Fuzzy-Based Ecological Vulnerability Assessment Driven by Human Impacts in China

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Abstract: Human activities have a significant impact on global ecosystems. Assessing and quantifying ecological vulnerability is a fundamental challenge in the study of the ecosystem’s capacity to respond to anthropogenic disturbances. However, little research has been conducted on EVA’s existing fuzzy uncertainties. In this paper, an ecological vulnerability assessment (EVA) framework that integrated the Exposure-Sensitivity-Adaptive Capacity (ESC) framework, fuzzy method, and multiple-criteria decision analysis (MCDA), and took into account human impacts, was developed to address the uncertainties in the assessment process. For the first time, we conducted a provincial-scale case study in China to illustrate our proposed methodology. Our findings imply that China’s ecological vulnerability is spatially heterogeneous due to regional differences in exposure, sensitivity, and adaptive capacity indices. The results of our ecological vulnerability assessment and cause analysis can provide guidance for further decision-making and facilitate the protection of ecological quality over the medium to long term. The developed EVA framework can also be duplicated at multiple spatial and temporal dimensions utilizing context-specific datasets to assist environmental managers in making informed decisions.

Keywords: ecological vulnerability assessment; fuzzy method; multi-criteria decision making; uncertainty; human impacts

1. Introduction

In the past one hundred years, humans have dominated the global and regional ecological environments. The increase in human activities has gradually altered natural processes [1–3]. Urbanization, industrialization, and resource exploitation all contribute to the deterioration of the urban living environment, ecological damage to river basins, soil erosion, and other global ecological problems [4–6]. In this context, research into adaptive ability of the ecological environment to deal with anthropogenic disturbance has become the most prominent and urgent problem in ecological management. Ecological vulnerability assessment (EVA) is an efficient method for resolving this issue.

China, as the world’s second-largest economy, has the most vulnerable ecological system, making it a hot spot for scientific research [7]. Government officials and scholars in China have conducted studies on ecological vulnerability in both theory and practice. The government has implemented a series of ecological management policies, such as Ecological Function Zoning, Principal Function Regionalization, and Red Line Delimitation Guidance for Ecological Protection, with environmental protection and human utility in consideration. The government has implemented a series of ecological management policies, such as Ecological Function Zoning, Principal Function Regionalization, and Red Line Delimitation Guidance for Ecological Protection, with environmental protection and human utility in consideration. In particular, the Ecological Function Zoning analyzed regional ecological environment characteristics, ecosystem service functions, and spatial sensitivity patterns in China [8]. The Principal Function Regionalization subdivided regions into ecological functions based on regional ecosystem structure, ecological sensitivity, and spatial distribution of ecosystem service. The Red Line Delimitation Guidance for Ecological Protection provided scientific
assessment methods to delimit essential areas of ecological function and severely vulnerable areas that should be strictly preserved and prohibited from development. The scholars focused on assessing vulnerability for specific natural environment systems [9,10], such as river basins [11,12], nature reserves [13,14], marine ecosystems [15,16], arid areas [17,18], coal mining areas [19], estuarine systems [20,21], and grassland ecosystems [22,23]. All of the aforementioned advice and research have provided EVA with a solid foundation.

Ecological vulnerability is a multidimensional and complex concept. Numerous assessment frameworks have been proposed to evaluate ecological vulnerability, including the Composite Index [24,25], the Pressure-Support-State-Response framework [26,27], the Driver-Pressure-State-Impact-Response framework [28,29], and the Exposure-Sensitivity-Adaptive Capacity framework [30–32]. Meanwhile, the EVA falls within the scope of the multiple-criteria decision analysis (MCDA) method. The MCDA has been employed to evaluate the ecological vulnerability of nature reserves [33,34], coastal cities [35,36], lakes and rivers [37,38], and other ecological areas. In addition, a number of researchers discovered that the vulnerability assessment procedure was riddled with fuzzy uncertainties [39–41]. First, the concept of “vulnerability” is not exact, as there is no consensus on the precise threshold that separates vulnerable from nonvulnerable. Second, there is an imprecise link between assessment indicators. Third, due to measurement flaws, assessment indicator data are uncertain. However, little research has focused on addressing these concerns in the EVA procedure.

Based on the aforementioned considerations, this paper aims to develop an EVA technique based on a fuzzy-MCDA and ESC framework that considers human influences and handles the aforementioned EVA process uncertainties. First, we developed a paradigm for ecological vulnerability assessment consisting of three elements: exposure, sensitivity, and adaptive capacity. The fuzzy method and MCDA were subsequently integrated to address fuzzy uncertainty in the EVA procedure. To illustrate our suggested technique, we present a provincial-scale case study in China from 2005 to 2020. To our knowledge, this is the first study in China to employ the fuzzy method in EVA driven by human impact at the provincial scale. The temporal and spatial variation of ecological vulnerability in China was analyzed, and the reasons for the diverse temporal and spatial patterns were discussed. The outcomes of our analyses can guide ecological management and conservation.

2. Materials and Methods

2.1. Study Area

According to the National Bureau of Statistics, China had a population of over 1.41 billion in 2021, making it the country with the highest population in the world. With a land area of nearly 9.6 million square kilometers, it is the third-largest country in the world. China has four distinctive seasons and a varied climate, with subtropical monsoon dominating. China’s economy has become the second largest in the world as a result of its rapid expansion from 1978 to the present. However, economic growth exerts huge pressure on ecosystems, resulting in significant ecological degradation and environmental contamination. Environmental contamination consists mostly of water, air, and solid waste contamination. Since 2010, the Chinese have been particularly concerned about particulate air pollution. China’s environmental issues are pervasive and threaten the country’s ecosystem stability and human health. China consists of 31 provincial-level divisions, two Special Administrative Regions (SARs), and the Taiwan province. Because data from the two SARs and Taiwan province are not available, this study only analyzes the ecological vulnerability of the remaining 31 provincial divisions.

2.2. Datasets

We collected fifteen indicators from China’s 31 provinces in 2005, 2010, 2015, and 2020, resulting in a total of 1860 values. The socioeconomic data are obtained from the National Economy and Society Developed Statistical Bulletins and Statistical Yearbook, issued by the National Bureau of Statistics of the People’s Republic of China (NBS PRC). The Environment

2.3. Methods
2.3.1. Ecological Vulnerability Assessment Framework

A reasonable and effective assessment framework provides a significant foundation for ecological vulnerability assessment, enabling assessment researchers through clear ideas and specific instructions. Within the ESC framework, the key ecological system indicators are exposure, sensitivity, and adaptive capacity [42]. The exposure index for ecological vulnerability assessment indicates the degree to which an ecological system is exposed to external disturbances or internal stress. The sensitivity index describes the probability of a potential pollution event in the ecosystem and its potential influence on human society without external perturbations or internal stress [43]. The adaptive capacity index characterizes an ecosystem’s capability to recover to a healthy state following degradation induced by environmental perturbations or stressors, as well as its capacity to maintain a certain configuration and set of functions in the face of an external disturbance [44].

Taking into account expert opinions, literature investigation [45,46], data availability, and locally observed situations, this work considers the fifteen indicators shown in Table 1 to represent ecological vulnerability. The indicator and the goal index have either a positive or negative relationship. For example, the annual mean concentration of fine particulate matter (PM$_{2.5}$) has a positive connection to ecological vulnerability, which indicates that a higher annual mean concentration of PM$_{2.5}$ results in a higher ecological vulnerability. The qualified rate of surface water quality has a negative relationship with ecological vulnerability. Therefore, a higher qualified rate of surface water quality is associated with lower ecological vulnerability. Figure 1 depicts the proposed research scheme for the ecological vulnerability assessment.

Table 1. The units, orientation, and data source for ecological vulnerability assessment indicators in China.

<table>
<thead>
<tr>
<th>Component</th>
<th>Indicator</th>
<th>Unit</th>
<th>Orientation with Ecological Vulnerability</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure</td>
<td>E1: Annual mean concentration of PM$_{2.5}$</td>
<td>µg/m$^3$</td>
<td>Positive [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E2: Annual mean concentration of PM$_{10}$</td>
<td>µg/m$^3$</td>
<td>Positive [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E3: Annual mean concentration of SO$_2$</td>
<td>µg/m$^3$</td>
<td>Positive [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E4: Annual mean concentration of NO$_2$</td>
<td>µg/m$^3$</td>
<td>Positive [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E5: Qualified rate of surface water quality</td>
<td>%</td>
<td>Negative [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E6: Qualified rate of drinking water quality</td>
<td>%</td>
<td>Negative [47]</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>S1: Population density</td>
<td>Pop. per km$^2$</td>
<td>Positive [48]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S2: Ecological index</td>
<td>%</td>
<td>Negative [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S3: Nature reserve proportion of administrative district</td>
<td>%</td>
<td>Negative [48]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S4: Water resources per capita</td>
<td>m$^3$/people</td>
<td>Negative [48]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S5: Vulnerable groups proportion</td>
<td>%</td>
<td>Positive [48]</td>
<td></td>
</tr>
<tr>
<td>Adaptive capacity</td>
<td>AC1: GDP per capita</td>
<td>$/people</td>
<td>Negative [48]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AC2: Harmless disposal rate of municipal waste</td>
<td>%</td>
<td>Negative [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AC3: R &amp; D investment rate</td>
<td>%</td>
<td>Negative [47]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AC4: Environmental protection investment rate</td>
<td>%</td>
<td>Negative [48]</td>
<td></td>
</tr>
</tbody>
</table>
2.3.2. Analytical Hierarchy Process (AHP) Method for Index Weight

The AHP is a common tool in MCDA for solving multi-attribute decision-making problems in real-world scenarios [49,50]. It is a trustworthy strategy for handling complex and unstructured problems that involve interactions and correlations between different objectives and goals [51]. It can classify the assessment objectives into attribute indicators and create a hierarchical model based on the interaction and influence among attribute indices. The determination of the index weight using the AHP method consists of three steps:

1. Model construction: The objective layer of this paper is “ecological vulnerability”, which is subsequently deconstructed into three sub-objects: Exposure, sensitivity, and adaptive capacity. Table 1 shows how the three sub-objects are further classified into 15 attribute indices.

2. Weight determination: The weights for the EVA indices were derived from pairwise comparisons within each sub-object layer. In the pairwise comparisons, a preference scaling approach was used with the following scale numbers: 9, 8, . . . , 2, 1, 1/2, . . . , 1/8, 1/9, where 9 indicates that one index is the most important for the assessment objective, while 1 means that the contributions of two indices to the assessment objective are equal, and so on down to 1/9, which represents the least important. Utilizing a survey questionnaire sent to eight ecological specialists and managers, we collected data for pairwise comparisons and constructed judgment matrices. To determine weights for each index, the largest eigenvalues ($\lambda_{\text{max}}$) of the judgement matrices were calculated as shown in Equation (1):

$$\lambda_{\text{max}} = \sum_{i=1}^{n} i \left[ \frac{\sum_{j=1}^{n} (a_{ij}w_j)}{w_i} \right]$$

(1)

3. Consistency check: Saaty used the consistency index (CI) to check the consistency of the generated judgment matrices [49,50]. The consistency index is calculated using Equation (2):

$$CR = \frac{CI}{RI}$$

(2)

where the consistency index (CI) is the consistency of a given assessment matrix and is derived according to Equation (3):
\[ CI = (\lambda_{\text{max}} - n)(n - 1) \] (3)

Depending on the order of the matrix, RI is a random matrix defined as the average of the resulting consistency index. If the value of CR is suggested to be less than 0.1, then the consistency of the judgment matrix is acceptable [49,50]. Table 2 presents the detailed index weights for EVA. Thus, the weight matrix W can be achieved.

Table 2. Weights for indicators in the ecological vulnerability assessment.

<table>
<thead>
<tr>
<th>Sub-Object Layer</th>
<th>Weight</th>
<th>Indicator Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure</td>
<td>0.4103</td>
<td>E1: 0.1318</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E2: 0.0755</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E3: 0.0331</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E4: 0.0331</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E5: 0.0863</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E6: 0.0504</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.3198</td>
<td>S1: 0.0765</td>
</tr>
<tr>
<td></td>
<td></td>
<td>S2: 0.1167</td>
</tr>
<tr>
<td></td>
<td></td>
<td>S3: 0.0345</td>
</tr>
<tr>
<td></td>
<td></td>
<td>S4: 0.0576</td>
</tr>
<tr>
<td></td>
<td></td>
<td>S5: 0.0345</td>
</tr>
<tr>
<td>Adaptive capacity</td>
<td>0.2700</td>
<td>AC1: 0.1046</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AC2: 0.0293</td>
</tr>
<tr>
<td></td>
<td></td>
<td>AC3: 0.0507</td>
</tr>
</tbody>
</table>

2.3.3. Fuzzy Theory for Ecological Vulnerability Assessment

Fuzzy theory processes an ecological vulnerability indicator to belong to many categories, or fuzzy sets, with a membership gradation described by a fuzzy membership function in the real unit interval [0, 1] [52,53]. A fuzzy set is a pair \( \mu_A: x \in X \), in which \( \mu_A: x \rightarrow [0, 1] \). The fuzzy theory-based EVA contains the following steps:

(1) Implement EVA indicators with fuzzy membership functions. The fuzzy membership function is utilized to determine the vulnerability level of each EVA index. According to relevant evaluation criteria, literature investigation [53–56], and expert opinions, the vulnerability level (displayed in Table 3) is divided into 1–5 scales, with 1 indicating potential and 5 indicating highly vulnerable. Depending on the data format, the EVA index can be divided into quantitative and qualitative indices. Based on the impact of the index on ecological vulnerability, it can also be categorized as a positive or negative indicator. According to the five vulnerability classes of EVA indicators, the membership value of each evaluation index is calculated by selecting the appropriate membership function. Thus, the fuzzy matrix \( R \) can be obtained.

A trapezoidal distribution function is selected to calculate the fuzzy membership degree of the quantitative index to the ecological vulnerability grade. The fuzzy membership function of a positive index can be calculated by Formulae (4) to (6), and that of a negative index can be seen in Formulae (7) to (9).

\[
\mu_1(x) = \begin{cases} 
1 & x \leq A_1 \\
\frac{A_2 - x}{A_2 - A_1} & A_1 < x < A_2 \\
0 & x \geq A_2 
\end{cases} \quad (4)
\]

\[
\mu_i(x) = \begin{cases} 
0 & x \leq A_{i-1} \\
\frac{A_{i-1} - x}{A_{i-1} - A_i} & A_{i-1} < x \leq A_i \\
\frac{A_i - x}{A_{i+1} - A_i} & A_i < x \leq A_{i+1} \\
0 & x \geq A_{i+1} 
\end{cases} \quad (5)
\]

\[
\mu_5(x) = \begin{cases} 
0 & x \leq A_4 \\
\frac{A_4 - x}{A_4 - A_5} & A_4 < x \leq A_5 \\
1 & x \geq A_5 
\end{cases} \quad (6)
\]
\[ \mu_1(x) = \begin{cases} 0 & x \leq A_2 \\ \frac{A_1 - x}{A_2 - A_1} & A_2 < x < A_1 \\ 1 & x \geq A_1 \end{cases} \] (7)

\[ \mu_i(x) = \begin{cases} 0 & x \leq A_{i+1} \\ \frac{A_{i+1} - x}{A_i - A_{i+1}} & A_i < x < A_{i+1} \\ \frac{A_{i+1} - x}{A_i - A_{i+1}} & A_{i+1} < x < A_i \\ 1 & x \geq A_i \end{cases} \] (8)

\[ \mu_5(x) = \begin{cases} 1 & x \leq A_5 \\ \frac{A_5 - x}{A_4 - A_5} & A_4 < x < A_5 \\ 0 & x \geq A_4 \end{cases} \] (9)

where \( \mu_i(x) \) is the fuzzy membership of the ecological vulnerability indicator at the \( i_{th} \) (\( i = 1, 2, \ldots, 5 \)) vulnerability class; \( A_i \) is the threshold value of the \( i_{th} \) ecological vulnerability class.

For the qualitative indicator, the membership degree can be obtained in the manner shown below: \( (\mu_1, \mu_2, \mu_3, \mu_4, \mu_5) = (1, 0, 0, 0, 0) \) if the qualitative index falls under level 1; \( (\mu_1, \mu_2, \mu_3, \mu_4, \mu_5) = (0, 1, 0, 0, 0) \) if it falls under level 2; \( (\mu_1, \mu_2, \mu_3, \mu_4, \mu_5) = (0, 0, 0, 0, 1) \) if it falls under level 5.

(2) Construct a fuzzy matrix. Set \( U = \{u_1, u_2, \ldots, u_m\} \) as the index set and \( V = \{v_1, v_2, \ldots, v_m\} \) as the vulnerability level set. The fuzzy relationship between the index set and the vulnerability level set can be described by the fuzzy matrix \( R \) as follows:

\[
R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} (10)
\]

\( R_{ij} \) is the \( j_{th} \) fuzzy membership of the \( i_{th} \) index \( u_i \). \( R_i \) is the \( i_{th} \) row in fuzzy matrix \( R \) and \( R_i = (r_{i1}, r_{i2}, \ldots, r_{in}) \) is the fuzzy sub-set of \( u_i \) in \( V \).

2.3.4. Ecological Vulnerability Aggregation

By multiplying the weight matrix \( W \) (from Section 2.3.2) and fuzzy matrix \( R \) (from Section 2.3.3) by Equation (11), the general ecological vulnerability can be calculated as follows:

\[
V_{x,E} = [W_{E1}, W_{E2}, \ldots, W_{E6}] \begin{bmatrix} \mu_1, E_1 \\ \vdots \\ \mu_n, E_n \\ \mu_1, E_6 \\ \vdots \\ \mu_n, E_6 \end{bmatrix} (11)
\]

The fuzzy memberships of sub-object layer “sensitivity” (\( V_{x,S} \)) and “adaptive capacity” (\( V_{x,AC} \)) under five levels can be obtained using the same method. Equation (12) is used to calculate the memberships of five classes for the goal layer “ecological vulnerability”, integrating the memberships of three sub-object layers by:

\[
V_{x,EV} = \sum_{i=1}^{3} V_{x,i} (12)
\]

According to the maximum membership principle, the maximum value among the memberships for the five scales is the ultimate ecological vulnerability outcome. Table 4 displays the fuzzy membership results under five classes and the vulnerability ranks of each indicator for Beijing in 2010.
Table 3. Five vulnerability classes of ecological vulnerability indicators in the fuzzy theory.

<table>
<thead>
<tr>
<th>Indicator Layer</th>
<th>1 (Potential)</th>
<th>2 (Slight)</th>
<th>3 (Low)</th>
<th>4 (Moderate)</th>
<th>5 (High)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1: Annual mean concentration of PM$_{2.5}$</td>
<td>15</td>
<td>35</td>
<td>55</td>
<td>90</td>
<td>120</td>
<td>54</td>
</tr>
<tr>
<td>E2: Annual mean concentration of PM$_{10}$</td>
<td>40</td>
<td>70</td>
<td>100</td>
<td>150</td>
<td>180</td>
<td>54</td>
</tr>
<tr>
<td>E3: Annual mean concentration of SO$_2$</td>
<td>20</td>
<td>40</td>
<td>60</td>
<td>80</td>
<td>100</td>
<td>54</td>
</tr>
<tr>
<td>E4: Annual mean concentration of NO$_2$</td>
<td>30</td>
<td>40</td>
<td>50</td>
<td>60</td>
<td>80</td>
<td>54</td>
</tr>
<tr>
<td>E5: Qualified rate of surface water quality</td>
<td>100</td>
<td>90</td>
<td>80</td>
<td>70</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>E6: Qualified rate of drinking water quality</td>
<td>100</td>
<td>90</td>
<td>80</td>
<td>70</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>S1: Population density</td>
<td>25</td>
<td>100</td>
<td>1000</td>
<td>3000</td>
<td>5000</td>
<td></td>
</tr>
<tr>
<td>S2: Ecological index</td>
<td>Very good</td>
<td>Good</td>
<td>Medium</td>
<td>Relatively bad</td>
<td>Bad</td>
<td>55</td>
</tr>
<tr>
<td>S3: Nature reserve proportion of administrative district (%)</td>
<td>30</td>
<td>22.5</td>
<td>15</td>
<td>10</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>S4: Water resources per capita</td>
<td>7500</td>
<td>2500</td>
<td>1700</td>
<td>1000</td>
<td>500</td>
<td>56</td>
</tr>
<tr>
<td>S5: Vulnerable groups proportion</td>
<td>5</td>
<td>10</td>
<td>20</td>
<td>30</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>AC1: GDP per capita</td>
<td>30,000</td>
<td>11,429</td>
<td>9000</td>
<td>6098</td>
<td>500</td>
<td>56</td>
</tr>
<tr>
<td>AC2: Harmless disposal rate of municipal waste</td>
<td>100</td>
<td>95</td>
<td>80</td>
<td>75</td>
<td>50</td>
<td>53</td>
</tr>
<tr>
<td>AC3: R&amp;D investment rate</td>
<td>3</td>
<td>2.5</td>
<td>2</td>
<td>1.5</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Fuzzy membership results under five classes and vulnerability rank of fifteen indicators and three sub-object layers in Beijing in 2010.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Observed Value</th>
<th>Membership at Different Classes</th>
<th>Vulnerability Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indicator</td>
<td></td>
<td>A1</td>
<td>A2</td>
</tr>
<tr>
<td>Annual mean concentration of PM$_{2.5}$</td>
<td>86.6</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Annual mean concentration of PM$_{10}$</td>
<td>109</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Annual mean concentration of SO$_2$</td>
<td>28</td>
<td>0.6000</td>
<td>0.4000</td>
</tr>
<tr>
<td>Annual mean concentration of NO$_2$</td>
<td>52</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Qualified rate of surface water quality</td>
<td>53.6</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Qualified rate of drinking water quality</td>
<td>90.8</td>
<td>0.0800</td>
<td>0.9200</td>
</tr>
<tr>
<td>Population density</td>
<td>1464</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>Ecological index</td>
<td>Good</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>Nature reserve proportion of administrative district (%)</td>
<td>8</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Water resources per capita</td>
<td>193.24</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Vulnerable groups proportion</td>
<td>17.98</td>
<td>0.0000</td>
<td>0.2000</td>
</tr>
<tr>
<td>Harmless disposal rate of municipal waste</td>
<td>99.1</td>
<td>0.0800</td>
<td>0.1800</td>
</tr>
<tr>
<td>R&amp;D investment rate</td>
<td>5.95</td>
<td>1.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Environmental protection investment rate</td>
<td>13,857.43</td>
<td>0.1308</td>
<td>0.8692</td>
</tr>
<tr>
<td>Exposure</td>
<td>-</td>
<td>0.0239</td>
<td>0.0596</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>-</td>
<td>0.1012</td>
<td>0.0596</td>
</tr>
<tr>
<td>Adaptive capacity</td>
<td>-</td>
<td>0.0962</td>
<td>0.0596</td>
</tr>
<tr>
<td>Ecological vulnerability</td>
<td>-</td>
<td>0.1123</td>
<td>0.2795</td>
</tr>
</tbody>
</table>

3. Results

3.1. Assessment Results of Exposure, Sensitivity, and Adaptive Capacity

The three sub-object layers are divided into five vulnerability levels from 1 to 5, which represent potential, slight, low, moderate, and high vulnerability, respectively, in order to analyze the spatiotemporal distribution of exposure, sensitivity, and adaptive capacity in China. A higher level means a greater contribution to the ultimate ecological vulnerability. Figures 2–5 present the assessment results.

(1) Exposure

The assessment results of exposure in China from 2005 to 2020 are depicted in Figure 2, which reveals a distinct regional variation in exposure over the four years. The lower exposure areas were mainly distributed in the southwestern and southeastern provinces of China. In the northern and southern provinces, higher exposure predominated. China’s central region, meanwhile, had the highest level of exposure. The exposure degree in 2010 was the worst, while some central, southwestern, and northeastern provinces experienced gradual improvement in 2015 and 2020, according to a temporal comparison of the four years. Four provinces—Beijing, Shandong, Yunnan, and Qinghai—showed an improvement in exposure from 2005 to 2020. A similar exposure situation persisted in fourteen provinces, including Shanxi, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hubei, Guangdong, Hainan, Chongqing, Guizhou, Tibet, and Xinjiang. The remaining thirteen provinces all showed worsening exposure. In terms of exposure, Figure 2d indicates that in 2020, the third-level (5,371,900 km$^2$ with 56.16% of the national territorial area, including
Beijing, Shanxi, Nei Monggol, Liaoning, Jilin, Jiangsu, Anhui, Shandong, Hubei, Hu’ nan, Chongqing, Sichuan, Shaanxi, Gansu, Ningxia, and Xinjiang) and first-level (2,674,000 km² with 27.96% of the national territorial area, including Fujian, Guangdong, Hainan, Yunnan, Tibet, and Qinghai) areas constitute the majority of China.

Figure 2. Assessment results of exposure in (a) 2005, (b) 2010, (c) 2015, and (d) 2020.

(2) Sensitivity

The results of China’s sensitivity assessment from 2005 to 2020 are depicted in Figure 3, which reveals strong regional disparities with a general decline from the eastern coast to the central and western interior. The longitudinal comparison from 2005 to 2020 showed that the sensitivity situation began to decline in 2010 and had nearly identical trends in 2015 and 2020. From 2005 to 2020, three provinces, namely Nei Monggol, He’ nan, and Xinjiang, appeared to have improved their sensitivity. Beijing, Liaoning, Jiangsu, and Anhui remained in the same sensitive situation. The sensitivity level of the remaining twenty-four provinces all deteriorated. This implied that 2010 was a turning point for the ecological sensitivity of China. Figure 3d presents that in 2020, the fourth-level areas (6,631,300 km², containing Hebei, Shanxi, Heilongjiang, Anhui, Jiangxi, He’ nan, Hu’ nan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Qinghai, Ningxia, and Xinjiang) account for...
the majority (69.33%) of China’s land area. It suggests that ecosystems in the majority of provinces are susceptible to disturbances or stresses.

Figure 3. Assessment results of sensitivity in (a) 2005, (b) 2010, (c) 2015, and (d) 2020.

(3) Adaptive capacity

Figure 4 depicts the assessment results of adaptive capacity for China from 2005 to 2020. It indicated that China’s general adaptive capacity is relatively optimistic, with obvious spatial heterogeneity and a downward trend from south to north. During the four study years, twenty provinces indicated progress, whereas ten provinces showed stable adaptive capacity. Only Tianjin experienced a drop from the second to the third level. The longitudinal comparisons of the four years revealed that 2010 marked a turning point in the adaptive capacity in nineteen central, southwestern, and southeastern provinces, with a clear improvement. Figure 4d shows that in 2020, the majority of China’s adaptive capacity was located in fifth-level (3,951,600 km$^2$ with 41.31% of the national territorial area, including Hebei, Shanxi, Nei Monggol, Jilin, Heilongjiang, Jiangxi, and Xinjiang) and third-level areas (2,620,700 km$^2$ with 27.40% of the national territorial area, containing Tianjin, Shandong, Tibet, Gansu, Qinghai, and Ningxia).
3.2. Assessment Results of Aggregated Ecological Vulnerability

Figure 5 depicts the spatially disparate assessment results of aggregated ecological vulnerability in China from 2005 to 2020. The central and northwestern provinces had the highest vulnerability, while the southern and southwestern provinces had the lowest vulnerability. In a temporal comparison, the ecological vulnerability of the northern and southern coastal provinces deteriorated significantly in 2010, although the southern coastal area improved in 2015 and 2020. From 2005 to 2020, the ecological vulnerability of four provinces, including Hebei, Shaanxi, Qinghai, and Ningxia, improved. The ecological vulnerability of twenty-four provinces, containing Tianjin, Shanxi, Heilongjiang, Shanghai, Jilin, manifested deterioration. Only four provinces, including Hebei, Nei Monggol, Liaoning, and Xinjiang, remained the same. In 2020, the third-level (2,946,200 km² with 30.80% of the national territorial area) areas account for

![Figure 4](image-url)

**Figure 4.** Assessment results of adaptive capacity in (a) 2005, (b) 2010, (c) 2015, and (d) 2020.

In 2020, the third-level (2,946,200 km² with 30.80% of the national territorial area) and first-level (2,516,300 km² with 26.31% of the national territorial area) areas account for
the majority of China, as shown in Figure 5d. At the first level, the ecosystems of Fujian, Guangdong, Guangxi, Hainan, Tibet, and Qinghai were stable and had a great capacity to rebound from external disturbances or internal stresses. Shanghai, Jiangxi, He’nan, and Xinjiang belonged to the fifth level of ecological vulnerability, which can be regarded as an unstable ecosystem with diminished resistance to external disturbance or internal stress. It suggests that these provinces’ ecosystems are more vulnerable to disturbance and would be harder to self-repair.

4. Discussion
4.1. Cause Analysis

China’s ecological vulnerability displayed diverse spatial patterns. High exposure and high sensitivity were the primary factors contributing to the central provinces’ high ecological vulnerability, according to our research. In the southern and southwestern areas, the potential for slight exposure, potential for slight adaptive capacity, and low to moderate

Figure 5. Aggregated ecological vulnerability assessment in (a) 2005, (b) 2010, (c) 2015, and (d) 2020.
sensitivity level contribute to slight ecological vulnerability. Most northern and eastern provinces had low exposure, slight to moderate sensitivity, and slight to high capacity activity, resulting in low ecological vulnerability.

Ecological vulnerability is spatially distributed for a variety of reasons [7]. The regional variation in ecological vulnerability was primarily influenced by the combination of variances in exposure, sensitivity, and adaptive capacity indicators. Concerning exposure, air quality is receiving increasing attention, particularly for PM$_{2.5}$ and PM$_{10}$. According to the source and transport rationale of air pollution, the inhomogeneous air pollution distribution between southern and northern provinces is mainly caused by diversity in topographic and meteorological conditions, coal consumption, and dust quantity [31]. The disparity in the qualified rate for surface water quality distribution, with better quality in western and southern China and worse quality in central China, was an additional element that influenced exposure differences. The spatial comparison suggested that the sensitivity of eastern coastal provinces was often lower than that of western provinces. This is mostly due to spatial distribution in the population density, ecological index, and water resource distribution. Extremely unequal population distribution, with a dense population in the southeast and a sparse population in the northwest, is a primary factor influencing sensitivity discrepancies. For ecological index diversity, which is strongly associated with geographical distribution patterns, provinces with a very good or good class of ecological index are primarily located in the eastern and southern provinces, whereas the central and western provinces are primarily of a medium and relatively poor class. In terms of the distribution of water resources, the western and southern provinces have higher water resources per capita than the central and northern provinces. From south to north, the overall trend of adaptive capacity gradually increased. This is mostly due to the fact that the economic development index and harmless garbage treatment rate in southern coastal areas are better than in central and northern inland areas, with the background of low investment in scientific research and environmental protection in China. Therefore, the assessment level of the adaptation index is relatively low in southern areas.

The longitudinal comparisons revealed that 2015 was an obvious turning point, with exposure and sensitivity deteriorating but adaptive capacity improving. This is mostly due to the fact that more provinces entered the mid-term stage of industrialization, resulting in a rise in GDP per capita and an improvement in adaptive capability. However, the rapidly expanding economy is exerting an increasing amount of strain on the ecosystem by consuming more resources and energy, which increases ecological exposure and sensitivity. However, by 2020, the exposure degree had gradually increased in many provinces. This is mostly because, since 2012, people and governments have become more aware of the substantial health risks posed by particulate air pollution. On February 29th, 2012, China’s Ministry of Environmental Protection issued the Ambient Air Quality Standards [54], which officially incorporate PM$_{2.5}$ into conventional atmospheric environment quality assessment. In June 2013, the State Council announced a target to reduce IPC (inhalable particle concentration) by 10 percent by the end of 2017. These two significant actions played a distinct role in reducing exposure levels in most provinces. However, there was little change in the general ecological vulnerability of the 31 provinces throughout the four study years, indicating that the five-year decrease in exposure had a minor impact on the general ecological vulnerability. It implies that controlling air pollution on a long-term basis is still a major challenge for China’s governors to reduce exposure degrees. This result is consistent with those of Jin et al. (2017) and Guo et al. (2017), indicating that prolonged and laborious efforts are necessary to enhance air quality [57,58]. The temporal comparison also revealed that the patterns of sensitivity and adaptive capacity were slightly different in 2015 and 2020.

Ecological vulnerability patterns may further affect ecological protection decisions. More specifically, China’s general lack of adaptive capacity is caused by inadequate investment in environmental protection and research development. These parameters in all provinces (except Qinghai and Tibet) were at the fifth level, with unsatisfactory circum-
stances in the four studied years. It suggests that the whole country should pay greater attention to increasing environmental protection and research development expenditure. At the same time, decreasing sensitivity in the northern and western interior and boosting adaptive capacity in most provinces is a long-term task to reduce the degree of general ecological vulnerability. In addition, high particulate air pollution and poor surface water quality contributed to the weak ecosystem in northern and central China. Therefore, promoting air and surface water pollution control should be a focus. The western provinces should be more concerned with improving the ecological index by boosting biological diversity, vegetation coverage, and water network density and reducing land stress, pollution load, and environmental restriction. Even the current ecosystem in Qinghai, Tibet, and most southern provinces can be treated as stable. The ecosystems in these provinces are particularly vulnerable to perturbation.

4.2. Benefits of the EVA Framework

The EVA framework is effective for assessing the ecological vulnerability driven by human impact by creating fuzzy membership functions of contributing indicators, thereby yielding the vulnerability level. This assessment framework has the following advantages: First, it has a clear connotation that evaluates vulnerability from three perspectives: Exposure, sensitivity, and adaptability. Second, it has a distinct evaluation level that divides ecological vulnerability into three sub-object layers, and the contributing indices contained in each sub-object layer are incrementally refined. Third, due to its high compatibility and malleability, it has a wide range of applications.

The EVA framework proposed in our paper employs the fuzzy method to address the fuzzy uncertainty inherent in the ecological vulnerability concept [39], data collection [40], and assessment process [41]. In contrast to the traditional MCDA, which is utilized in ecological vulnerability assessment in India [59,60], Bangladesh [61,62], the Alps [63,64], and other climatologically vulnerable zones [7,16,17,24,30] and whose assessment result is an exact value according to classical logic, the assessment result of fuzzy-MCDA is typically a fuzzy vector rather than a value. The fuzzy logic permits an indicator to belong to more than one category or fuzzy set, with a fuzzy membership function defining the degree of membership. It is the evaluated object’s membership degree in each grade’s fuzzy subset that can provide more information than conventional MCDA.

The established EVA framework may determine which indicators of exposure, sensitivity, and adaptive capacity dominate the existing stable or unstable ecosystem. This paradigm can be used to examine the influence of historical policies on ecological vulnerability and provide direction for further decision-making, taking into account the temporal dimension. In addition, it offers the benefit of evaluating the effectiveness of new urban development management decisions on ecosystem conservation in order to accomplish medium- to long-term protection of ecological quality. The proposed framework permits the representation of ecological vulnerability changes if the status quo is maintained or if new decisions are introduced as a result of natural or anthropogenic change in response to internal or external stresses.

4.3. Limitations of the EVA Framework and Future Scope

Due to restricted data resources, the EVA framework built in this paper does not reflect an entire collection of ecological vulnerability indices, although it incorporates a number of indices ranging from environmental pollution to socioeconomic indicators to convey the concept of ecological vulnerability. For instance, the soil environment quality [65–67] and the groundwater quality [68,69] are omitted from the EVA framework despite their significant ecological vulnerability.

In addition, the fuzzy-MCDA method proposed in our study only resolves the fuzzy uncertainty that existed in the EVA process, rather than random and interval uncertainties that existed. However, linking the method of multiple uncertainty analysis in MCDA may be more useful for assessing ecological vulnerability and developing adaptive measures.
Future research can focus on how to improve the ecological vulnerability framework, identify the complexity and uncertainty of the ecological system, and develop a more robust decision-making analysis method that considers and handles the existing multiple uncertainties, such as interval, fuzzy, and random.

5. Conclusions
This research developed an EVA framework based on the fuzzy-MCDA method to assist decision makers in comprehending the differential effects of natural and anthropogenic eco-environmental changes. This approach classifies natural and artificial elements into three categories: Exposure, sensitivity, and adaptive capacity. This paper’s objective is to confirm the availability of the EVA framework and provide the groundwork for further ecological conservation and management.

The application of this developed method to China’s 31 provinces indicated that it is reliable and generally consistent with the Bulletin on the State of China’s Ecological Environment. The results show that ecological vulnerability in China exhibits strong regional disparities, with the central and northwestern provinces having higher vulnerability and the coastal and southwestern provinces having lower vulnerability. The synergistic effect of variances in exposure, sensitivity, and adaptive capacity indices influences the reasonableness of the various spatial patterns. Since ecological vulnerability patterns may have additional effects on ecosystem conservation programs, decisions should be based on the specific situation.

This research can be replicated at several spatial and temporal scales according to context-specific datasets, thereby assisting ecological managers in making informed decisions. The question of how to better identify the complexity and uncertainty of the ecological system and design a more robust decision-making analysis approach to represent and resolve the existing multiple uncertainties, such as interval, fuzzy, and random, is a valuable topic for future research.

Author Contributions: The contributions of the three authors have been balanced in all phases of the development of this study, both in the methodological part and in the writing of this manuscript. C.H. reviewed the literature and acquired the data. Y.Z. theorized and designed the study, critically commented, and wrote the original draft of the manuscript. J.S. contributed to the conceptualization and design of the study, interpreted the results, wrote the original manuscript and did critical revision, and edited the final version of the manuscript. All authors have read and agreed to the published version of the manuscript.

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