# A Study on Combating Illegal Trade in Green Sea Turtles based on a Multi-Model Strategy

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**Abstract.** This study addresses the long-standing and increasingly complex issue of global illegal wildlife trade, proposing a system solution aimed at monitoring and combating this trade, with a special emphasis on the protection of green sea turtles. The ARIMA Predict Model was utilized to demonstrate that increased enforcement efforts and higher operational expenses are significantly associated with reduced volumes of illegal wildlife trade. An illegal trade risk model was developed, employing SLSQP to enhance accuracy, constrained by budget allocation, maximum RFID reader capacity, and device failure rates. Furthermore, the Sea Turtle Movement Model was crafted by examining seasonal behaviors, agent-based movement patterns, temperature preferences, stochastic elements, and simulation time steps, enabling the delineation of migratory paths of sea turtles across different seasons. Ant Colony Optimization (ACO) was applied to optimize patrol routes. The findings underscored the necessity for additional governmental support, encompassing legal authorization, environmental access, international collaboration, and financial backing. The project's effectiveness was assessed using the Risk Reduction Coefficient Model and Monte Carlo simulations, which significantly reduced illegal trade by 34.43%, with projections indicating continued declines over the subsequent five years.

**Keywords:** Illegal Wildlife Trade, RFID Technology, ARIMA, Ant Colony Optimization.

## 1. Introduction

Over centuries, the illegal wildlife trade has deeply entwined itself with the fabric of human history, evolving from simple barter systems into a complex global crisis [1]. Initially driven by the demand for medicinal, decorative, and luxury goods, this trade has escalated in scope and severity with the development of global transportation and digital communication technologies, further amplified by the anonymity offered by the internet. The consequences of the illegal wildlife trade extend beyond the increased risk of species extinction; they also include the disruption of ecological balance and the elevation of public health risks [2]. While international agreements such as the Convention on International Trade in Endangered Species (CITES) of Wild Fauna and Flora have imposed certain restrictions on this trade, the continued demand and the lucrative profits associated with illegal wildlife transactions still fuel its expansion [3]. To curb illegal wildlife trade, a unified approach combining technology, global collaboration, and strict enforcement is essential.

To stop the global illegal wildlife trade, Roe and Booker proposed engaging communities within and near wildlife territories to establish a monitoring and enforcement network in the areas surrounding wildlife [4]. Biggs et al. proposed that communities discourage the proximity of wild herds of elephants through chili pepper cultivation while promoting local small businesses to develop chili sauce enterprises; and, informally strengthening disincentives to illegal wildlife trade practices by sanctioning poachers and formally employing Boy Scouts and game guards [5].

Facing the long-term and increasingly complex challenges of the global illegal wildlife trade, the monitoring and combating approaches of previous studies show certain limitations and face the problems of insufficient enforcement and limited monitoring coverage in practical applications. In this paper, we propose an innovative systematic solution by combining the ARIMA prediction model and SLSQP algorithm to increase enforcement efforts and operational costs by integrating the high-precision illegal trade risk model and sea turtle movement model, thus effectively reducing the volume of illegal trade. To improve the efficiency of monitoring and combating, this paper optimized the patrol routes using the ant colony optimization algorithm. In addition, this paper introduced innovative elements such as seasonal behavior and agent-based movement model, which provided new perspectives and methods to protect endangered species such as green sea turtles. The predicted results show that illegal wildlife trade activities will be further reduced in the next five years through government support, legal authorization, environmental access, and enhanced international cooperation, and the project is highly effective.

## 2. Data Preparation

The foundation for creating a comprehensive index system lies in the acquisition of adequate data. The data sources we used are shown in Table1.

**Table 1.** Database Information

| Database | Website |
|---|---|
| World Bank | https://data.worldbank.org/ |
| BEA Data | https://www.bea.gov/data |
| INTERPOL | https://www.interpol.int |
| CITES Wildlife Trade View | https://tradeview.cites.org |

In the process of data preparation, an interpolation method was utilized for imputing missing data when a strong correlation was observed between different years, employing iterative polynomial fitting to fill in missing values based on the available data. Conversely, in the absence of a significant correlation, missing values for specific years were replaced with average values from other years. For outlier identification, a boxplot was used initially, followed by the application of the Z-score method to calculate standardized scores, and identify outliers for removal, thus ensuring data reliability and accuracy. Lastly, data scaling and standardization were conducted to normalize differences among various indicators, categorizing them into benefit and cost types and scaling them to a [0,1] range, facilitating comparative analysis on a uniform scale.

## 3. Model Introduction

### 3.1. Illegal Trade Risk Assessment: Probabilistic Approach

In the model developed, the calculation of the probability of illegal wildlife trade risk at a specific point in time, $t$, is necessary. This value was obtained from real-time monitoring data and statistical modeling to assess the likelihood of animal populations being threatened by illegal trade at any given time. The indicator captured the dynamics of various factors, including enforcement intensity, market demand, and environmental changes. Utilizing data from previous years, projections for future illegal wildlife trade turnover are presented in Figure 1. The line graph indicates that, notwithstanding the anomaly in 2020 due to the epidemic, the risk of illegal trade is anticipated to maintain its downward trajectory, suggesting the potential long-term effectiveness of measures implemented to counteract illegal trade.

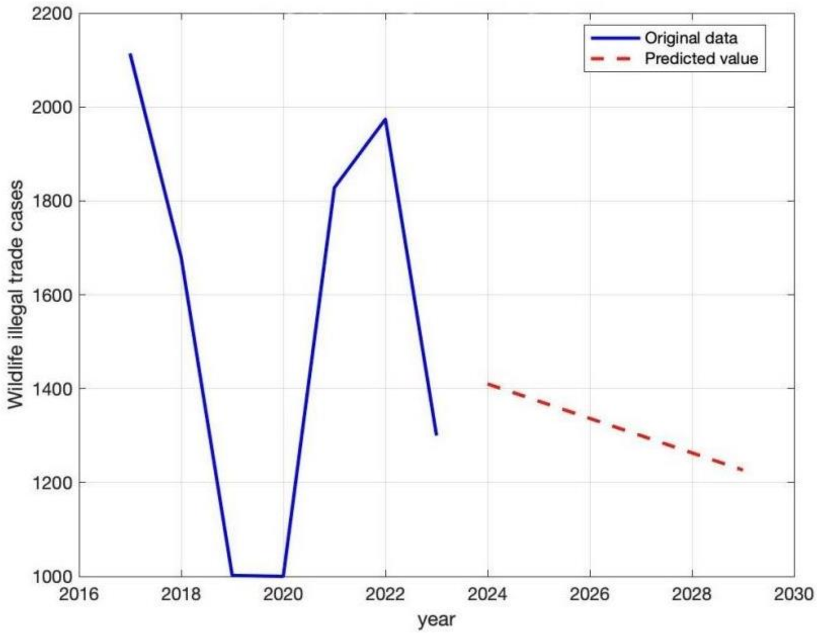


**Figure 1.** Forecast of illegal wildlife trade cases

### 3.2. Sea Turtle Movement Analysis: Agent-Based Model

The Animal Movement Pattern Model adopted an Agent-Based Modeling approach to simulate animal movements by modeling their natural behaviors, foraging, resting, breeding rules, and interactions between behaviors [6]. Several key factors were meticulously considered in the model's design, including seasonal behaviors, agent-based movement of turtles, stochasticity, temperature preferences, and simulation time steps. The integration of these factors enabled the model to comprehensively simulate the movement behavior of green sea turtles, as depicted in Figures 2 and 3.

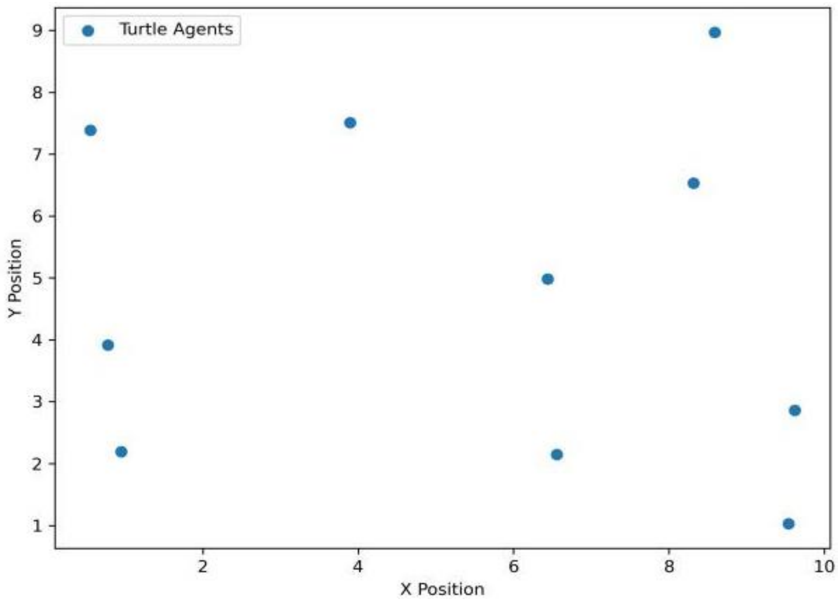


**Figure 2.** Turtle Agent Position

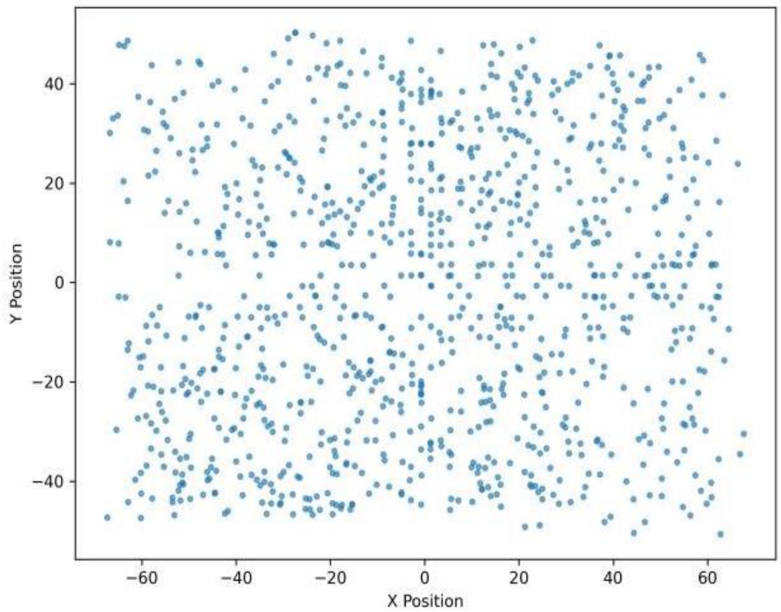


**Figure 3.** Turtle Movement

Initially, the concept of seasonal behavior was introduced, representing each season by an integer $s$, with $s = 1$ for spring, $s = 2$ for summer, etc. Each season has its specific mean temperature.

$T_s$ and these temperature values were constructed in a randomly generated manner to ensure that the range of temperatures suitable for sea turtles to live in the simulation was [28,32]. The construction of these temperature variations was based on data from the literature.

The agent-based movement is represented by two-dimensional coordinates $(X_t, Y_t)$, where $t$ denotes a time step. At each time step, the sea turtle agent's position is updated using the following equations:

$$\begin{cases} X_{t+1} = X_t + \Delta X_t \\ Y_{t+1} = Y_t + \Delta Y_t \end{cases} \tag{1}$$

Where $\Delta X_t$ and $\Delta Y_t$ values represent small, randomly generated increments that simulate the turtle's movement at each time step.

Furthermore, stochasticity was introduced by generating the values of $\Delta X_t$, $\Delta Y_t$, and $T_t$ through a random number generator, reflecting the unpredictability of the turtles' movement and temperature changes, thereby bringing the model closer to real-world conditions.

Temperature preferences are crucial in the model. At each time step $t$, the model assessed whether the temperature $T_t$ at the current location fell within the optimal range for sea turtle survival. If so, the turtles were more inclined to remain; otherwise, they moved in search of a more suitable temperature zone. This process was verified against actual temperature data recorded by the RFID system to enhance simulation accuracy.

Lastly, the simulation time steps were calibrated using data from the RFID monitoring system, allowing the model to update the agent's location and temperature assessments accurately, thus more precisely simulating sea turtle movements. Figure 4 illustrates the simulated movement paths of sea turtle agents across different seasons.

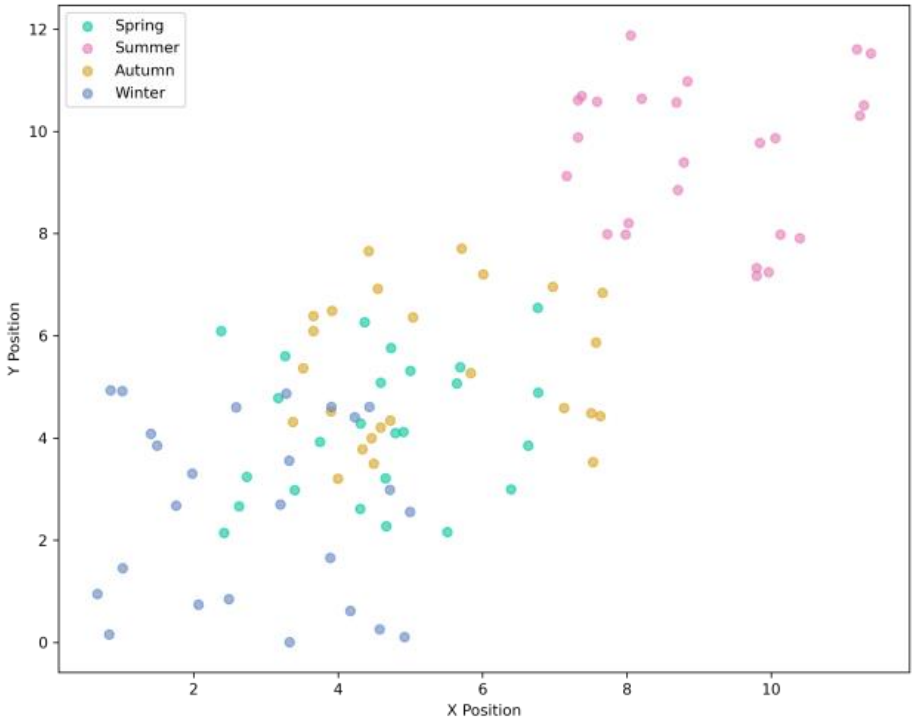


**Figure 4.** Turtle Movement During Different Seasons

This model serves as a robust tool for examining sea turtle behavior, offering valuable insights for ecological studies and the development of conservation strategies.

### 3.3. RFID Accuracy Enhancement: SLSQP Algorithm

Utilizing the previously discussed Animal Movement Pattern Model, this section introduces a sophisticated optimization algorithm aimed at refining the data interpretation from RFID tracking systems.

We implemented the Sequential Least Squares Quadratic Programming (SLSQP) approach to judiciously allocate monitoring resources for the tracking of the green sea turtle [7]. The objective function formulated for optimization is $max \sum_{i=1}^{n} x_i$ , where each variable $x_i$ quantitatively represents an aspect of the tracking process, such as data acquisition frequency or the quantity of RFID tracking points. This model ensures a thorough monitoring framework subject to three constraints:

(1) Budget Constraint: This constraint dictated that the sum of all decision variables $x_i$ must not exceed a pre-defined budget $B$. Mathematically, it was represented as:

$$\sum_{i=1}^{n} x_i \leq B \tag{2}$$

Here, $n$ represents the number of decision variables. This constraint ensured that the total expenditure on all decision variables did not surpass the available budgetary resources.

(2) Maximum Reader Constraint: This constraint is related to the number of RFID readers, although the complete equation is not fully visible in the image. Assuming the symbol represents the upper limit $M$ of readers that can be used, it could be represented as:

$$n \leq M \tag{3}$$

Where $n$ could stand for the actual number of readers being used or required, and $M$ is the maximum allowable number of readers.

(3) Device Failure Rate Constraint: This constraint pertains to the device failure rate $k$, which must be less than a threshold $F$. It is likely set to ensure the reliability of the system and can be written as:

$$\frac{k}{n} < F \tag{4}$$

Here, $k$ may indicate the number of device failures within a certain period, and $n$ is the total number of devices, thus $\frac{k}{n}$ represents the failure rate, which needs to be below the allowable maximum failure rate $F$.

The application of the SLSQP algorithm yielded a solution where resources were allocated uniformly across the decision variables, as evidenced by each $x_i$ being set to the value of 1. This result implies an equitable distribution of monitoring resources, adhering to the constraints, and achieving an optimal solution with a sum of 99.999999973042 for the objective function, which shows the model can maximize data collection efficiency within resource limitations.

The optimized distribution of resources is critical for accurately simulating the migratory behavior of green sea turtles as indicated by the RFID system. Cross-referencing the model's outputs with real-world temperature data and recorded movement patterns ensures the reliability of the simulation. Moreover, this optimization process informs the strategic deployment of RFID sensors to capture essential data, particularly concerning the turtles' behavior and seasonal migration.

### 3.4. Patrol Route Optimization: Ant Colony Optimization

The framework established in this study utilizes Ant Colony Optimization (ACO) to enhance the interpretation of RFID tracking data, specifically tailored to optimize patrol routes for wildlife monitoring [8]. ACO is a bio-inspired probabilistic technique for solving computational problems that can be represented by finding optimal paths in a graph [9].

This model incorporates several critical factors:

(1) The visibility factor $\eta_{ij}$, indicating the desirability of moving from point $i$ to point $j$, is often inversely related to the distance between the points.

(2) Pheromone levels $\tau_{ij}$, symbolizing the learned desirability of a path which is updated as simulated ants traverse and establish efficient routes.

(3) An update rule for pheromones that considers the evaporation rate and the addition of new pheromones, given by:

$$\tau_{ij} = (1-\rho) \cdot \tau_{ij} + \Delta\tau_{ij} \tag{5}$$

Where $\rho$ is the pheromone evaporation rate, and $\Delta\tau_{ij}$ is the amount of pheromone deposited, typically a function of the quality of the path taken.

The probability of an ant choosing to move from point $i$ to point $j$ is calculated by the following equation:

$$p_{ij} = \frac{[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in_{allowedk}} [\tau_{il}]^{\alpha} \cdot [\eta_{il}]^{\beta}} \tag{6}$$

Where $\alpha$ and $\beta$ balance the influence of pheromone trails and visibility, respectively, and $\text{allowed}_k$ is the set of next possible locations from point $i$ for ant $k$.

Through the ACO model, optimal patrol routes were determined for different seasons, as reflected by the distinct paths taken in spring, summer, fall, and winter. The routes were assessed based on their length and the volume of RFID readings collected, showcasing the adaptability of the model to seasonal variations and its effectiveness in data collection.

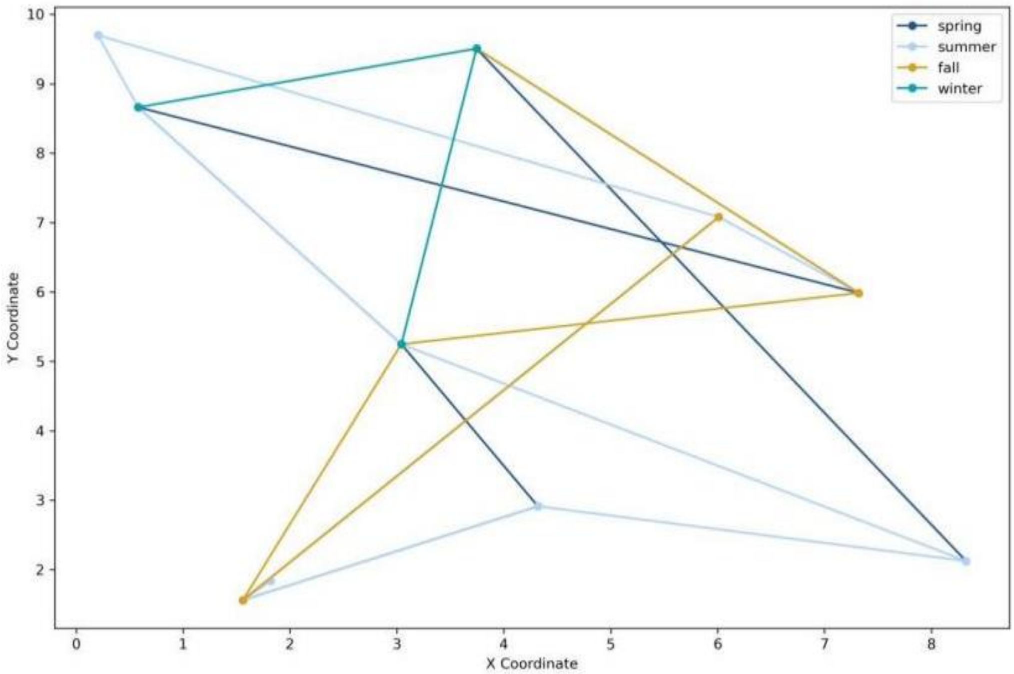


**Figure 5.** Comparison of optimal patrol routes across seasons

In summary, the application of ACO for RFID data analysis marks a significant advancement in ecological monitoring, offering a dynamic and efficient approach to adapting to environmental and behavioral changes in wildlife [10].

## 4. Project Evaluation

### 4.1. Evaluation Process

The project's impact on reducing illegal wildlife trade was assessed through a comprehensive evaluation, focusing on the effectiveness of patrol strategies, underpinned by RFID monitoring data and turtle movement modeling. The evaluation encompassed several key components:

#### 4.1.1. Risk Reduction Factor

This analysis focused on the influence of patrol frequency, RFID coverage, and implementation efficiency on illegal trade risks. The relationship was quantified by the formula:

$$R = r + f\text{frequency} + g\text{area} + h\text{efficiency} \tag{7}$$

Which demonstrated that increased patrol frequency and efficiency significantly reduce illegal trade risks, with diminishing returns from expanded RFID coverage.

#### 4.12. Monte Carlo Simulation

Simulations estimated the number of illegal trade events $Y_i$ with a normal distribution, as expressed by:

$$Yi = N(\mu, \sigma 2) \times (1 - R) \tag{8}$$

This method quantified the project's efficacy in diminishing illegal trade, with Figure 6 illustrating a significant reduction in incidents post-intervention.Specifically, the average number of postintervention events decreased by about 34.49 events, with an average percentage reduction of 34.43%. The 95% confidence interval [12.15, 80.99] further explains the confidence in the intervention effect.

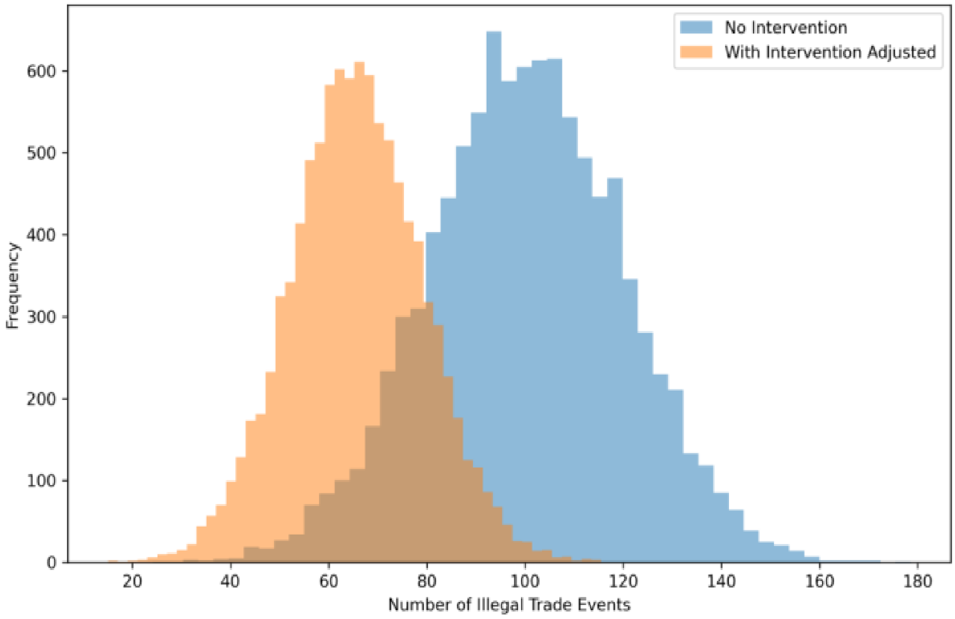


**Figure 6.** Prediction of the illegal wild trade in Monte Carlo

### 4.1.3. Time Impact Analysis

To examine the impact of a five-year plan on intercepting illicit trade over time, a linear regression model was established:

$$Y = \beta_0 + \beta_1 \cdot C + \beta_2 \cdot T + \beta_3 \cdot C \cdot T + \epsilon \quad (9)$$

Here, $Y$ denotes the number of illicit trade incidents, $C$ is a binary variable (0 for the control group, 1 for the intervention group), and $T$ is a continuous variable representing time to reflect the changing effectiveness of interventions. The result is shown in Figure 7.

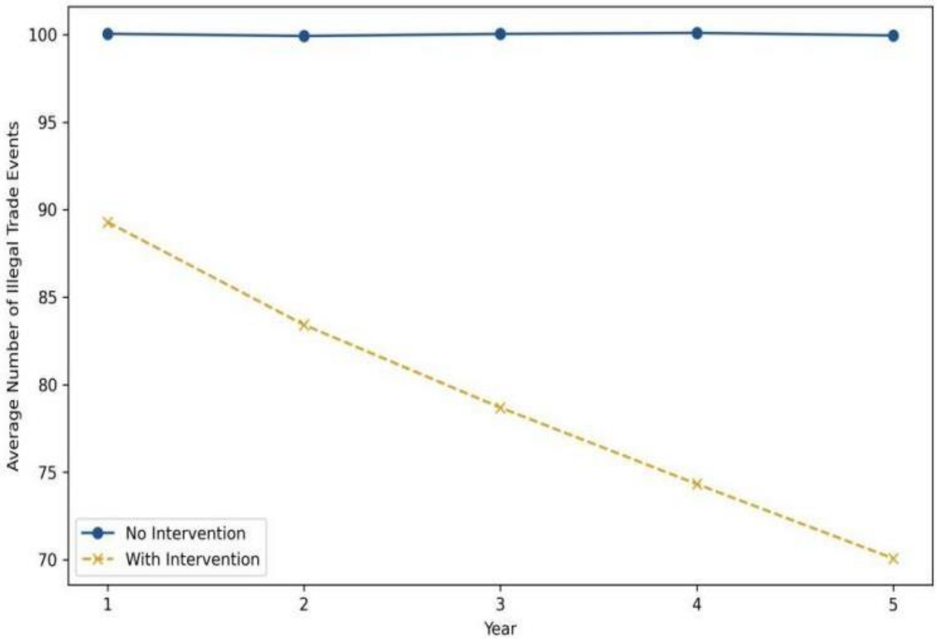


**Figure 7.** Impact of Intervention on Illicit Trade Over Time

This analysis, through statistical modeling and empirical data, demonstrates the increasing success in mitigating illegal wildlife trade via strategic patrols and advanced technology integration, highlighting the longitudinal effectiveness of these interventions.

## 5. Conclusion

This paper established a model based on RFID technology to help intercept illegal wildlife trade. Using the existing historical data, the model was first performed with ARIMA prediction and Monte Carlo simulation and then evaluated with RFID tracking data and a turtle movement model built using the ant colony algorithm. The results showed that the number of illegal wildlife trade cases decreased by 34.43 percent. The model has strong accuracy and effectiveness, and its characteristics of low cost, high efficiency, and optimal resource allocation have long-term feasibility and success potential in protecting endangered species and ecosystems around the world.

Nevertheless, there are certain restrictions on the ARIMA model's forecast since it is challenging to gather thorough data to document the illicit wildlife trade. In the Monte Carlo simulation, only three key factors were selected in this paper, and the variable index system needs to be further improved, and there is still room for improvement. This requires cooperation with governments and non-governmental organizations to strengthen the data collection and sharing mechanism. With the continuous improvement of data information and the solution of sudden factors, and after strict simulation and prediction, the model will provide a feasible new path for accurate tracking, forecasting, and prevention of illegal wildlife trade.

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