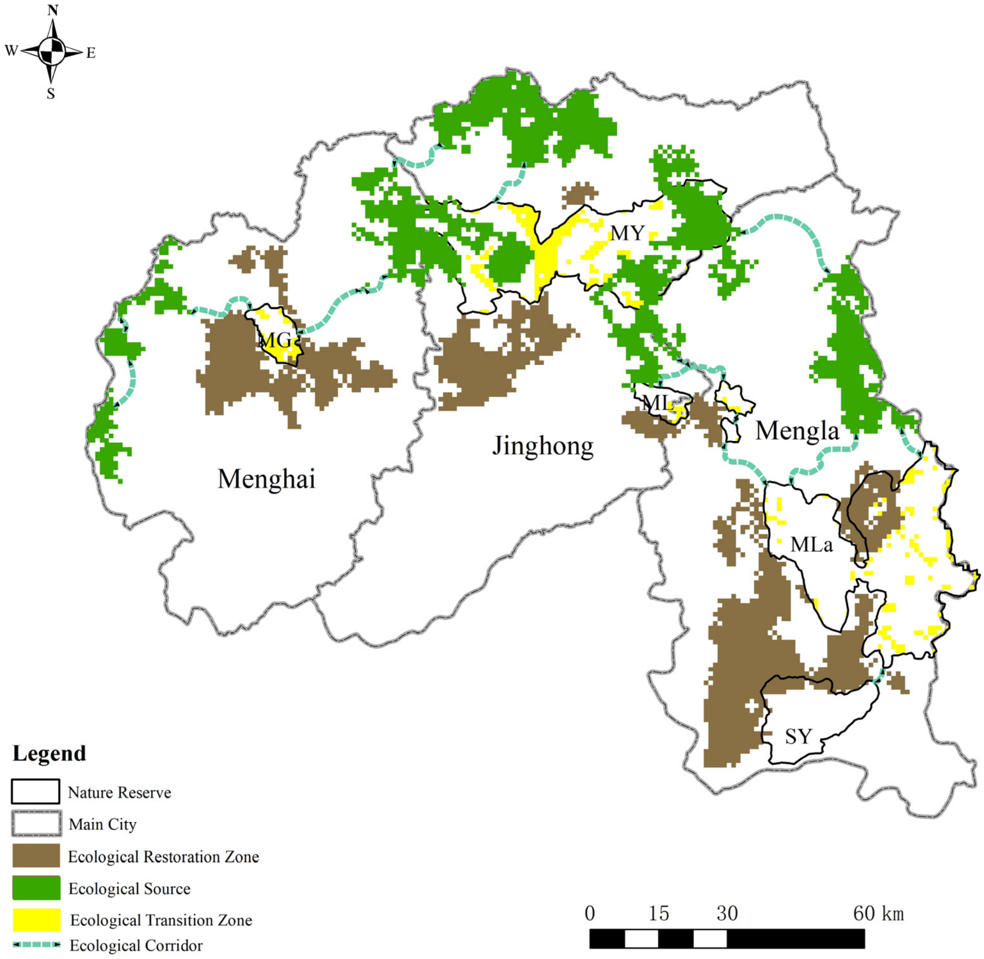

Figure 7. Proposed ecological corridors with strategic placement to avoid areas with high conflict risk and to maximize habitat connectivity between protected areas. (MG = Mangao, MY = Mengyang, ML = Menglun, MLa = Mengla, SY = Shangyong).

5. Discussion

Globally, wildlife and biodiversity conservation has become an increasingly urgent issue. With the expansion of human activities, wildlife habitats and biodiversity face severe challenges [53]. Xishuangbanna, located in Yunnan, China, is a critical tropical rainforest reserve essential for biodiversity conservation, particularly for the Asian elephant [15,54]. However, expanding human activities have led to habitat degradation and increased human–elephant conflicts in the region [16,55]. This study provides new insights into these challenges by integrating habitat quality assessments with the spatial analysis of conflict risks, offering a novel framework for conservation planning.

Human activities, including urbanization, agriculture, and infrastructure development, are the primary drivers of large-scale ecological disturbances in Xishuangbanna. Our findings highlight that agricultural expansion for cash crops (e.g., rubber and tea) and infrastructure development are key contributors to habitat degradation and human–elephant conflicts. For example, the conversion of forest lands in agricultural areas and the construction of roads to service these areas is an issue. These roads cut into habitats and corridors, driving fragmentation. This fragmentation in turn impedes natural elephant movement and increases human–wildlife interactions. This is backed up by our spatial analysis, which revealed significant habitat fragmentation and clusters of low-quality habitats near high-conflict zones, particularly in areas adjacent to reserves such as Mengyang, Mengla, and Shangyong. These results align with previous studies showing that agricultural intensification reduces forest cover and fragments habitats, intensifying human–wildlife conflicts [56,57].

Moreover, habitat fragmentation is exacerbated by infrastructure projects, such as constructing roads to increase human accessibility to remote areas. This disrupts elephant movement corridors, creating ecological traps [26,58]. Elephants are often attracted to human-dominated landscapes due to the availability of high-energy crops such as rubber, tea, and rice, leading to frequent conflicts [16,59]. These interactions underscore the urgency of the need for strategies that mitigate the dual challenges of habitat degradation and human–elephant conflicts.

The concept of disturbance regimes—i.e., the patterns and intensities of disruptions, both natural and anthropogenic, to ecosystem structure, function, and biodiversity—is vital for understanding the cumulative impacts of human activities on ecosystems [60]. Agricultural and infrastructure developments in Xishuangbanna have fundamentally altered disturbance regimes, as evidenced by our spatial analysis. The InVEST model indicates that intensive cropland use and proximity to roads increases habitat degradation indices, leading to ecological thresholds being exceeded. Combining that with our conflict data, we see, for example, areas near the Shangyong and Mengla reserves exhibiting both high human–elephant conflict and low habitat quality. As with this example, this adverse impact on disturbance regimes is particularly evident in areas where high-intensity human activities coincide with poor habitat quality and high conflict risks.

The Intermediate Disturbance Hypothesis further supports these findings, suggesting that moderate disturbances foster biodiversity by creating spatial and resource heterogeneity, whereas when disturbances exceed ecosystem resilience thresholds, as in the case of continuous deforestation for plantations, they lead to irreversible degradation [14]. This study extends this hypothesis by using spatially integrated analysis to demonstrate a link between high-intensity disturbances and increased conflict risks. For instance, the Mengyang reserve is surrounded by dense agricultural activities and road networks. It also shows a high concentration of human–elephant conflict incidents. GIS-based conflict risk models reveal that areas adjacent to croplands with steep degradation gradients are hotspots for such conflicts. The overlap of high-risk conflict zones and low-quality habitat areas, as shown in Figure 5, further supports this connection. These findings highlight the cascading effects of habitat degradation and fragmentation, where reduced habitat quality amplifies the frequency and intensity of human–elephant conflicts.

The innovation of this study lies in the integration of the InVEST model with GIS-based spatial analysis to address conservation challenges in Xishuangbanna. By identifying specific areas where habitat quality is low and conflict risks are high (e.g., Mengyang reserve), this approach provides actionable insights for targeted interventions such as ecological corridors and restoration zones. Unlike conventional methods, this integrated framework quantifies habitat quality and conflict risks simultaneously, offering a more holistic perspective for conservation planning.

However, there are limitations to this study. For instance, using insurance claim data to model conflict risk may not capture all incidents, potentially underestimating the frequency and severity of conflicts. Additionally, relying on village-level development indicators may not fully account for the finer-scale impacts of human activities on habitat quality. Future research should consider more granular data and incorporate additional factors such as climate change, land-use scenario modeling, and socio-economic dynamics to enhance the applicability and predictive accuracy of the model. These enhancements could improve the precision and effectiveness of conservation decisions.

In comparison to other studies, this research offers valuable insights into developing integrated conservation strategies that address both ecological and social challenges. Previous studies indicate that many protected areas face similar challenges, such as habitat loss and wildlife endangerment, as observed in conservation areas in Africa [61,62] and regions in Indonesia, including Borneo [63] and Sulawesi [64]. However, these ecosystems are facing severe degradation due to threats such as logging, oil palm plantations, mining, and forest fires. According to our findings, establishing ESAs, ERZs, and ecological corridors could effectively address these challenges. Furthermore, the InVEST model and

ArcGIS analysis provide a robust platform for sustainable conservation. The InVEST model aids in objectively assessing ecosystem service values and integrates multi-source data, while ArcGIS modeling provides accurate spatial information to support more effective conservation strategies.

6. Conclusions

The integration of habitat quality and human–elephant conflict (HEC) risk models has provided a comprehensive framework for conservation planning in Xishuangbanna, highlighting critical areas where targeted interventions are necessary. The spatial analysis revealed significant overlap between high-risk HEC zones and regions of low habitat quality, particularly around key protected areas, such as the Mengyang (MY), Mengla (MLa), and Shangyong (SY) reserves. These findings indicate that areas with intensive human activity and degraded habitats are at the highest risk for human–elephant conflicts, underscoring the urgent need for focused management strategies in these regions.

By identifying Ecological Source Areas and Ecological Restoration Zones, this study offers a strategic approach to prioritizing conservation efforts. Ecological Source Areas were identified in places of high-quality habitats, mainly situated in the northern and peripheral regions. These require strict protection to preserve their ecological integrity. Ecological Restoration Zones were identified in areas of significant habitat degradation and high conflict risk, as described in Section 4.3. Specifically, areas classified as low–low clusters indicate severe habitat degradation, and are primarily concentrated around Shangyong (SY), Menggao (MG), and Menglun (ML) (Figure 6), with significant overlap with high-risk conflict (Figure 5). These require targeted restoration actions to improve habitat quality and mitigate conflict risks. From these, ecological corridors were proposed to strategically connect high-quality habitats while avoiding high-risk zones. These are crucial for enhancing habitat connectivity and reducing landscape fragmentation, thereby supporting the safe movement of Asian elephants and other wildlife.

This study's findings demonstrate the importance of integrating habitat quality assessments with conflict risk analyses to guide effective conservation planning. By leveraging spatial models and data-driven approaches, conservation efforts can be more precisely targeted, ensuring resources are allocated where they are most needed to achieve both ecological and social objectives. The model validation results, with high predictive accuracy for identifying high-risk areas, provide confidence in the utility of these models for informing future conservation policies and strategies in Xishuangbanna.

In conclusion, this research highlights the critical need for a multi-faceted approach to conservation planning that combines habitat protection, ecological restoration, and conflict mitigation. The integrated use of habitat quality and conflict risk models offers a powerful tool for conservationists and policymakers to prioritize actions that protect biodiversity, enhance habitat connectivity, and foster coexistence between humans and wildlife. Future research should focus on refining these models with more granular data and exploring their applicability in other regions with similar conservation challenges. Ongoing monitoring and adaptive management are essential to respond effectively to changing ecological conditions and human dynamics in Xishuangbanna.

Author Contributions: Primary data analysis, H.T.; supervisor, L.L. and L.Z.; review and editing, T.J.S.; data collection, H.T., L.L., L.Z., C.P., P.G., E.A., H.G. and G.W. All authors have read and agreed to the published version of the manuscript.

Funding: Financial support was provided by the project of the National Natural Science Foundation of China (No. 31100351), supported by the Open Fund of MOE meng Laboratory of Biodiversity science and Ecology Engineering, Second Tibetan Plateau Scientific Expedition and Research Program (No. 2019QZKK0501), and the Biodiversity Survey and Assessment Project of the Ministry of Ecology and Environment, China (No. 2019HJ2096001006).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available on request.

Acknowledgments: This study was supported by the Sino-French Joint Laboratory of Wildlife and Ecosystem Health, Leshan Normal University. Xishangbanna supported field trip work and data collection. We also thank countless people who have regularly provided invaluable support and aid during our field expeditions.

Conflicts of Interest: The authors declare no conflicts of interest.

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