Prediction and Study of Illegal Wildlife Trade Based on ESI-ARIMA Algorithm and SPELIT Differential Equation Model

Xianqi Dai*,#
Chang' an Dublin International College of Transportation
Chang'an University
Xi'an, China
2112808228@qq.com

Mingxian Wen#
Chang' an Dublin International College of Transportation
Chang'an University
Xi'an, China
1660914236@qq.com

Ruiheng Li#
Chang' an Dublin International College of Transportation
Chang'an University
Xi'an, China
1405773940@qq.com
#These authors contributed equally to this work

***Abstract*—The conservation of wildlife has become a global concern, necessitating the need for enhanced power and resources for governmental wildlife protection organizations. In this paper, we present a case study focused on Africa, aiming to demonstrate the potential for global collaboration in bolstering wildlife conservation efforts. We utilized "National Policy and Institutional Assessment" as a metric for wildlife conservation and developed the ESI-ARIMA algorithm to forecast its value over the next five years. Following intervention measures, in the fifth year, the predicted assessment value significantly increased from a baseline of 3.330 to 3.859, indicating substantial potential support for our project. Furthermore, to illustrate the impact of the project on wildlife conservation, we selected the volume of illegal wildlife trade as a measurable indicator. Through the establishment of the SPELIT differential equation model, we found that considering four indicators and their interactions, the volume of wildlife trade is projected to plummet from $100 billion to $1.62 million over the next five years. This suggests that our project holds the potential to substantially reduce illegal wildlife trade. Finally, we build a Logistic Regression Model to assess project success probability under the previous question's impact coefficient and find that the probability of success is 79.9%.**

Keywords*—*ESI-ARIMA algorithm, SPELIT differential equation model, Logistic Regression Model

I. Introduction

The contemporary epoch has witnessed an increasing problem of illegal wildlife trade. Many people collect, transport, sell, and purchase wildlife and its products unlawfully to earn a large amount of money. According to the Wildlife Conservancy Society, the size of the illegal wildlife trade is the fourth largest among all illegal trades around the world. Additionally, the money that it involved has reached an astounding 26.5 billion dollars. Even worse, this illegal trade gives rise to myriads of negative consequences, and the decreasing global biodiversity and the deteriorating environment are case in point. Consequently, it is time for us to take some actions to wrestle with the problem of illegal wildlife trade to alleviate the negative consequences that it brings.

Currently, some scholars have carried out relevant research. The study by T.P. Moorhouse et al [1] included an experimental survey aimed at revealing prior consumption or ownership of wildlife-sourced products in Peruvian cities and testing the effectiveness of a consumer-centered approach to reduce demand for illegal wildlife-sourced products. Michael F. Tlusty et al [2] described a real-time automated species-level detection (RTASLD) system that evaluates cargo declarations and invoices to collect data on species being traded. The paper used this as an example of how imprecise classification on declarations and invoices can blur trade statistics and, in the worst-case scenario, be deliberately manipulated to conceal illegal wildlife. Chloé Gerstenhaber et al [3] analyzed the data to determine whether products on the market were available due to proximity to source populations or due to proximity to trade and transport hubs. The study provides an evidence-based and monitoring baseline to identify and evaluate interventions to address in-hunting wildlife and ultimately reduce illegal wildlife trafficking. In addition, predictions of future illegal wildlife trade are important for developing appropriate prevention measures. In recent years, more and more prediction models with strong predictive performance have been proposed by scholars. Chen and Liu et al [4] designed a hybrid ARIMA-LR model based on a Bayesian combinatorial model, in which the ARIMA algorithm and the LR algorithm dynamically assign different combination weights. These portfolio weights were determined based on historical forecast performance. Bojan Irsag et al [5] investigated long-term energy demand forecasting in the tourism and catering sector, with special emphasis on the future growth of the Croatian tourism industry and the different mechanisms that may lead to certain energy savings.

The protection of wildlife remains a critical global issue, necessitating concerted efforts to empower wildlife protection organizations. By focusing on Africa, this paper endeavors to provide evidence supporting the notion that enhanced collaboration and resources for governmental wildlife protection agencies can yield significant positive outcomes. Our study leverages innovative methodologies, including the ESI-ARIMA algorithm and the SPELIT differential equation model, to forecast the future trajectory of wildlife conservation indicators and illegal wildlife trade. Through these efforts, we aim to demonstrate the potential impact of bolstered support for wildlife protection initiatives on a global scale.

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II. Presentation of the Intervention and Prediction of its Application

Wildlife protection departments in governments can ask other departments for help, such as police stations and the military. However, the WPDG can only connect with local departments. Thus, the WPDG should have the resources and powers to contact a department that can make the whole world take action. Therefore, we assume that our client, WPDG, can make a cooperation with UNEP and, the UN Environment Programme, which can organize many departments around the world to pull together to reduce the number of wildlife poaching behaviors.

A. Powers and Resources that UNEP Can Provide for WPDG

In the following part, we will discuss what UENP can provide for WPDG based on support, education, protection, and law severity.

Send expert teams

For support, UNEP can send teams composed of animal protection experts, ecologists, lawyers, and other experts in related fields to conduct on-site inspections in different countries, evaluate the current situation and needs of animal protection, and provide targeted advice and solutions. For example, ecologists can analyze how to enlarge the population of wildlife so that animals themselves can cooperate to conserve themselves.

Volunteer Program

For education, they can encourage and organize volunteers around the world to participate in animal protection projects.

Establishing an international cooperation framework agreement

For protection, signing cooperation agreements with other countries and international organizations to share resources and information. This framework agreement would outline the key areas of cooperation, including but not limited to data sharing, funding mechanisms, and capacity building. It would also establish a mechanism for regular communication and coordination between the parties involved, enabling them to work together more effectively towards common goals in animal protection.

Provide policy and legal support

For law severity, UNEP can assist governments in formulating and implementing laws and regulations to protect animals, ensuring that they are fully protected. At the same time, UNEP can provide an international legal framework and best practices for animal protection departments in different countries to promote cooperation and communication.

B. Assessing the Cooperation in Africa Based on ESI-ARIMA Model

To verify that the additional resources and powers provided by UNEP to the WPDG can play a role in reducing wildlife poaching, we take Africa as an example. In Africa, UNEP supports WPDG with additional manpower to undertake our project. So, in the following part, we will analyze the effect of the additional manpower from UNEP.

Selecting COUNTRY POLICY AND INSTITUTION ASSESSMENT as an Indicator of Assessing the Effect of Intervention

After UNEP participates in the intervention, if the illegal poaching of wildlife in Africa decreases, then the wildlife populations in Africa will increase. Therefore, we utilize COUNTRY POLICY AND INSTITUTION ASSESSMENT (Country Policy and Institution Assessment) as an evaluation indicator to assess the environmental sustainability in Africa before and after the UNEP intervention. The COUNTRY POLICY AND INSTITUTION ASSESSMENT score ranges from 1 to 6, where 1 indicates the worst and 6 is the best. In other words, the bigger the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT, the better the intervention effects.

Assessing the Effect of Intervention Based on the ESI Model

First, we build an ESI (Expert Support Intervention) Model to evaluate the effects of interventions.

$$Z(t) = a + b(t - 2023) + c(t - 2023)^2 \tag{1}$$

In the formula above, a is the primary impact of additional UNEP manpower, and b is the benefit enhancement factor due to additional manpower, and c is the coefficient of effect of successful intervention on the accelerated lifting of this function.

By reading and concluding the literature on Google Scholar, we can assume that $a = 0.05, b = 0.025, c = 0.015$.

Therefore, we can know the formula for the effect of the intervention over time. Now, we build an ARIMA Model. Based on the ARIMA Model, and according to the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT from 2005 to 2023, we can predict the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT with and without intervention from 2024 to 2028 combined with ESI Model. The following part shows the process of establishing the ARIMA Model.

Predicting the Value of COUNTRY POLICY AND INSTITUTION ASSESSMENT Based on the ARIMA Model

ARIMA model, also known as integrated moving average autoregressive model, is one of the methods of time series forecasting and analysis. In terms of $ARIMA\ (p, d, q)$, firstly, AR is the "autoregressive", p is the number of autoregressive terms. Secondly, MA is the "sliding average", q is the number of sliding average terms, and d is the number of differences to make it a smooth series. Thirdly, d is the number of differences made to make it a smooth series.

(1) AR Model

The autoregressive model is suitable for predicting phenomena related to one's own pre-existing period, and the mathematical model expression is as follows, where y_t is the current value, μ is the constant term, p is the order, r_i is the autocorrelation coefficient, ϵ_t is the error, while ϵ_t should conform to a normal distribution.

$$y_t = \mu + \sum_{i=1}^{p} r_i y_{t-i} + \epsilon_t \tag{2}$$

(2) Integrated

The difference must be made once the time series reaches a stationary state, and the difference's order is noted using the d value. Usually, the first order is sufficient.

(3) MA Model

The moving average model is concerned with the accumulation of the error term in the autoregressive model, and the order of the MA Model is recorded as q value. The mathematical model expression is as follows.

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{3}$$

Subsequently, we can obtain the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT next five years with intervention and without intervention. From Figure 1, we know that the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT for the next five years without intervention is 3.308, 3.297, 3.301, 3.299, and 3.300, respectively. Additionally, the value of the COUNTRY POLICY AND INSTITUTION ASSESSMENT for the next five years with intervention is 3.391, 3.467, 3.568, 3.697, and 3.859. This suggests that through additional manpower from UNPE, the value of COUNTRY POLICY AND INSTITUTION ASSESSMENT has increased significantly over time, indicating a gradual decrease in cases of illegal wildlife poaching.

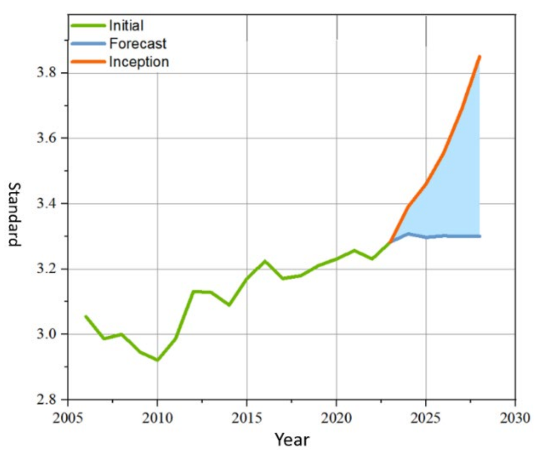

Fig. 1. Values of COUNTRY POLICY AND INSTITUTION ASSESSMENT with and without intervention

Consequently, we can conclude that the additional resource that WPDG needs is cooperation with UNEP. And with the additional resources, the effect of our project will be better.

III. Predicting the Amount of Illegal Wildlife Trade Based on the SPELIT Model

In the following part, we will discuss what the impacts of illegal wildlife trade will be after our project is implemented. To make the impacts measurable, we use the change in the amount of illegal wildlife trade as an indicator for our assessment. We use the SPELIT Model, also known as the SPEL on Illegal Trade Model, to predict the change in the amount of illegal wildlife trade over five years after the project was implemented.

Algorithm 1: The process of predicting the amount of illegal wildlife trade next five years

input: the assumed amount of illegal wildlife trade in 2023, w
output: the predicted amount of illegal wildlife trade next five years, $w_k, k = 1,2,\cdots,5$
for $j = 1$ *to* 4 *and* $i = 1$ *to* 4 **do**
  Based on the weight, find p_i, p_j, the value of the effect coefficient
  Find the hypothetical values of the interaction coefficients, h_{ij}
  According to h_{ij}, p_i, p_j, find the predicted amount of illegal wildlife trade, w_k
end

The model is based on differential equations to describe changes in the scale of the illegal wildlife trade over time. The effects of interventions are introduced parametrically, taking into account the interactions between them. Figure 2 shows the relationship between each parameter, including support, protection, education, and law severity, and the formula of the SPELIT Model is shown below.

$$\frac{dw}{dt} = -w\left(\sum_{i=1}^{4} p_i + \sum_{j=1,i=1}^{6} \left(h_{ij} \cdot p_i \cdot p_j\right)\right) \tag{4}$$

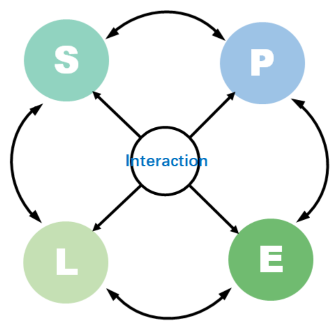

Fig. 2. Parameters' Relationship

w is the amount of illegal wildlife trade, and p_i is the effect coefficient for the i th parameter, and h_{jk} is the interaction coefficient for the jth and kth methods. Firstly, since our aim is to assess the intervention effects of our project, we can assume that the total amount of the initial illegal trade in wildlife is \$10 billion. Then, since we use the CRITIC Model to obtain the weight of each parameter impacting the crime rate in task 2, we can get the value of p_i according to it. Specifically, we can know that $p_1 = 0.2125, p_2 = 0.3074, p_3 = 0.2336, p_4 = 0.2564$. Moreover, based on the case studies and expert opinions, we can assign hypothetical values to the interaction coefficients, reflecting the synergies between different measures. To be specific, we assume that if the correlation between two parameters is high, the hypothetical value of the interaction coefficient is 0.05. If the correlation between two parameters is medium, the hypothetical value of the interaction coefficient is 0.03. If the correlation between two parameters is low, the hypothetical value of the interaction coefficient is 0.01. Table I shows the value of each hypothetical and interaction coefficient.

TABLE I. Value of Each Hypothetical Value of the Interaction Coefficient

	h_{12}	h_{13}	h_{14}	h_{23}	h_{24}	h_{34}
Value	0.05	0.03	0.01	0.03	0.05	0.01

After knowing the interaction coefficient value between each parameter, we can also see the size of the correlation between them, which is shown in Figure 3.

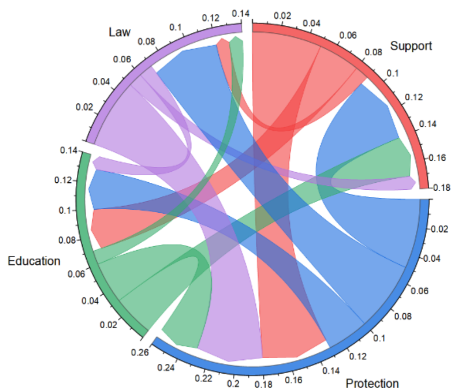

Fig. 3. Correlation Size between Each Parameter

By solving the differential equations, we obtained predictions of the amount of wildlife trade for the following five years. From Figure 4, we can see that the amount of wildlife trade is 5,614 million dollars in the first year, 2,306 million dollars in the second year, 872 million dollars in the third year, 371 million dollars in the fourth year and 162 million dollars in the fifth year.

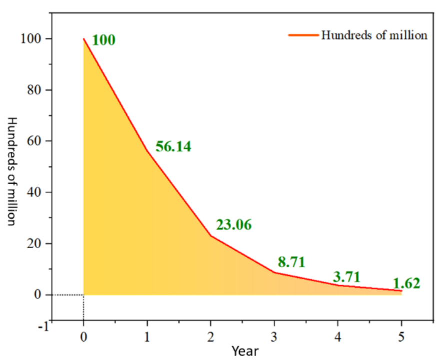

Fig. 4. Amount of Wildlife Trade Prediction

As a result, we can conclude that in the implementation of the project, as these four methods can interact with each other, a "$1+1+1+1>4$" effect was produced, which led to a rapid decline in the crime rate of poaching wildlife illegally. This instigates the fact that the amount of illegal wildlife trade dropped sharply. Consequently, our project will lead to the reduction of wildlife trade.

In the following part, we will discuss the probability of reaching this result.

IV. Calculating the Possibility of Success Based on the Logic Regression Model

Sigmoid function

Logistic regression is a widely used statistical model for classification problems that uses a logistic function to map the output of a linear regression model to probabilities between 0 and 1. The formula for the logistic function is as below.

$$P(y=1)=\frac{1}{1+e^{-\left(\beta_0+\beta_1\cdot x_1+\beta_2 x_2+\cdots+\beta_n x_n\right)}} \tag{5}$$

In the formula above, $P(y=1)$ is the probability of $y=1$ with a given value of x, and β is the coefficients, and x are the characteristic variables. Based on the circumstance, in this task, $n=4$, and x is the coefficient of effectiveness. What is more, β is the effect of each indicator. Specifically, β_1 is the effect of support, and β_2 is the effect of protection, and β_3 is the effect of education, and β_4 is the effect of law severity.

Log loss function

In logistic regression, the calculation of the parameters usually involves minimizing the log loss function, which measures the difference between the probabilities predicted by the model and the actual observations. For a given data set, the loss function is defined as the following equation.

$$L(\beta)=-\frac{1}{N}\sum_{i=1}^{N}\left[y_i log\left(p_i\right)+\left(1-y_i\right)log\left(1-p_i\right)\right] \tag{6}$$

In this formula, N is the number of samples, y_i is the actual label of the i th sample and p_i is the predicted probability of the ith sample. In our task, $i=1,2,3,4$ and $N=16$.

Gradient descent

The parameter values are calculated by a gradient descent algorithm which gradually adjusts the parameter values to minimize the loss function through an iterative process. In each iteration, the parameters are updated as follows.

$$\beta_j := \beta_j-\alpha\frac{\partial L}{\partial \beta_j} \tag{7}$$

In this formula, α is the learning rate, which determines the step size of the parameter update, and $\frac{\partial L}{\partial \beta_j}$ is the gradient of the loss function with respect to β_j.

Data sets of indicators' weight

Since our effect coefficients take the average coefficients under the global statistics, in order to make our calculation more accurate, we found the data from four relevant countries. Specifically, we will use the data in China, India, Canada, and France, and calculate the weights of the four main indicators in each country based on CRITIC Model. The results are shown in Table II.

TABLE II. Weight of Four Indicators in Each Country

	Support	Protection	Education	Law
China	0.22	0.31	0.23	0.25
India	0.21	0.30	0.21	0.24
Canada	0.22	0.31	0.24	0.26
France	0.23	0.32	0.25	0.27

Training results

Then through training, we can get the value of β_i. Specifically, $\beta_0 = 1.371$, and $\beta_1 = 0.0204$, and $\beta_2 = 0.0134$, and $\beta_3 = 0.0127$, and $\beta_4 = 0.0132$.

Bringing results into sigmoid function

Subsequently, we can bring the value of β_i into the initial aggressive model.

$$P(success) = \frac{1}{1 + e^{-\left(\substack{1.371+0.0204\times0.2125 \\ +0.0134\times0.3074+\cdots+0.0132\times0.2564}\right)}} = 0.799 \quad (8)$$

As a result, we can conclude that the possibility of success for our project is 79.9%, indicating that our project has a very good chance of success.

V. Conclusion

In conclusion, our study underscores the potential for substantial positive change in wildlife conservation efforts through enhanced support for governmental wildlife protection organizations. The application of the ESI-ARIMA algorithm demonstrated a significant increase in the predicted assessment value, signifying the potential effectiveness of our project. Moreover, the use of the SPELIT differential equation model highlighted the projected drastic reduction in illegal wildlife trade, further emphasizing the potential impact of our initiative. These findings collectively underscore the significance of global collaboration and resource allocation in fortifying wildlife protection efforts, offering a promising outlook for the future of wildlife conservation.

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