

Study on the assessment of illegal wildlife trade projects based on LSTM model and Monte Carlo simulation

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Abstract. The aim of this paper is to conduct an assessment study of illegal wildlife trade projects using LSTM models and Monte Carlo simulation techniques. Firstly, based on the data from 1994-2023, we predicted the number of illegal animal and plant trade in the next five years using LSTM model, and the results showed that although the number was on a decreasing trend, it was still high, indicating that the problem still needs to attract global attention. Subsequently, we used the Kendall correlation coefficient to analyse the relationship between the number of illegal trade counts and economic, environmental and climate indicators, and found a positive correlation with the economic losses from natural disasters and the number of extreme weather events. Finally, we identified seven key parameters affecting project success and simulated the posterior distributions of these parameters using the Markov Chain Monte Carlo method, and then conducted Monte Carlo simulations to estimate the probability of project success as 93.12%. Sensitivity analyses indicate that project success is most sensitive to the level of financial support and monitoring technology. Overall, using a data-driven approach, this paper provides an important reference for assessing illegal wildlife trade projects..

Keywords: Illegal wildlife trade; LSTM modelling; Monte Carlo simulation; project evaluation.

1. Introduction

Illegal wildlife trade is the trade in wildlife and its products without legal authorization and regulation. Many wildlife species are threatened with extinction due to over-exploitation and illegal trade. In addition, illegal wildlife trade disrupts the balance of natural ecosystems, leading to loss of biodiversity and degradation of ecosystem functions.

Border control plays an important role in stopping illegal wildlife trade. Effective border control measures can monitor illegal trade in wildlife entering the country illegally, intercept illegal wildlife trade items and prevent them from reaching the market. It also reduces illegal harvesting and illegal trade in wildlife by weakening illegal trafficking networks and reducing the profit margins of illegal trade. Border control can also enhance the ability of law enforcement and relevant agencies to monitor and combat illegal wildlife trade.

Considering the background information and restricted conditions identified in the problem statement, we need to solve the following problems:

(1) Why is your chosen project appropriate for this client? What published literature and your own analysis support your selection of this project? Using data-driven analysis, how would you convince the client to implement this project to reduce illegal wildlife trade?

(2) What is the likelihood that the project will achieve its intended objectives? In addition, based on the contextual sensitivity analysis, are there certain conditions or events that could disproportionately help or hinder the project's ability to achieve its objectives?

2. Project-Client Fit

2.1. Project fit with client's strengths

2.1.1 Fit between the client's needs and the project objectives:

The project aims to intercept items from the illegal wildlife trade and stop them from reaching the market by monitoring the illegal trade in flora and fauna that enter the country illegally, which is fully in line with the mission and objectives of the Trade in Wildlife Research Organization for International Consumption (TRAFFIC). Traffic's mission is to ensure that the trade in wildlife species is legal and sustainable for the benefit of the planet and its people. Traffic has set two 2030 goals to significantly reduce the illegal and unsustainable trade in wild species and to increase the social, economic and environmental benefits to humanity of the legal and sustainable trade in wild species.

2.1.2 Client Fit between the work and project implementation

The project aims to help airlines and airport authorities identify and combat illegal trade activities. Therefore, the work of both organizations is highly compatible and the client was able to provide relevant experience and guidance to the project.

2.1.3 Fit of the technology application to the client's strengths

The project utilizes drones and thermal imaging technology for border patrol and monitoring. And TradeMapper, a tool developed by TRAFFIC and WWF-UK, is used by TRAFFIC to map wildlife trade data (e.g. CITES and customs data). It can be seen that the technology required for the project can be integrated with the technology owned by the client to achieve better results.

2.1.4. Data-driven fit with client's strengths

The project relies on data analysis and alert systems to identify potential illegal trade activities. TRAFFIC, as an organization specializing in research and monitoring of wildlife trade, is committed to research and data collection. They collect and analyze data related to illegal wildlife trade by conducting a wide range of research work, which includes trade trends, species threat levels, trade networks, etc. Therefore, the data collected by the client can be applied to this project.

2.1.5 Cooperation and coordination fit with client's strengths

The project emphasizes cooperation with relevant government agencies, international organizations and stakeholders to share intelligence and technical resources. TRAFFIC, on the other hand, has established a wide range of networks and partnerships globally, including government departments, law enforcement agencies, international organizations and civil society organizations, and has a certain degree of networks and partnerships, especially in the area of transportation, which has strong influence and sustainability, and can promote the policy formulation and implementation of border control and inspection measures, and work together to fight against cross-border illegal trade.

2.2. Basis for project selection

When it comes to reducing the illegal wildlife trade, enhanced border control and inspection measures are recognized as an effective tool. This view is supported by a number of studies that have drawn positive conclusions through ivory and pangolin case studies and assessments of the impact of border control measures. Enhanced border control and inspection measures imply stricter inspection procedures at border crossings, increased inputs of personnel and technical equipment, and improved identification of illegal trade. These measures can be effective in stemming the cross-border flow of illegal wildlife trade. Pilot studies in places such as India and Nepal have shown that strengthening border controls, detaining illegally traded items at border crossings and detaining those involved can effectively reduce the incidence of illegal trade activities.

In addition, strengthening border control also requires enhanced cooperation with States in addressing cross-border illegal trade. The study on international biosecurity strategies and

biodiversity conservation practices provides recommendations for strengthening border controls to protect wildlife resources and biodiversity. Meanwhile the study on governance of cross-border security complexes points to the need to integrate multiple factors and to strengthen international cooperation, information-sharing and coordination among law enforcement agencies. In addition, the complexity and innovative nature of the illegal wildlife trade posed certain difficulties for border control, and therefore measures needed to be continuously updated and improved.

The project focuses on the application of drone technology and thermal imaging in border control, where drones can quickly locate illegal trade practices and protect wildlife and their habitats through aerial photography and image recognition. Thermal imaging technology detects the heat signature of animals and helps to find illegally traded items hidden in packages or carriers.

2.3. Data-driven analysis based on LSTM modeling

2.3.1 Background and urgency of the project

Today, the illegal wildlife trade is one of the largest and most lucrative criminal activities on the planet, estimated to be worth between \$7 billion and \$23 billion annually, involving a wide range of species including elephants, rhinoceros, and what is probably the world's most traded mammal, the pangolin (Source: Global Environment Facility). These species are highly sought after for their meat and scales, e.g. pangolins must be killed to collect their scales. Preliminary data shows that up to 59 seizures have been recorded in the first two and a half months of 2023, suggesting a continuation of the trend in 2022, especially with regard to the ivory trade (source: news.mongabay.com). The graph below shows the number of times that elephants and pangolins have been illegally traded each year since 1996 to 2023, and it can be seen that the number of illegal trades of both species has shown a significant upward trend from 1996 to 2023, with a significant increase in illegal trade activity, especially after 2010, and even though the number of presentations has declined after 2020, the number is still higher compared to the beginning of the century by a Even if the number declines after 2020, it is still much higher than at the beginning of the century(Figure 1).

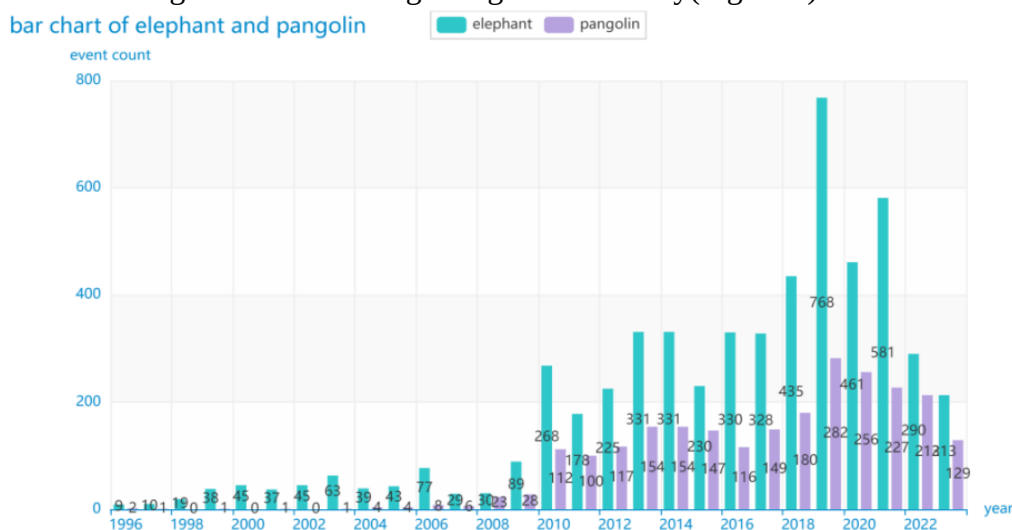


Figure 1. Volume of illegal trade in ivory and pangolin over the years

Illegal trade in wildlife has a wide range of negative ecological and socio-economic impacts, and WWF's Vitality of the Planet Report 2022 states that, with wildlife populations declining by an average of 69 per cent over the past few decades, the natural ecosystems are facing a serious challenge, and that it is imperative for governments, businesses and the public to take transformative action without delay in order to reverse the trend of biodiversity degradation. Socio-economically, illegal trade activities lead to a loss of resources, diminishing opportunities for economic development and sustainable income, and are often associated with problems such as organized crime, corruption and social instability. Illegal wildlife trade can also raise public health concerns, as wildlife in the animal trade can carry pathogens that can spread disease to humans (source: Global Environment Facility).

Strengthening border controls and inspections is essential to reducing the illegal wildlife trade, a measure that can directly disrupt transnational transportation routes for illegal commodities. Illegal wildlife trade often involves cross-border activities, with the illegal import and export of animal and plant products through borders. Strengthened controls and inspections can effectively identify and intercept illegally traded goods and reduce the circulation and sale of illegal species, thereby protecting biodiversity and avoiding the overcapture and destruction of wild species. In addition, stringent border inspections can also help combat the associated transnational criminal networks, raising the risks and costs of illegal trade and acting as a deterrent. This is in line with our client's mission to protect wildlife and ensure its long-term survival and prosperity by preventing illegal trade.

2.3.2 LSTM Predicts Number of Illegal Plant and Animal Trades in the Next Five Years

For traditional neural networks, despite their excellent performance in many domains, they often encounter difficulties when dealing with time series prediction problems. This is mainly because they lack the ability to capture long-term dependencies in the data. In a problem such as the prediction of the number of illegal trade in plants and animals, such long-term dependencies are crucial, as past events may have a profound effect on future illegal trade activities.

One of the significant drawbacks of traditional neural networks is that they have difficulty in maintaining information as it is passed through the layers of the network. As the time step increases, the impact of the relevant information diminishes until it disappears completely, which is known as the "gradient vanishing" problem. This means that it is difficult for the network to learn and retain early input information that is critical to the current prediction.

This is where the advantages of Long Short-Term Memory (LSTM) networks come to the fore. LSTMs address this shortcoming of traditional neural networks by introducing a complex gating mechanism[1]. These gating units are capable of deciding which information is retained, which is forgotten, and which new information is added at any point in time[2]. This mechanism allows the LSTM to retain information over long periods of time while processing long sequences of data without losing important information over time. Its structure is shown below(Figure 2).

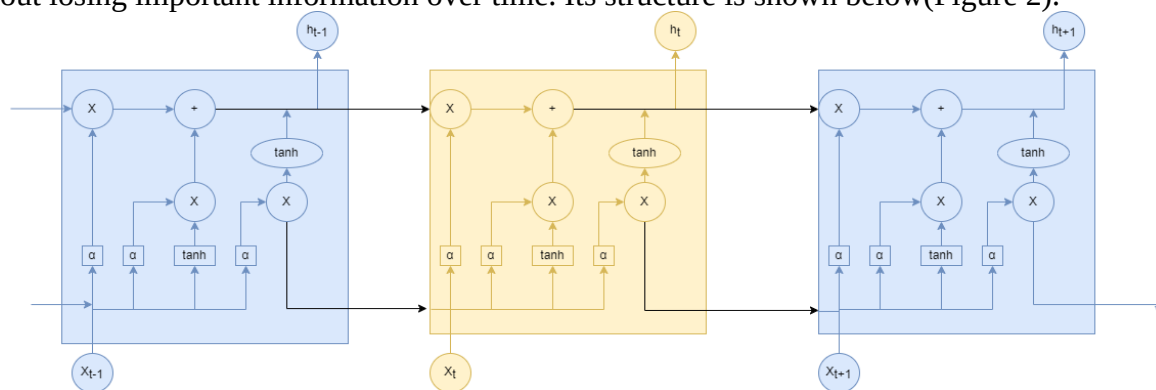


Figure 2. Schematic diagram of LSTM structure

In the schematic structure of the LSTM, each black line transmits an entire vector from the output of one node to the input of other nodes. The "+" signs represent arithmetic operations (e.g., vector sums), while the rectangles represent learned neural network layers. Lines that converge together represent connections of vectors, and lines that diverge indicate that content was copied and then distributed to different locations[3,4].

The principle of this structure of LSTM is to introduce a connection called cell state. This state cell is used to store things that are wanted to be memorized, and its core lies in three gates, the forget gate, which is responsible for deciding when to forget the previous state, the input gate, which is responsible for deciding when to add a new state, and finally the output gate, which decides when to put the inputs and the state together and output them[5].

Next, the modeling and solving is done by first determining the dataset, here we choose the number of times illegal trafficking of plants and animals occurred in the world in each year during the period from 1994 to 2023. This is shown in the Figure 3 below:

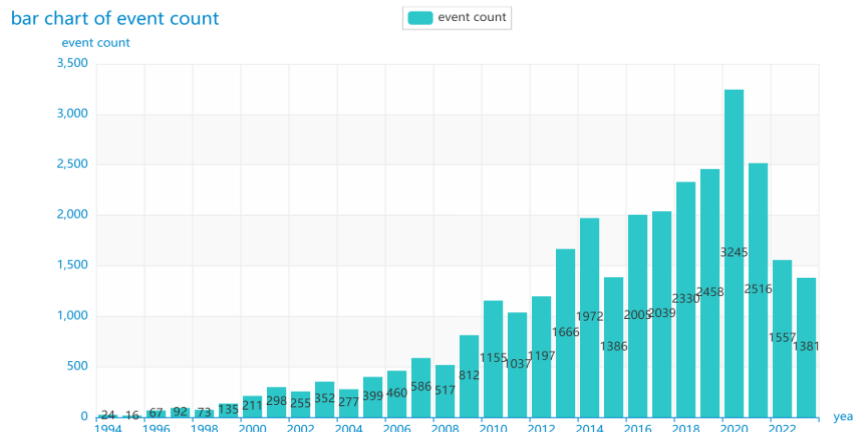


Figure 3. Number of incidents of illicit trafficking in flora and fauna, by year

The data was also standardized to ensure consistency and validity of the model inputs. The formulas are as follows:

$$\max Value = \max(data) \quad (1)$$

$$\min Value = \min(data) \quad (2)$$

$$normalizedData = \frac{data - \min Value}{\max Value - \min Value} \quad (3)$$

After the dataset is finalized, the model definition is performed, which mainly consists of an LSTM layer and a fully connected layer. The LSTM layer is used to process the event sequence data and capture the long-term dependencies in the data, while the fully connected layer is responsible for converting the output of the LSTM layer into the predicted values.

In order to train the model, we need to construct a suitable training dataset. By defining a sliding window, we extracted a series of consecutive time series (3 consecutive years of data) from the original data as inputs to the model, while using the data in the last bit of the window as the prediction target.

During the training of the model, we used the mean square error as the loss function and chose the Adam optimizer to optimize the model continuously. Through many iterations of training, the parameters of the model gradually converge and the value of the loss function continues to decrease, showing the effectiveness of the model for time series prediction. During the training process, the relationship between the loss value and the change of the training stage is shown in the Figures 4 and 5 below.

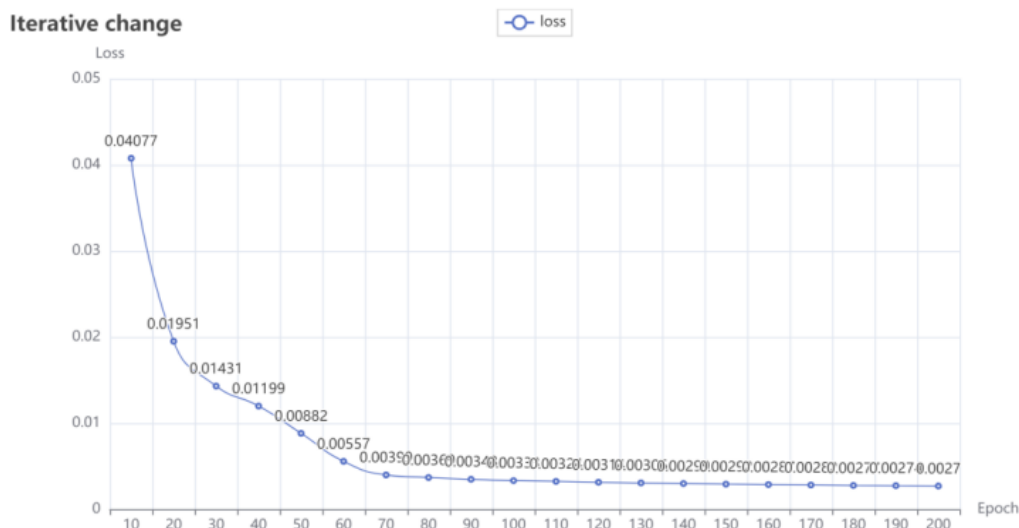


Figure 4. Relationship

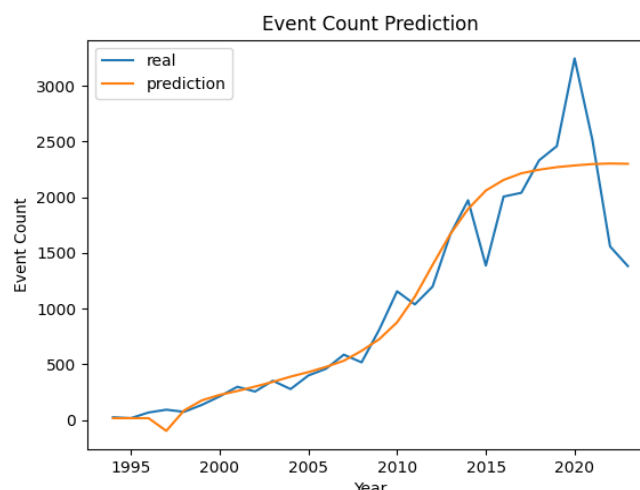


Figure 5 Fitting results

It can be noticed that the loss value gradually decreases from 0.04077 to 0.0270 as the number of training sessions increases. This progression indicates an improvement in the model's ability to fit the data, and the rapid decrease in the loss value during the initial phase suggests that there is a lot of room for improvement early on. As the training progresses, the rate of decline in the loss values slows down, indicating that the model is beginning to converge towards a solution, especially after the 100th training, where the change is very small. By the end of the 200th training session, the loss rate of the model is at 0.00270 and the last few fluctuations are small, indicating that the model predicts better. The final fit is shown in the figure above.

Once the model was trained, we set the model in evaluation mode and made predictions for the entire dataset. Predictions of the number of event occurrences for the next five years were made using the trained model. By progressively using the prediction results as inputs for the next prediction, we simulated the process of generating future time series to obtain predicted values for the number of event occurrences in the next five years. The prediction results are shown in the table 1 below:

Table 1. prediction results

particular year	2024	2025	2026	2027	2028
Number of illicit animal and plant trafficking	500.022	458.023	421.820	354.863	291.06

Based on the analysis of the data on the number of illegal animal and plant trafficking from 1996 to 2023 and the application of the LSTM prediction model, we observe that even though the number of illegal trafficking shows a decreasing trend between 2024 and 2028, its frequency is still at a relatively high level. This suggests that the problem of illegal animal and plant trafficking remains a serious challenge that requires global attention and action. According to the study by rare and phys, illegal wildlife trade not only poses a great threat to biodiversity, but may also lead to new outbreaks of zoonotic diseases, posing a risk to global public health security. In addition, cobras pointed out that illegal wildlife trade jeopardizes the balance of ecosystems, affects economic development, and even has a bearing on national security.

Strengthening border management and taking other effective measures to reduce illicit trafficking in flora and fauna have therefore become crucial. Through the implementation of this project, we will not only be able to reduce the incidence of illegal animal and plant trafficking at its root causes, but will also be able to effectively protect biodiversity and the balance of ecosystems. More importantly, it will help to prevent new zoonotic diseases that may be triggered by inappropriate contact between humans and wildlife, thereby protecting global public health security.

2.4. Kendall-based correlation coefficient test

2.4.1 Data quantification and model selection

In order to analyze more precisely the relationship between the number of illegal plant and animal trades and the economy, the natural environment and the climate.

The first step is to select a representative country for detailed data analysis. By checking the number of illegal trade in flora and fauna in each country in a certain period of time (the results are shown in the figure 6 below), we found that China ranked first in the world in illegal trade in flora and fauna, with 977 cases. The number of illegal trade in animals and plants in China is the highest in the world, with 977 cases, while the second place, Thailand, has only 219 cases. Considering the size of China's population and economy, we believe that China occupies an important position in the global illegal trade of plants and animals. This not only reflects China's influence in global trade, but also suggests that China faces particularly serious environmental and biodiversity conservation challenges. It is therefore appropriate and important to examine the relationship between China's illegal trade in flora and fauna and its economy, natural environment and climate.

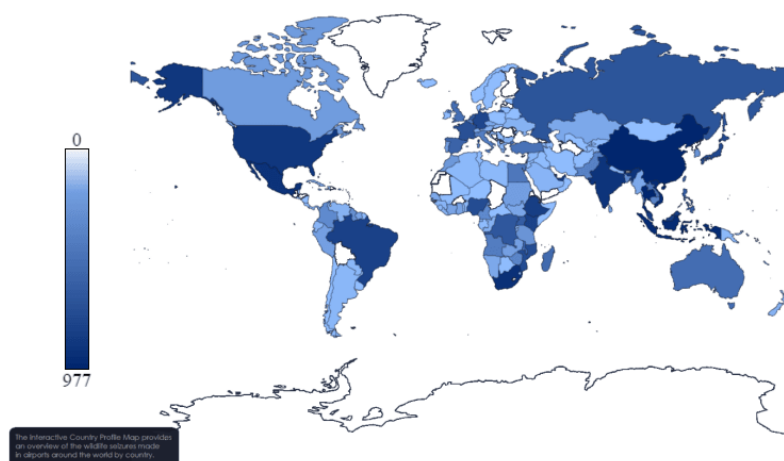


Figure 6. Number of incidents of illegal trade in flora and fauna by country

Considering quantitative data analysis, we first need to express the goodness of economy, environment and climate by some indicators, i.e. quantification of data. Here we use the growth rate of GDP, direct economic loss from natural disasters, and direct economic loss from geologic disasters to measure a country's economy, forest cover to measure the environment, and extreme weather to measure the climate. The underlying quantitative part of the data is shown in the table 2 below.

Table 2. underlying quantitative part of the data

	count	GDP growth rate	Forest cover (%)	Direct economic losses from natural disasters (billions of dollars)	Direct Economic Losses from Geological Disasters (Billions of Yuan)	Extreme weather
2009	145	9.4	21.6	5086.5	190109	27
2010	402	10.6	21.6	5339.9	638509	19
.....						
2022	142	3	23	2386.5	150281	68

The following correlation between the number of illegal wildlife trade and variables such as GDP growth rate can be explored to investigate the impact of illegal wildlife trade on the economy, environment and climate. Thus, we decided to use Pearson's correlation coefficient or Kendall's correlation coefficient for the analysis.

According to this matrix scatter plot, we can see that there is no obvious linear relationship between COUNT and the rest of the variables. Considering that the Kendall's correlation coefficient of non-

parametric test is more accurate compared to Pearson's correlation coefficient for small sample size data, we use Kendall's correlation coefficient for analysis(Figure 7).

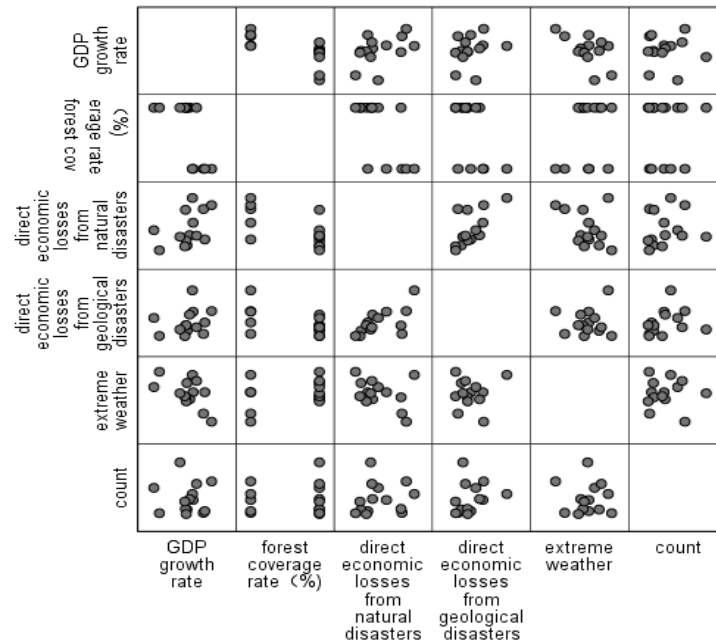


Figure 7. Kendall's correlation coefficient for analysis

2.4.2 Model Solving and Analysis

Kendall's correlation coefficient is a nonparametric statistic that measures the correlation between two variables. It is calculated by counting the agreement (homoscedasticity) and disagreement (heteroscedasticity) of all pairs of data, and is applied to ordinal data. When two variables are in the same order, they are considered congruent; otherwise, they are considered incongruent. The Kendall coefficient has a value between -1 (perfect negative correlation) and 1 (perfect positive correlation), with 0 indicating no correlation. Compared to Spearman's correlation coefficient, another nonparametric statistical method, Kendall's correlation coefficient is less sensitive to outliers and is more suitable for analyzing small samples of data.

Kendall's correlation coefficient is calculated as:

$$\tau = \frac{2}{n(n-1)} \sum \text{sign}(x_i - x_j) \cdot \text{sign}(y_i - y_j) \quad (4)$$

Where n is the number of observations in the dataset, (x_i, y_i) and (x_j, y_j) are any two pairs of observations, and $\text{sign}(x_i - x_j)$ and $\text{sign}(y_i - y_j)$ denote the sign function of the difference between x and y respectively. By comparing each pair of observations, the difference in the number of concordant and discordant pairs is calculated, and then the value of τ is calculated according to the formula to obtain the degree of correlation between the two variables.

A program was written in python to solve for the Kendall's correlation coefficient between the indicators and the results are shown below.

Looking at the picture, of the five indicators available, the relevance of illegal wildlife trade has the strongest correlation with direct economic losses from natural disasters, followed by a positive correlation with direct economic losses from geologic disasters, as shown below(Figure 8).

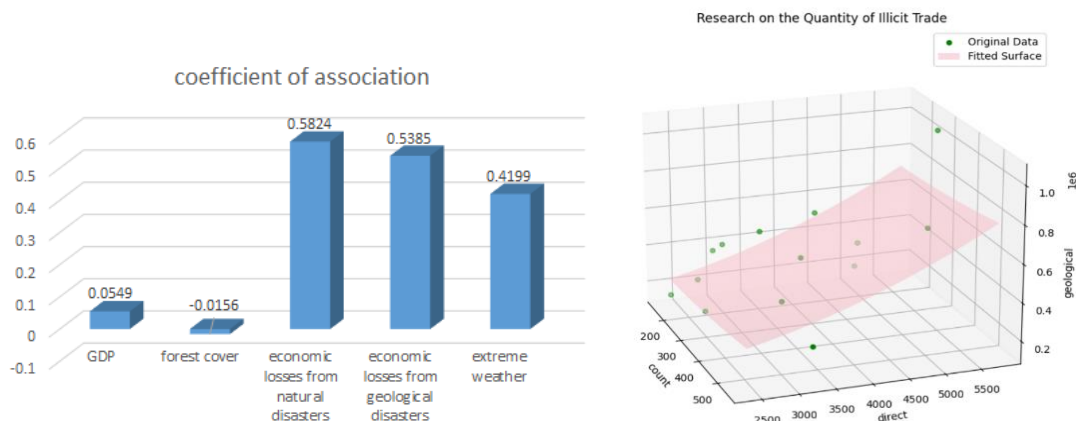


Figure 8. coefficient of association and Research on the Quantity of Illicit Trade

It is not difficult to see that with the rise in the number of illegal wildlife trade, the economic losses of the two disasters also show a synchronized increase in the range of error, which also shows that the rise in the number of illegal wildlife trade will bring about expenditure on disaster management and affect the national economy.

Apart from the two disasters, the highest correlation is the number of extreme weather occurrences, due to the fact that the capture of flora and fauna by sellers in the illegal wildlife trade can damage the ecology to a certain extent, thus worsening the climate and leading to the occurrence of extreme weather.

However, for the GDP growth rate, the correlation between the GDP growth rate and the increase in the number of illegal wildlife trade is weak in the correlation analysis due to the many influencing factors and policy reasons. For forest cover, the correlation is also weak due to China's policy of returning farmland to forests. However, the economic losses from disasters and the number of extreme weather events still indicate that the number of illegal wildlife trade will have a negative impact on a country's economy, natural environment and climate.

3. Evaluation of projects

3.1. Parameter selection

In addressing the issue of reducing the likelihood of project success, the selection of parameters that are closely linked to project success is critical. We have identified seven key parameters that are considered to play a central role in the fight against illegal wildlife trade.

The effectiveness of combating illegal trade is influenced by the following key factors: the strength of legal enforcement, the level of public awareness, the degree of international cooperation, the level of financial support, the sophistication of monitoring and technological means, the vulnerability of ecosystems, and the sophistication of policy and legal frameworks. The level of legal enforcement is directly related to the effective curbing of illicit activities. The level of public awareness is a key factor in reducing demand for illicit products. The level of international cooperation is crucial for effectively combating transnational illicit trade. Financial support is the basis for realizing the objectives of the project, and the lack of adequate financial support will affect the implementation of surveillance, education and enforcement actions. The level of sophistication of monitoring and technical means is critical to increasing the efficiency of the fight against illegal trade. Ecosystem vulnerability, which takes into account the impact of illegal trade on the environment, becomes an important factor. Finally, the degree of sophistication of policy and legal frameworks is fundamental to effectively combating illegal trade.

The seven parameters were chosen based on their importance in program success and the complexity of their interactions. We aimed to construct a comprehensive and in-depth analytical framework to assess the likelihood of success of projects to reduce illegal wildlife trade(Figure 9).

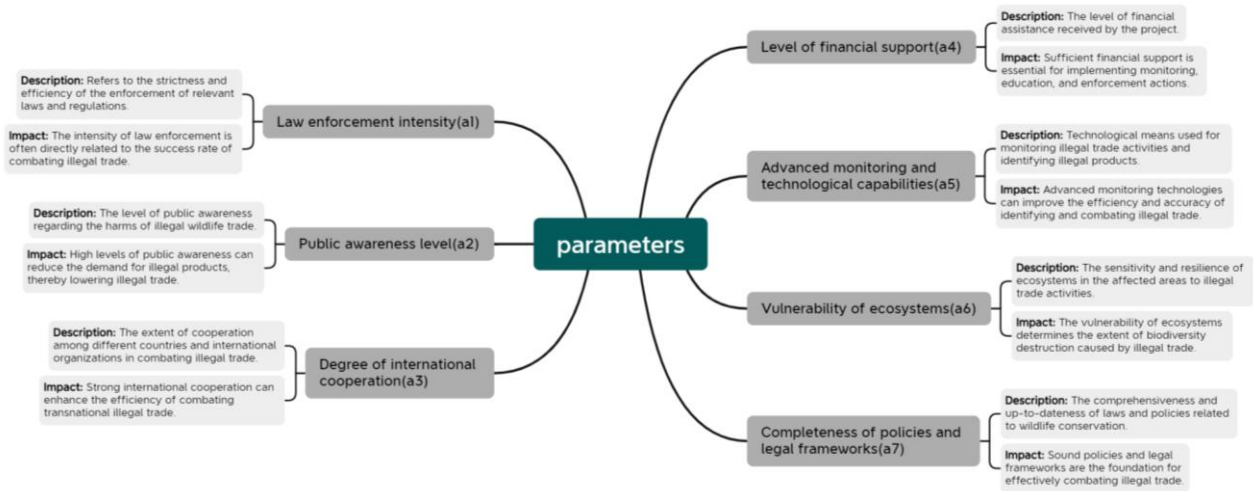


Figure 9. Selection of parameters

3.2. Posterior distribution of MCMC sampling simulation parameters

Considering the multiple variables and their complex interactions, direct computation becomes very difficult, based on which we use Markov chain Monte Carlo (MCMC) method to approximate these distributions by random sampling[6-8]. The implementation process can be categorized into the following steps, below I take the variable.

Step 1: Initialization of the project

An initial point x_0 is chosen as the starting point of the algorithm, denoted as $\theta^{(0)}$, which represents the location where the algorithm starts exploring the parameter space, here θ denotes the

Step 2: Proposed distribution

A proposal distribution is chosen for each variable. This distribution is used to generate new candidate samples at each future step θ' . In this example, we choose the normal distribution.

Step 3: Generate candidate samples

Candidate samples for the next state are generated by drawing samples from the proposal distribution.

Step 4: Acceptance and rejection of candidate samples

Use the Metropolis criterion to decide whether to accept this candidate sample. The acceptance probability α is as follows:

$$\alpha(\theta', \theta^{(t)}) = \min\left(1, \frac{p(\theta')q(\theta^{(t)}|\theta')}{p(\theta^{(t)})q(\theta'|\theta^{(t)})}\right) \quad (5)$$

Since in step 2, we propose a normal distribution, the rate of the proposed distribution $q(\theta'|\theta^{(t)})/q(\theta^{(t)}|\theta') = 1$, and therefore the probability of receiving α can be simplified to the following form:

$$\alpha(\theta', \theta^{(t)}) = \min\left(1, \frac{p(\theta')}{p(\theta^{(t)})}\right) \quad (6)$$

Where $p(\theta)$ is the probability density function of the target distribution

Step 5: Repeat steps 3 and 4

Repeat steps 3 and 4 until a sufficient number of samples are generated. This iterative process will construct a Markov chain with a smooth distribution close to the target distribution[9,10].

Step 6: Posterior distribution analysis

Using the collection of samples collected at $\{\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(N)}\}$, the posterior distribution is analyzed. In this problem, we calculate the mean, median of the sample to gain a deeper understanding of its properties, see the table below, and plot a frequency histogram for each variable to visualize its probability distribution, as shown below (Table 3 and Figure 10).

Table 3. Description of variable statistics

	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Mean	4.220	2.962	5.363	3.942	3.962	7.193	3.721
Median	4.237	2.988	5.413	3.942	3.980	7.246	3.743
Standard Deviation	0.492	0.397	0.597	0.453	0.467	0.682	0.442

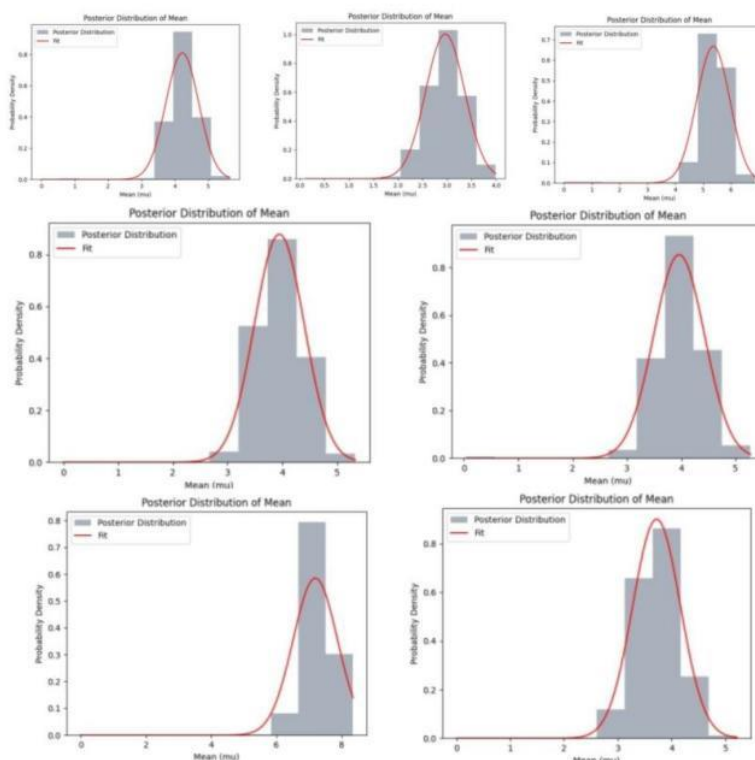


Figure 10. Frequency histogram of variables

3.3. Estimating the likelihood of project compliance based on Markov simulation

In order to estimate the likelihood that the project will meet its intended goals, we will use Monte Carlo simulation methods. The following are the specific implementation steps:

Step 1 Parameter Probability Distributions: Based on the target setting and previous parameter analysis, probability distributions for each key parameter (e.g., strength of law enforcement, level of public awareness, degree of international cooperation, etc.) are determined. These distributions describe the range of possible values and corresponding probabilities for each parameter.

Step 2 Simulation process: a large number of Monte Carlo simulations are performed. In each simulation, a specific value is randomly extracted from the probability distribution of each parameter, representing the actual value of the parameter taken in that simulation. A predefined logic or model is then used to determine whether the project can achieve the predefined objectives based on the extracted parameter values. For example, judging whether a project is successful in meeting its objectives based on the extracted values of the level of public awareness and the amount of financial support.

Step 3 Recording and statistics: record at the end of each simulation whether the project was successful or not, and repeat the process several times to ensure that the results are robust and representative.

Step 4 Calculate the probability of success: count the number of times the project succeeds in all simulations and divide it by the total number of simulations to get the percentage of likelihood that the project meets the standard. To solve the program and show the process graph, we can use Python code. It is shown below(Figure 11).

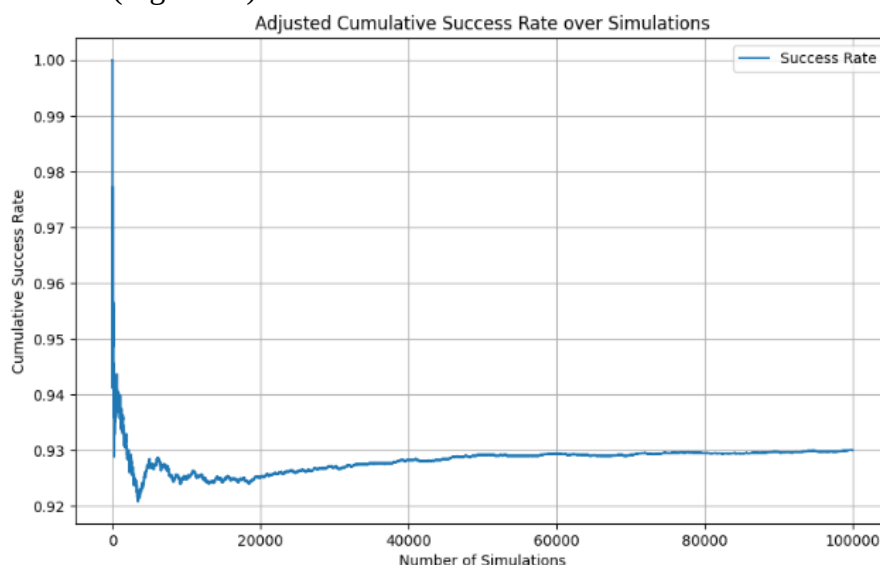


Figure 11. Trends in the probability of project success

After a large number of simulations, the final probability of success fluctuates up and down from 0.93, and the final probability of this simulation is 0.9312 (with four decimal places).

3.4. Contextual sensitivity analysis

In order to assess the feasibility of the project objectives and to understand the sensitivity of the key parameters, we used a Monte Carlo simulation approach. First, we performed simulations based on the posterior distributions of seven variables previously obtained through the Markov Chain Monte Carlo (MCMC) method. Then, we selected one parameter and fixed its value at a specific point while keeping the other parameters simulated based on the posterior distribution obtained by the MCMC method. Next, we perform Monte Carlo simulations to estimate the new probability of the project reaching its goal with fixed parameter values. In order to fully assess the impact of the parameters on the success of the project, we gradually changed the values of the fixed parameters and repeated the Monte Carlo simulation for each value. Through repeated simulations, we collected a series of data reflecting the probability of project success for different parameter values. Finally, we plotted the data as a line graph to visualize the trend of project success probability with parameters. By looking at the graphs, we can analyze the sensitivity of these variables to project success to better understand the relationship between the parameters and the impact of each parameter on the project outcome.

Now using a particular variable as an entry point, the specific steps are unfolded as follows:

Step 1 Determination of the value of the fixed parameter: the value of the variable is divided into a number of equal parts in its range, in this case, the value of the parameter is between 0-10, here we are divided into 100 equal parts, from small to large one by one to select the value of the parameter

Step 2 Determination of other parameter values: for the other non-fixed parameters, we continue to vary the posterior distribution obtained using MCMC in 9.3

Step 3 Monte Carlo simulation: after the completion of steps 1 and 2, a Monte Carlo simulation is performed to estimate the probability of the project's success, recording the values and the current values of the fixed parameters

Step 4 Fixed parameter value change: keep changing the value of the fixed parameter, perform step 3 and know that a Monte Carlo simulation has been performed for all values of the fixed parameter

Step 5 Change of fixed parameters: Change the fixed parameters, e.g., from "Strength of Law Enforcement" to "Level of Public Awareness", and perform steps 1 to 4.

Step 6 Data Visualization and Sensitivity Analysis: Visualize all the data collected, draw line graphs, observe the graphs and analyze the sensitivity of each variable.

Following the steps, the final result is a line graph of the seven variables ($a_1, a_2, \dots, a_7$) versus the success rate of the project as shown below (Figure 12).

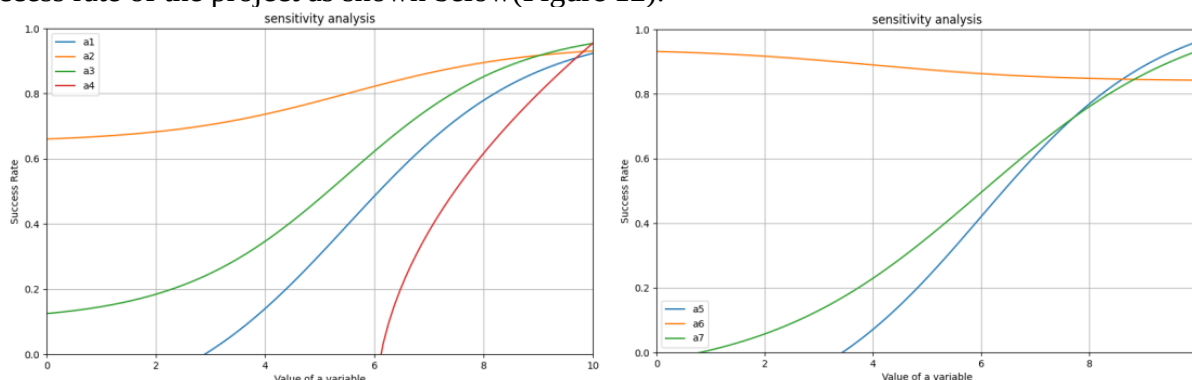


Figure 12. Sensitivity of variables

It can be noticed that most of these variables show an example of a slow increase followed by a leveling off. Of course there are exceptions, the level of financial support (variable a_4) has a tendency to increase rapidly, while the vulnerability of the ecosystem (variable a_6) does not have a high impact on the project success rate and slowly decreases as the vulnerability of the ecosystem rises. The overall analysis reveals that project success is most sensitive to the variable a_4 , because project implementation requires a large amount of money to operate, and if the money falls below a certain value, the project cannot be sustained and will naturally be difficult to succeed. The variable a_1, a_5, a_7 is the next most sensitive. It means that the project is also highly affected by these variables because our project requires a high level of technical skills as well as policy and legal assistance. The variable a_3 is not as sensitive as the previous variables, but it is also very important because the borders often require different countries and international organizations to work together in the fight against illegal trade. Finally, the variable a_2, a_6 is the least sensitive, especially the variable a_6 .

4. Conclusion

In this paper, the LSTM model was used to predict the number of illegal wildlife trade in the future, and it was found that, despite the decreasing trend, the number was still high, and therefore continued attention to the problem was needed. The relationship between the number of illegal trade and economic, environmental and climate indicators was analysed using the Kendall correlation coefficient, and some positive correlation was found. Seven key parameters affecting project success were identified and the probability of project success was estimated at 93.12 per cent using Markov Chain Monte Carlo and Monte Carlo simulations, and a sensitivity analysis was conducted. The findings indicate that project success is most sensitive to the level of financial support and monitoring technology. Overall, this paper provides an important reference for assessing illegal wildlife trade projects using a data-driven approach. Future research could continue to refine the model and collect data from more countries for analysis, with a view to providing a more comprehensive reference for Governments in formulating relevant policies.

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