Study on Illegal Wildlife Trade Based on Gray Prediction and TOPSIS Methods

Yulin Yang [1, *], Hongjiang Zhang [2] and Zhongyang Xia [2]

[1] School of English and International Studies, Beijing Foreign Studies University, Beijing, China

[2] International Business School, Beijing Foreign Studies University, Beijing, China

* Corresponding author: jackyang@bfsu.edu.cn

Abstract. In this paper, the protection of wildlife resources was studied, and an effective and universal assessment method was established by using the illegal wildlife trade index model. Firstly, through literature reading and open data collection, we creatively set up the Illegal Wildlife Trade Index System (IWTI). Then, the entropy weight method and TOPSIS method were used to evaluate countries, and four important constraints were identified: economic power, governance effectiveness, population status and local power. Secondly, we use the grey prediction model to predict the change trend of these constraint indicators in the next five years. Finally, we construct a two-objective fuzzy optimization model to obtain the optimal values of the four constraints by maximizing the benefits of protecting wildlife from illegal trade (Net-PER) and minimizing the costs. This study provides scientific assessment and decision support for wildlife conservation, and helps to formulate effective forecasting and planning strategies.

Keywords: illegal wildlife trade, grey prediction, entropy weight method, double objective fuzzy programming.

1. Introduction

Wild animals are important resources on the earth. They are of great significance for maintaining ecological balance, maintaining biodiversity and promoting the sustainable development of human economy and society. In recent years, the number of wild animal populations has declined sharply. In addition to habitat degradation, exploitation, invasive alien species, pollution, climate change and disease, the worldwide illegal wildlife trade is also a major contributor. According to a report by the United Nations Environment Programme and Interpol, the global illegal wildlife trade is estimated at US $7-21.3 billion annually, making it one of the largest illegal trades in the world.

This paper will select appropriate indicators to model the illegal wildlife trade based on the entropy weight method and TOPSIS methodology. The entropy weight method can automatically determine the weight of each indicator by calculating the information entropy between the indicators. Compared with the traditional subjective weighting method, entropy weight method is more objective and scientific, and can accurately reflect the importance of indicators [1]. TOPSIS method can comprehensively consider the relative gap between various indicators, effectively evaluate the performance of each country or object on multiple indicators, and find the optimal solution [2]. Further explore the factors affecting the illegal wildlife trade, and establish a suitable index system. On this basis, based on the economic strength, local capacity, governance effect, population status and other constraints of illegal wildlife trade, the grey prediction model [3] and dual objective fuzzy programming model [4] are constructed. The work will help maintain ecological balance, maintain biodiversity, promote sustainable economic and social development of mankind, and contribute to the cause of global wildlife protection.

2. Establishment of Index System and Evaluation Model

2.1. Index Selection

The Illegal Wildlife Trade Index model is a model to measure the living status of wildlife in a region. It can reflect whether the wildlife in a region is vulnerable to illegal poaching and trade. Since there is no imitated wildlife living condition evaluation model, we have established a set of our own index system, including primary and secondary indicators, based on the actual local conditions.

First, we set up four first-level indicators from multiple perspectives, including Economic Power, Governance Effectiveness, Population Status and Local power. Population status represents the living environment of local wildlife and the possible risks of illegal poaching and trade, which also reflects the local willingness and effectiveness of wildlife protection. Local capacity refers to the ability of local conservation agencies or organizations to mobilize local resources and protect themselves.

Having identified a suitable primary indicator framework, we finalised secondary indicators using data from open sources on the Internet and authorized data stations, including the World Bank, OECD Database, CITES Trade Database, CITES Elephant Poaching Monitoring item MIKE, TRAFFIC Wildlife Trade Data Dashboard database, Global Firearms Holdings data from the Small Arms Survey, Vision of Humanity's Peace Index database, etc.

Finally, we integrated the available data for countries around the world to arrive at 17 secondary indicators.

2.2. The Index Weights Are Calculated Based on Entropy Weight Method

The entropy weight method (EWM) is a method that excludes subjective factors and reflects the information content entirely according to the degree of data dispersion. Its basic idea is that the smaller the variation of the index, the less information it reflects, and the lower its corresponding weight should be, and vice versa [5-6]. We use the entropy weight method to estimate the weight of the secondary index.

Suppose we have a total of n evaluation indicators and m countries as the evaluated objects to form a positive matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Then, it is normalized to obtain the matrix Z. For each element in Z:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad i = 1,2,\cdots,n; \; j = 1,2,\cdots,m \tag{2}$$

Considering that all the data of the secondary index selected by our model are positive, the matrix Z is the final normalized matrix. Next, we compute the probability matrix P, where each element in P:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}} \quad i = 1,2,\cdots,n; \; j = 1,2,\cdots,m \tag{3}$$

For the j-th index, the formula for calculating its information entropy is:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \quad j = 1,2,\cdots,m \tag{4}$$

Information utility value:

$$d_j = 1 - e_j \tag{5}$$

The greater the information utility value d_j, the more information it corresponds to. After normalization, we can get the weight of each secondary indicator:

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j (j=1,2,\cdots,m)} \quad (6)$$

Then, we get the weight vector for each first-level indicator, including n second-level indicators:

$$S_j = \sum_{i=1}^{n} w_i p_{ij} \quad i = 1,2,\cdots,n; \; j = 1,2,\cdots,n \quad (7)$$

IWTI is divided into four first-level indicators, namely, economic capacity, autonomous effectiveness, population status, and local capacity, including $n_{ea}, n_{age}, n_{ps}, n_{la}$, respectively. Therefore, we apply EWM to these four first-level indicators and calculate their respective weights S_j to obtain the weight vector.

$$w = (0.4507,0.4047,0.0381) \quad (8)$$

The weight calculation results of each primary indicator and secondary indicator are shown in Table 1.

Table 1. Weight Calculation Result

First Level	Weight	Second Level	Weight
EC	0.4507	Poverty Rates	0.0037
		GDP per Capita	0.1159
		Minimum Wage	0.1293
		Comparative Advantage of Environmental Technologies	0.1111
		Unemployment Rates	0.0095
		International Assistance	0.0812
GE	0.1066	Government Stability Index	0.0280
		Government Effectiveness	0.0325
		Integrity Rates	0.0139
		Corruption Control Index	0.0322
PS	0.4047	Elephant Number	0.2286
		Illegal Poaching Rates	0.0193
		Terrestrial Protected Areas of Total Land Area	0.0200
		Densities of All Personnel ($km^2$of PA per person)	0.1368
LA	0.0381	Peace Index	0.0042
		Law-Based Index	0.0316
		Weapons Possession Number per 100 persons	0.0022
		Illegal ivory number (seized by customs)	

2.3. Wildlife Illegal Trade Index calculation based on TOPSIS methodology

We introduce the Illegal Wildlife Trade Index as an overall description of a country's level of Illegal Wildlife trade (IWTI). We use TOPSIS method to score the level of illegal wildlife trade in 60 selected countries and calculate their IWTI [7].

According to the standardized matrix Z calculated by the entropy weight method, the highest level L^+ and the lowest levelL^- are determined:

$$L^+ = (max\{z_{11}, z_{21}, \cdots, z_{n1}\}, max\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) = (Z_1^+, Z_2^+, \cdots, Z_m^+) \quad (9)$$

$$L^- = (min\{z_{11}, z_{21}, \cdots, z_{n1}\}, min\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}) = (Z_1^-, Z_2^-, \cdots, Z_m^-) \quad (10)$$

The difference between the i-th country and the highest level D_i^+ and the lowest level D_i^- is:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} w_j (z_j^+ - z_{ij})^2} \quad (11)$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} w_j (z_j^- - z_{ij})^2} \quad (12)$$

Finally, the i-th country's normalized score:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (0 \le S_i \le 1) \tag{13}$$

Among them, the larger S_i is, the closer it is to the highest level.

According to our Wildlife Illegal Trade Index, we used TOPSIS to calculate the scores of each country. The higher the scores, as shown in Fig.1, the more significant the achievements in the field of wild elephant conservation.

3. Prediction Model and Planning Model

3.1. Construction of Grey Prediction Model

Through in-depth analysis of wildlife data, the following data characteristics can be obtained: non-negative data measured by year, the number of data periods is short, and the correlation is not strong. In addition, the time series diagram drawn according to Fig.2 shows that the four primary indicators have no seasonality, no obvious trend and are relatively stable.

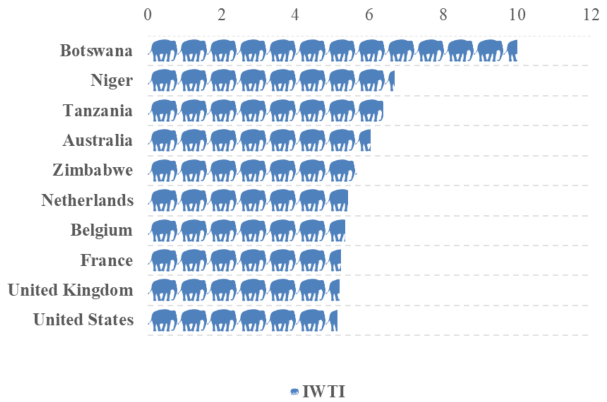

Figure 1. Results of IWTI index for wild elephants

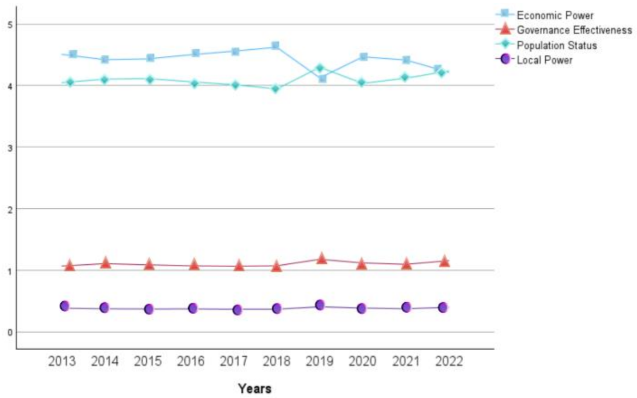

Figure 2. Time series diagram of primary indicators

Then, we divided the data into the training group and the experimental group, and modelled the training group with different models conforming to the characteristics of the above time series graphs, and used the data of the experimental group to determine which model had the best prediction effect. After screening, the prediction error of the grey prediction model is the smallest, its SSE value is small, and it passes the quasi-index law test [8-9]. We decide to use the grey prediction model to predict the weight of the 5-year planning period.

Step1 Set the initial non-negative data column $x^{(0)}$:

$$x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right) \tag{14}$$

Step2 Generate the 1-AGO sequence of the cumulative sequence $x^{(0)}$:

$$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right) \tag{15}$$

$$x^{(1)}(m) = \sum_{i=1}^{m} x^{(0)}(i) \qquad m = 1,2,\cdots,n \tag{16}$$

Step3 Generate the adjacent mean generating sequence $z^{(1)}(k)$:

$$z^{(1)}(m) = 0.5x^{(1)}(m) + 0.5x^{(1)}(m-1) \qquad m = 2,3,\cdots,n \tag{17}$$

Step4 Define the grey differential equation GM (1,1):

$$x^{(o)}(k) + az^{(1)}(k) = b \qquad k = 2,3,\cdots,n \tag{18}$$

Ream:

$$u = (a, b)^T \tag{19}$$

$$Y = \left(x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right)^T \tag{20}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{21}$$

The

$$Y = Bu \tag{22}$$

Least squares solution:

$$\hat{u} = \binom{\hat{a}}{\hat{b}} = (B^T B)^{-1} B^T Y \tag{23}$$

Step5 GM (1,1) Bleaching:

$$\frac{dx^{(1)}(t)}{dt} + \hat{a}x^{(1)}(t) = b \tag{24}$$

Step6 Get the prediction formula by recursion method:

$$\hat{x}^{(0)}(m+1) = \hat{x}^{(1)}(m+1) - \hat{x}^{(1)}(m) = \left(1 - e^{\hat{a}}\right)\left[x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}m} \quad m = 1,2,\cdots,n-1;\ m \geq n \tag{25}$$

Four input capacity corresponding prediction formulas are obtained:

$$x(k)_{ep} = -1696.5715 \times e^{-0.0026(k-1)+1701.0781} \tag{26}$$

$$x(k)ge = 217.0204 \times e^{0.0050(k-1)-215.9544} \tag{27}$$

$$x(k)_{ps} = 3841.8836 \times e^{0.0011(k-1)-3837.8368} \tag{28}$$

$$x(k)_{lp} = 92.4712 \times e^{0.0040(k-1)-92.0906} \tag{29}$$

Step7 Final prediction result.

As shown in Fig.3, we use the grey prediction method to forecast the weights of the input proportion of EP, GE, PS and LP in the next five years, and get the weight changes in the next five years. This represents how the impact of EP, GE, PS, LP input on illegal wildlife trade will change in the next five years. As Fig.3 shows, economic power is playing a less and less important role in wildlife conservation. Instead, population status, governance effectiveness, and local capacity are becoming more important.

It is important to note that we have scaled the weights in our forecasts to give a more intuitive representation of our predictions.

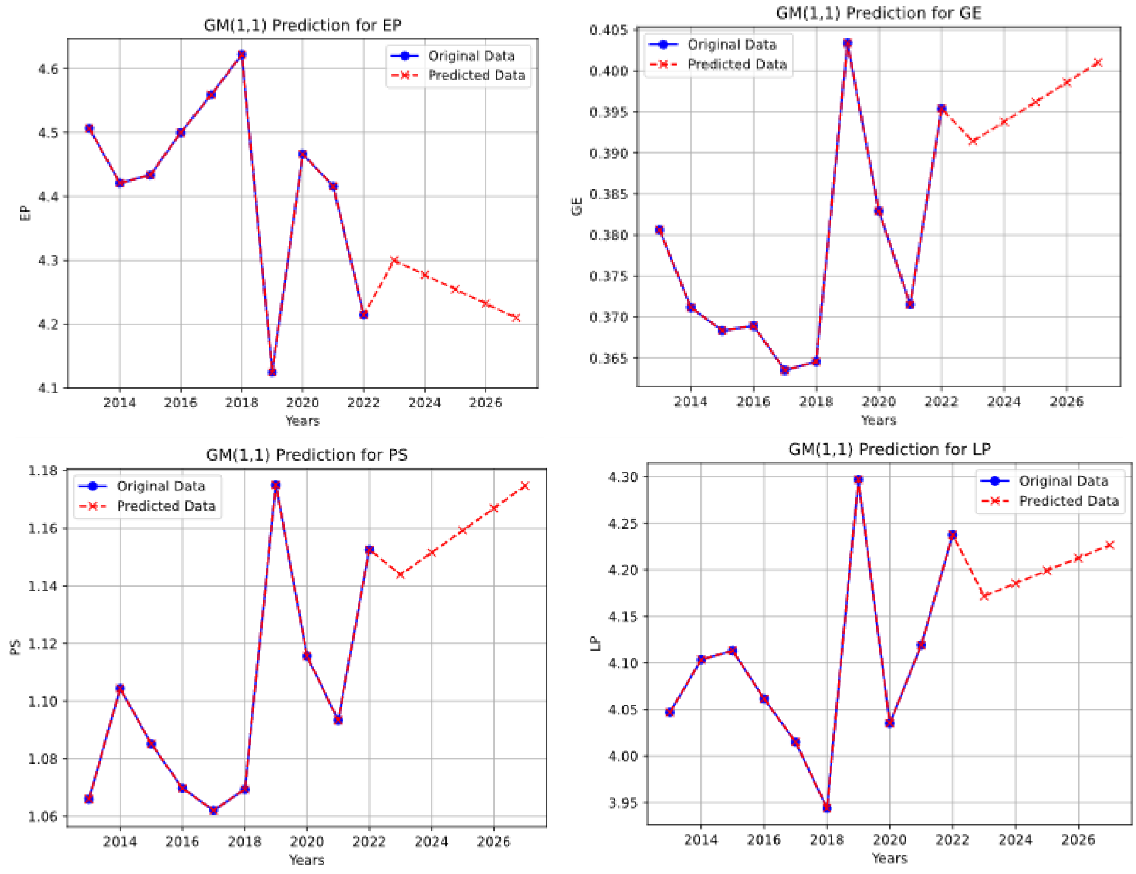

Figure 3. Weight prediction results of input proportion of first-level indicators

Step8 Model test.

Table 2. Model test results

	EP	GE	PS	LP
Average relative residuals$\overline{\varepsilon_\gamma}$	0.1470	0.0085	0.0743	0.0010

The table 2 shows that the three indexes $\overline{\varepsilon_\gamma} < 0$, a $\overline{\varepsilon_\gamma} < 0.2$, suggesting that model GM (1, 1) of the original data of the fitting effect is very good.

3.2. The Construction of Dual Objective Fuzzy Programming Model

In order to find suitable customers, we construct a double objective fuzzy programming model.

Here, we choose the four first-level indicators x_{ep}, x_{ga}, x_{ps} and x_{lp} built in the previous model as the indicator quantity respectively, which represent the investment of our target customers in the four aspects of economic strength, self-governance efficiency, population status and protection ability to improve the living environment of local wild elephants. The ability to protect them from poaching and illegal trade.

Due to the fuzziness of the constraint conditions, considering the possible best and worst cases, we introduce the expansion index s_1 of the average return rate and s_2 of the risk loss rate, where $s_1 > 0$; $s_2 > 0$.

Set an average return on investment for $\widetilde{g_\iota}$, is$\widetilde{g_\iota} = [\widetilde{g_{0\iota}}, s_1]$, $U = [x_{ep}, x_{ga}, x_{ps}, x_{lp}]$, then $x_i \in U$; If the upper limit of a resource input is x_{iub} and the lower limit is x_{ilb}, then$x_i \in (x_{ilb}, x_{iub}) \cup (0, x_{iub})$ is set.

According to our practical experience and the open data on the Internet, we have obtained the proportion of the benefits and costs after the entity organization carries out environmental protection actions. Next, we construct the payoff function $\widetilde{G_\iota}(x_i)$ and the total payoff function $\tilde{G}(x)$ for each resource:

$$\widetilde{G_\iota}(x_i) = (\widetilde{a_\iota} + 1)\omega_i x_i \quad x_i \in U \tag{30}$$

$$\tilde{G}(x) = \sum_{i=0}^{n} \widetilde{G_\iota}(x_i) \tag{31}$$

At the same time, we obtain the relevant mapping matrix, thus mapping the coefficient of the cost function, obtaining the cost function of each resource $\widetilde{C_\iota}(x_i)$ and the total cost function $\tilde{C}(x)$:

$$\widetilde{C_\iota}(x_i) = 0.8\left(1 + \widetilde{d_\iota}\right)\omega_i x_i \tag{32}$$

$$\tilde{C}(x) = \sum_{i=0}^{n} \widetilde{C_\iota}(x_i) \tag{33}$$

Fixed cost $C = 0.8$ when $\widetilde{d_\iota} = 0$.

It should be noted that the concept of costs and benefits we give here is not the traditional economic concept of the return of inputs to money. Here, we interpret costs as the resources required to implement a five-year project. The benefits represent the positive improvement of wildlife conditions after the implementation of the project, as well as a series of additional benefits. We define this as Protective Effectiveness and Returns (PER).

Meanwhile, set the investment loss risk rate$\widetilde{c_\iota}$,, then $\widetilde{c_\iota} = [c_{0i}, s_2]$,

Considering that the rapid economic development will cause damage to the environment, and it can be seen from the correlation analysis that x_{ep} and x_{ps} are significantly negatively correlated, it is stipulated that the environmental carrying coefficient E meets:

$$\frac{x_{ep}}{x_{epub} - x_{eplb}} + \frac{x_{ps}}{x_{psub} - x_{pslb}} \leq E \quad E \in [0,1] \tag{34}$$

Therefore, according to the principle of maximum benefit and minimum cost, a dual-objective optimization model can be established, which is summarized as follows:

$$max\, \tilde{R}\,(x) = \sum_{i=0}^{n} \widetilde{R_\iota}\,(x_i) \tag{35}$$

$$min\, \tilde{C}\,(x) = \sum_{i=0}^{n} \widetilde{C_\iota}\,(x_i) \tag{36}$$

$$max\left(\tilde{R}(x) - \tilde{C}(x)\right) \tag{37}$$

$$s.t.\begin{cases} \widetilde{g_\iota} = [\widetilde{g_{0\iota}}, s_1] \\ \widetilde{c_\iota} = [c_{0i}, s_2] \\ E \in [0,1] \\ x_i \in (x_{ilb}, x_{iub}) \cup (0, x_{iub}) \\ x_i \in U \\ U = \left[x_{ep}, x_{ga}, x_{ps}, x_{lp}\right] \end{cases} \tag{38}$$

Here is the solution process:

Considering the diminishing marginal return, that is, when a country has a strong investment in a certain resource, the further return on investment will decline. Therefore, when solving specific problems, we can set the expansion degree of constraints combined with the actual situation, further write the membership function of the average return rate, and set the expansion index of the average return rate:$s_1 = 0.2g_0$.

$$\widetilde{A_1}(x) = \begin{cases} 0, \widetilde{g_\iota} \leq 0.8g_{0i} \\ \frac{\widetilde{a_\iota} - \widetilde{a_{\iota lb}}}{\widetilde{a_{\iota ub}} - \widetilde{a_{\iota lb}}}, 0.8g_{0i} \leq \widetilde{g_\iota} \leq 1.2g_{0i} \\ 1, \widetilde{g_\iota} \geq 1.2g_{0i} \end{cases} \tag{39}$$

Were, $\widetilde{g_\iota} = [g_{0i}, 0.2g_{0i}]$.

Set the expansion index of risk loss rate $s_2 = 0.2c_0$, and the cost membership function is:

$$\widetilde{A_2}(x)=\begin{cases}1, \widetilde{c_i}\leq 0.8c_{0i}\\ \frac{\widetilde{c_{iub}}-\widetilde{a_i}}{\widetilde{a_{iub}}-\widetilde{a_{ilb}}}, 0.8c_{0i}\leq\widetilde{c_i}\leq 1.2c_{0i}\\ 0, \widetilde{c_i}\geq 1.2c_{0i}\end{cases} \tag{40}$$

Were, $\widetilde{c_i}=[c_{0i},0.2c_{0i}]$.

Then we get the fuzzy constraint set:

$$\tilde{A}=\widetilde{A_1}\cap\widetilde{A_2} \tag{41}$$

It can be calculated that the optimal solution of the total average yield of $\tilde{G}$ is$\tilde{G}_{max}$, and the corresponding total cost is $\tilde{C}_{\max}$. The optimal solution for the total cost $\tilde{C}$ is $\tilde{C}_{\min}$.

According to the above results, select the scaling index respectively:

$$d_3=\tilde{G}_{max}-\tilde{G}_{min} \tag{42}$$

$$d_4=\tilde{C}_{max}-\tilde{C}_{min} \tag{43}$$

Construct the respective fuzzy object sets accordingly, the membership functions are:

$$\widetilde{D_1}(x)=\begin{cases}0, max\,\tilde{G}\,(x)\leq\tilde{G}_{max}-d_3\\ \frac{1}{d_3}max\,\tilde{G}\,(x), \tilde{G}_{max}-d_3<max\,\tilde{G}\,(x)\leq\tilde{G}_{max}\\ 1, \tilde{G}_{max}<max\,\tilde{G}\,(x)\end{cases} \tag{44}$$

$$\widetilde{D_2}(x)=\begin{cases}1, max\,\tilde{C}\,(x)\leq\tilde{C}_{min}\\ 1+\frac{1}{d_4}\left(\tilde{C}_{min}-max\,\tilde{C}\,(x)\right), \tilde{C}_{min}<max\,\tilde{C}\,(x)\leq\tilde{C}_{min}+d_4\\ 0, \tilde{C}_{min}+d_4<max\,\tilde{C}\,(x)\end{cases} \tag{45}$$

Therefore, the comprehensive fuzzy object set can be expressed as:

$$\widetilde{D}=\widetilde{D}_1\cap\widetilde{D}_2 \tag{46}$$

In the cost-benefit problem based on fuzzy programming, both the constraints and the objective function have an important impact on the value of the optimal solution. In particular, when the objective function and the constraints are equally important, it is a symmetric fuzzy programming model. For A symmetric fuzzy programming model, the fuzzy superiority set $\widetilde{H}(x)$ is the intersection of fuzzy objective set $\widetilde{D}(x)$ and fuzzy constraint set $\tilde{A}(x)$. Namely:

$$\widetilde{H}=\tilde{A}\cap\widetilde{D} \tag{47}$$

In order to find the fuzzy optimal solution x^*, we introduce the maximum value of the fuzzy superior set λ:

$$\lambda=\widetilde{H}(x^*)=max\,\widetilde{H}\,(x) \tag{48}$$

λ is satisfied:

$$\begin{cases}\lambda\in[0,1]\\ \tilde{A}\geq\lambda\\ \widetilde{D}\geq\lambda\end{cases} \tag{49}$$

According to the principle of maximum membership, we can solve for λ and x^*. In this way, double objective fuzzy programming is transformed into ordinary linear programming [10]. The summary is as follows:

$$s.t.\begin{cases}\frac{1}{d_3}(max\,\tilde{G}\,(x)-\tilde{G}3_{max}\\ 1+\frac{1}{d_4}(\tilde{C}\,max\,\tilde{C}_{min}\\ \frac{\widetilde{a_i}-\widetilde{a_{ilb}}}{\widetilde{a_{iub}}-\widetilde{a_{ilb}}}\geq\lambda\\ \frac{\widetilde{c_{iub}}-\widetilde{a_i}}{\widetilde{a_{iub}}-\widetilde{a_{ilb}}}\geq\lambda\\ \widetilde{c_i}=[c_{0i},0.2c_{0i}]\\ \widetilde{g_i}=[g_{0i},0.2g_{0i}]\\ \lambda\geq0\\ x_i\geq0\{\end{cases}\tag{50}$$

Finally, we obtained the optimal solution of the annual index quantity of the 5-year plan through comprehensive solution, as shown in Table 3:

Table 3. Optimal solution of indicator quantity in the next five years

Year	PER	Cost	EP	GE	PS	LP
2024	72.7773	54.7127	4.5857	1.4260	9.7856	0.4532
2025	76.2664	55.1836	4.5608	1.4320	9.9159	0.4574
2026	80.7256	55.6172	4.5308	1.4383	10.0417	0.4617
2027	84.1640	56.0234	4.4970	1.4445	10.1643	0.4660
2028	87.5937	56.4145	4.4602	1.4528	10.2845	0.4704

This represents the change of the index quantity of the optimal solution in the next five years, and only by constantly approaching the optimal solution can the maximum return be achieved.

At this point, we get the maximum net benefit PER Cost, where Cost is the minimum value under this condition, and the degree of EP, GE, PS, LP input corresponding to the maximum benefit, which should be the customer's economic strength, autonomous efficiency, population state, and local capacity under this condition. This will be the key factor for us to select the right customer. We will therefore determine the client's final 5-year project to drive the client's capabilities towards optimal solutions to improve the environment for wildlife and protect it from poaching and illegal trade.

4. Summary

This paper focuses on the impact of illegal wildlife trade on wildlife and human biological resources, and proposes an effective and generalized index model of illegal wildlife trade. First, through extensive literature reading and searching for public data, we construct the Illegal Wildlife Trade Index System (IWTI), which includes four primary indicators and 17 secondary indicators, including economic power (EP), governance effectiveness (GE), population status (PS) and local power (LP). Secondly, we used the entropy weight method (EWM) to obtain the weights of all levels of indicators, and combined TOPSIS method to calculate the IWTI of various countries. Finally, we use the grey prediction model to predict the change trend of the four key constraint indicators in the next five years. A dual-objective fuzzy optimization model was constructed to try to obtain the optimal values of the four important constraint conditions, which are 4.5857, 1.4260, 9.7856 and 0.4532, when the Net PER of wildlife protection from illegal trade is the largest and the cost is the smallest. This study provides a scientific assessment method and decision support for wildlife conservation, and helps to formulate effective forecasting and planning strategies.

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