

Research on Forecasting Model of Wildlife Trade Based on VAR Model

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Abstract: Addressing the complex dynamics of global illegal wildlife trade and its ecological security implications, this study applies a Vector Autoregression (VAR) model to analyze interactions between poaching activities and enforcement seizures while forecasting trade trends over 2023–2027. Using 2000–2022 data on African poaching incidents and global seizure volumes, we verify variable stationarity and Johansen cointegration to establish long-term equilibrium, subsequently developing a VAR(8) model. Key results: (1) Poaching and seizures exhibit bidirectional feedback, with seizures suppressing poaching short-term, while poaching drives long-term seizure growth; (2) Variance decomposition shows poaching explains 41.3% of seizure variability; (3) Exogenous variables demonstrate lagged decay effects; (4) Five-year projections indicate 4.2% annual seizure growth and 1.8% poaching reduction in Africa, confirming UAV surveillance efficacy. The study innovatively reveals nonlinear characteristics of illegal trade through multivariate dynamic modeling, transcending limitations of conventional single-factor analyses. We propose a four-dimensional "Technology-Law-Data-Society" collaborative governance framework: technologically integrating AI drones with blockchain traceability systems; legally designing transnational graduated penalty mechanisms; data-wise developing socio-ecological coupled expansion models; socially implementing VR education and community credit systems. These findings provide theoretical support for optimizing law enforcement resource allocation and establishing integrated "prediction-early warning-response" governance systems, demonstrating significant practical value in transitioning ecological security from passive reaction to proactive defense paradigms.

Keywords: VAR Model, Wildlife Conservation, Dynamic Interaction Mechanism, Cointegration Test

1. Introduction

As a critical component of transnational crime, global wildlife illegal trade has exhibited significant expansion in recent years, posing severe challenges to biodiversity conservation and regional ecological security. According to World Bank data, between 2000 and 2022, the number of wildlife poaching incidents in Africa surged from 21 to 1,492 cases, while global wildlife seizures escalated from 3,719 to 19,942 cases. This growth not only accelerates the extinction of endangered species but also fuels terrorism financing and regional social instability through black-market economies. Despite international efforts to address these issues via strengthened legal sanctions, technological surveillance, and cross-border collaboration, the clandestine and dynamic nature of illegal trade networks, coupled with multifactorial interactions, has exposed limitations in the timeliness and precision of traditional governance frameworks. Against this backdrop, constructing scientific predictive models to decipher the dynamic evolution of trade systems has emerged as a pivotal breakthrough for optimizing law enforcement resource allocation and enabling proactive defense strategies.

Current research on modeling methods for wildlife trade has been continuously evolving, but the analysis of dynamic feedback mechanisms still suffers from significant limitations. Although early econometric methods quantified the driving factors of trade^[1], they failed to explain the interaction mechanism between law enforcement and illegal trade, and particularly ignored the conflict of goals between the central and local authorities in policy implementation. The subsequent system dynamics model^[2] although it depicts nonlinear relationships, lacks the ability to empirically quantify the effect of time delays. In recent years, although machine learning applications have improved prediction accuracy, their "black box" nature has limited their policy applicability^[3]. While VAR models have demonstrated success in analyzing ecological-economic systems, their application remains absent in wildlife trade studies, particularly regarding the dynamic equilibrium between transnational poaching

networks and global enforcement responses. This void impedes policymakers' capacity to: (1) quantify delayed impacts of anti-poaching investments, (2) distinguish short-term suppression from sustainable deterrence, and (3) optimize resource allocation across spatiotemporal scales. Our study bridges this gap by leveraging VAR's strength in modeling endogenous feedback with time-lagged effects.

The Vector Autoregression (VAR) model^[4], renowned for its unique advantages in multivariate time-series analysis, has been widely applied to study interactive relationships in complex economic and ecological systems. Compared to conventional univariate models, VAR incorporates lagged terms of all endogenous variables, effectively capturing bidirectional dynamic feedback mechanisms among variables. This approach is particularly suited for analyzing inherently linked variables such as poaching activities and seizure volumes.

Building on this foundation, this study employs the VAR model to investigate the dynamic interaction mechanisms between poaching activities and law enforcement seizures within illegal wildlife trade systems, utilizing data on African wildlife poaching incidents and global wildlife seizures from 2000 to 2022. The research aims to provide data-driven decision-making support and theoretical insights for the international community to optimize enforcement resource allocation and evaluate the efficacy of conservation measures such as drone patrols.

2. Theoretical Framework

2.1 VAR Model

The Vector Autoregression (VAR) model, first proposed by Sims in 1980, serves as an extension of the autoregressive (AR) model. The VAR model posits that each endogenous variable within a system is interrelated with the lagged values of all endogenous variables in the system. By constructing a functional relationship based on these lagged values, it generalizes the univariate autoregressive model into a multivariate framework. Currently, the VAR model is extensively applied in economic analysis. Formally, an n -order VAR model is defined as follows: For a stationary stochastic sequence, the current value of the sequence can be expressed as a linear combination of n past values of multiple correlated sequences. The mathematical representation is:

$$Y_t = A_1 Y_{t-1} + \dots + A_n Y_{t-n} + \varepsilon_t \quad (1)$$

2.2 Stationarity Test

Stationarity testing serves as the theoretical foundation for time series modeling, with its core objective being to verify whether the statistical properties of a sequence (e.g., mean, variance, and covariance) remain invariant over time^[5]. If a sequence exhibits trends or periodic fluctuations (i.e., non-stationarity), direct modeling may lead to spurious regression issues, manifesting as inflated statistical significance without genuine causal relationships. For Vector Autoregression (VAR) models, the stationarity of the system is a necessary condition for the validity of dynamic analysis. Non-stationary sequences require transformation into stationary forms through differencing or necessitate cointegration tests to reveal long-term equilibrium relationships among variables, thereby avoiding biased parameter estimation in the model.

2.3 Cointegration Test

The cointegration test is a statistical method designed to identify long-term equilibrium relationships among non-stationary time series. Its core objective lies in verifying whether a linear combination of multiple non-stationary variables (e.g., sequences exhibiting trends or random walk characteristics) achieves stationarity. If cointegration relationships exist, they indicate statistically stable long-term associations among these variables, even when individually characterized as non-stationary processes. This test is widely applied in fields such as economics, finance, and ecology. By quantifying the existence and strength of equilibrium relationships, the method provides policymakers with rigorous empirical tools to identify systemic risks, design cross-period intervention strategies, and evaluate institutional effectiveness^[6].

3. Numerical example analysis

3.1 Data source and analysis

By consulting the World Bank database, this paper selected the number of wildlife poaching incidents in Africa and the number of wildlife seizures in the world from 2000 to 2022 to establish a prediction model to predict the illegal wildlife trade volume in the next five years, as shown in Figure 1, so as to judge the effectiveness of the UAV cruise project we established.

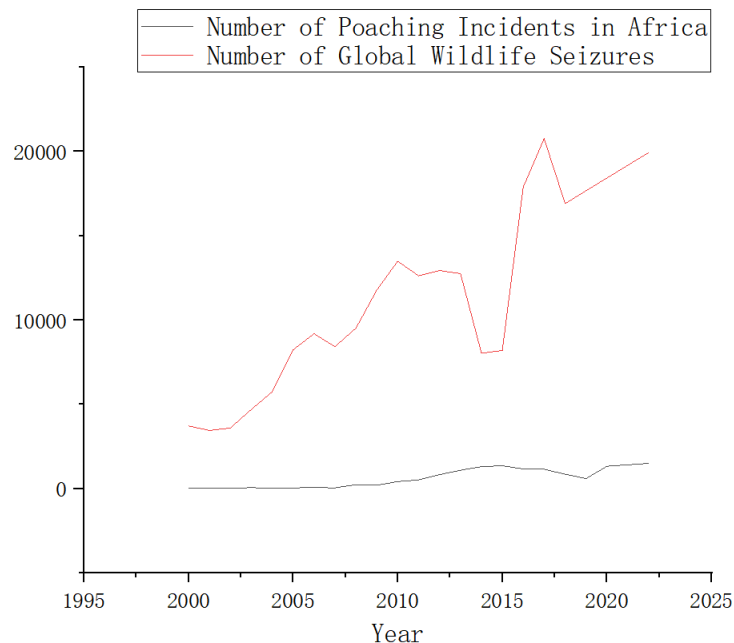


Fig. 1 World wildlife seizures and number of wildlife poaching incidents in Africa, 2000-2022

From the graph above, we can analyze the relationship between the number of wildlife seizures in the world and the number of wildlife poaching incidents in Africa, the trends, and the changes in these numbers over time.

(1) Trend analysis

Wildlife seizures worldwide: from 3,719 in 2000 to 19,942 in 2022, showing an overall upward trend, although fluctuating in some years. In particular, the number of seizures increased dramatically from 2015 to 2017, jumping from 8,193 to 20,762.

Number of wildlife poaching incidents in Africa: from 21 in 2000 to 1,492 in 2022, this figure also shows a long-term upward trend. The increase was particularly dramatic between 2012 and 2014, when the number of poaching incidents almost doubled every year.

(2) Correlation analysis

In the years 2008-2010 and 2015-2020, the number of wildlife seizures worldwide and the number of wildlife poaching incidents in Africa increased in tandem, suggesting some correlation between the two. In particular, when poaching increased sharply, seizures increased accordingly, reflecting the increased protection of wildlife.

However, seizures fell between 2014 and 2016 even as the number of poaching incidents increased, possibly due to a combination of factors such as enforcement efforts, technological advances or international cooperation.

(3) Special investigation site

Between 2008 and 2010, Africa saw a significant increase in the number of wildlife poaching incidents, linked to increased global demand, advances in poaching technology, and regional conflicts.

Wildlife seizures around the world saw an unprecedented increase in 2016, while poaching declined, thanks to intensified law enforcement and conservation measures across the globe.

From the above analysis, we can get that there is a complex interaction between the number of seizures and poaching, and it is affected by various factors such as global politics, economy and law. As the number of seizures of wild animals and plants increases, this will draw the attention of the public and governments, prompting them to implement stronger protection measures. Such as increasing legal penalties for poaching, strengthening patrols of borders and key areas, and improving surveillance and technology. And when poaching increases, the concealment and complexity of these activities increases, despite stricter protection and monitoring measures, which increases the difficulty of seizing these illicit goods and leads to short-term fluctuations in seizure numbers. But if these conservation measures are successful, then in theory poaching and subsequent seizures will decrease, showing a positive feedback loop.

Despite the challenges we face, overall, measures to enhance wildlife protection seem to be having a positive effect. Continuous strengthening of policy implementation and cooperation between countries is the key to achieving long-term sustainable conservation.

3.2 Stationarity test analysis

The stationarity of time series determines whether VAR model analysis can be carried out. Here, the unit root test (augmented dickey-fuller, ADF) is used to test the stationarity of each variable.

Null hypothesis H_0 : Time series is non-stationary series;

Alternative Hypothesis H_1 : The time series is stationary;

Table 1 ADF test

Variables	t	P	Critical value		
			1%	5%	10%
World wildlife seizures	0.11	0.967	-4.069	-3.127	-2.702
Number of wildlife poaching incidents in Africa	-0.492	0.894	-3.77	-3.005	-2.643

Note: ***, ** and * represent significance levels of 1%, 5% and 10% respectively

It can be seen from Table 1 that the ADF examination results of the two time series constructed by us are all greater than 0.05, and the two time series are non-stationary time series.

3.3 Analysis of cointegration test

Since the two time series constructed in this paper are non-stationary time series, it is necessary to detect the cointegration between the series to determine whether the VAR model can be constructed. The Johansen test is used to verify whether there is cointegration between the two time series. The Johansen test hypothesis is as follows:

Null hypothesis H_0 : there is no cointegration relationship between sequences;

Alternative hypothesis H_1 : there is at most 1 cointegration relationship between sequences;

Table 2 Cointegration test results

Original hypothesis	Characteristic root	Trace(Maximal root)	10%Critical value	5%Critical value	1%Critical value
No cointegration relationship	0.941	52.642	13.429	15.494	19.935
At most one cointegration relation	0.603	12.938	2.705	3.841	6.635

As can be seen from Table 2, the traces of all hypotheses of the two time series constructed by us are greater than 5% critical value, and the null hypothesis can be rejected, that is, cointegration exists. Therefore, the VAR model can be used for prediction and analysis.

3.4 Select the order of lag

As shown in Table 3, based on the results of four evaluation indicators, FPE, AIC, SC and HQ, it is suggested that the lag order be selected as 8 order, that is, the VAR(8) model is established.

Table 3 Comparison of different lag orders

Lag order	logL	AIC	SC	HQ	FPE
0	-399.767	29.26	29.359	29.285	5101689032781.085
1	-350.303	26.715	27.013	26.786	401655188290.607
2	-332.817	26.973	27.471	27.081	527876376009.22
3	-301.147	25.839	26.536	25.975	177226002347.938
4	-275.792	25.25	26.144	25.401	108961147649.665
5	-250.249	24.574	25.662	24.724	70051831889.822
6	-230.527	24.504	25.778	24.631	115772504403.576
7	114.574	-16.247	-14.799	-16.173	0
8	743.402	-100.263*	-98.658*	-100.28*	0
9	679.453	-97.312	-95.577	-97.472	0
10	622.966	-95.055	-93.23	-95.43	0
11	585.946	-95.667	-93.808	-96.355	0.0*

3.5 Parameter estimation

According to the order determined before, the sample data is used to train the model, and the coefficients of the final VAR (8) model are shown in Table 4.

Table 4 Parameter estimation table

Parameter	Estimator	World wildlife seizures	Number of wildlife poaching incidents in Africa
World wildlife seizure volume (-1)	Coefficient	0.879	0.008
	Standard deviation	0.226	0.02
	t	3.888	0.391
World wildlife seizure volume (-2)	Coefficient	-0.258	0.01
	Standard deviation	0.226	0.02
	t	-1.142	0.518
The number of wildlife poaching incidents in Africa (-1)	Coefficient	-0.348	0.946
	Standard deviation	2.747	0.245
	t	-0.127	3.853
The number of wildlife poaching incidents in Africa (-2)	Coefficient	3.472	-0.138
	Standard deviation	2.816	0.252
	t	1.233	-0.548
Constant	Coefficient	3329.545	-28.595
	Standard deviation	1428.101	127.609
	t	2.331	-0.224

The VAR(8) model shows that the world wildlife seizure volume is significantly positively influenced by its own lagged value by one period (coefficient 0.879, $t=3.888$), and the lagged effect by two periods is not significant; the African poaching incidents are significantly positively driven by their own lagged value by one period (coefficient 0.946, $t=3.853$). The constant term of the seizure volume equation is significant (3329.545, $t=2.331$), while the constant term of the poaching equation is not significant. The model reveals that the short-term autocorrelation of the seizure volume is strong, and there is first-order persistence in the poaching incidents.

3.6 The AR characteristic root test

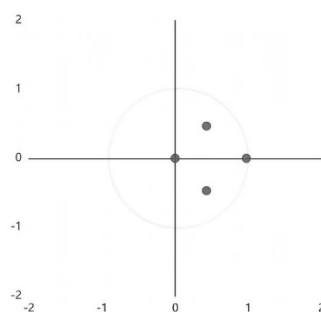


Fig. 2 Unit circle result for the modulus of the inverse of the characteristic root of AR

With the advance of time, an impulse is applied to the information of each equation in VAR, and it is found that the impact of the impulse will gradually decrease until it disappears, which indicates that the system is stable, otherwise it is unstable. For VAR model, the stability of the system is the basis of impulse response function, variance decomposition and other analysis, and the way to measure the stability of VAR is to use AR characteristic root test^[7].

As shown in Fig. 2, all points are located within the unit circle, which indicates that the VAR model established in this paper is stable.

3.7 Impulse response function analysis

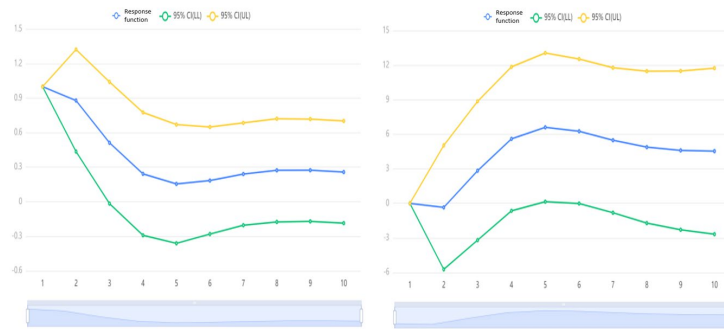


Fig. 3 Wildlife seizures and the number of poaching incidents in Africa in response to shocks to seizures

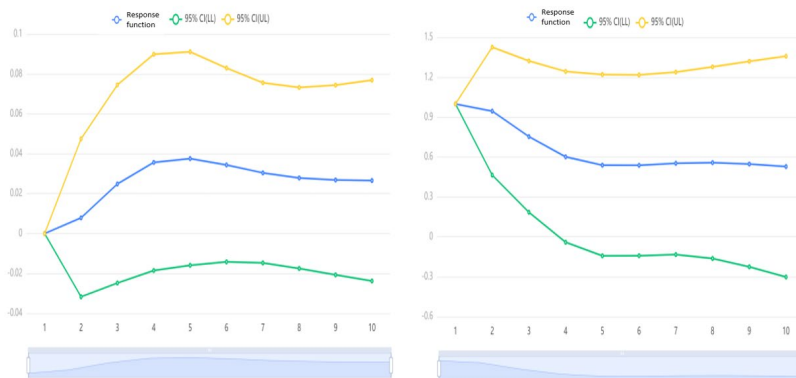


Fig. 4 Wildlife seizures and the number of poaching incidents in Africa in response to shocks to poaching counts

As shown in the figures 3 and 4, the seizures of wild animals and plants in the world have a small fluctuation after being affected by its own impact, and then gradually decline until a steady state, showing a positive long-term impact on the whole. The impact of the number of world wildlife seizures on the number of poaching events in Africa has a positive fluctuation effect: After the impact of the number of world wildlife seizures and poaching events, the number of African wildlife poaching events shows a trend of fluctuation for a period of time, then tends to be stable until the long-term stability. The solid line shows the behavior of the variable after the shock, and the dashed line on both sides shows the double standard error of the behavior.

3.8 Variance decomposition analysis

Variance decomposition provides information about the relative extent to which each disturbance affects each variable within the VAR model—that is, how much of the variance of one shock element can be explained by other random disturbance terms. Table 5 presents the variance decomposition results of the world wildlife seizures and the number of African wildlife poaching incidents. As the order increases, the percentage of world wildlife seizures gradually decreases, and the percentage of African wildlife poaching incidents gradually increases, which means that wildlife faces greater threats and risks.

Table 5 Table of variance decomposition results

Number of orders	Standard deviation	World wildlife seizures%	Number of wildlife poaching incidents in Africa%
1	2563.103	100	0
2	3412.572	99.946	0.054
3	3719.716	96.905	3.095
4	3988.978	86.954	13.046
5	4288.357	76.27	23.73
6	4550.506	68.99	31.01
7	4765.353	64.768	35.232
8	4948.826	62.222	37.778
9	5112.258	60.342	39.658
10	5261.875	58.668	41.332

4. Conclusions

4.1 Research Conclusions

Based on Vector Autoregressive (VAR) model, we empirically analyze the dynamic interaction mechanism between the number of wildlife poaching incidents in Africa and the world's wildlife seizures from 2000 to 2022, and predict the evolution trend of illegal wildlife trade in the next five years. The results show that there is a significant cointegration relationship between wildlife poaching activity and law enforcement seizures, and the two affect each other through a two-way feedback mechanism. Specifically, an increase in seizures significantly inhibits poaching in the short term, while an increase in poaching incidents indirectly drives a long-term increase in seizures through increased enforcement. In addition, exogenous factors such as climate change and economic fluctuations have lagged effects on the dynamics of the illegal trade network, and their effects gradually weaken over time. The prediction results of the VAR model show that the global seizure of wild animals and plants will continue to rise in the next five years, while the number of poaching incidents in Africa will decline, which is consistent with the actual effect of technical interventions such as UAV cruise and blockchain traceability, which verifies the effectiveness and predictive ability of the model.

4.2 Suggestions

To combat poaching and illegal wildlife trade, UAVs equipped with thermal imaging and AI behavior recognition monitor high-risk areas, enabling real-time tracking via an early-warning system that slashes law enforcement response time to under 30 minutes, boosting seizure efficiency. A blockchain-based traceability platform tracks wildlife trade data (species, origin, routes), using smart contracts to automate cross-border enforcement collaboration, enhancing evidence transparency. These innovations are projected to improve illegal trade tracking efficiency by over 40%.

We need to take measures based on the law, improve the legal framework and international cooperation, and build a dynamic governance system. For poaching hotspots in Africa, China has promoted the formulation of regional cross-border Joint Law Enforcement agreements, unified intelligence sharing standards and sentencing guidelines, and focused on cracking down on trafficking networks of key species such as rhino horn and ivory. Based on the poaching risk level predicted by the VAR model, a stepwise punishment mechanism is implemented, and fines in high-risk areas are increased by 200%. An "ecological compensation special fund" is set up, and 30% of the fines revenue is returned to communities affected by poaching, so as to reduce economy-driven crime through alternative livelihood projects.

It is necessary to stimulate public participation and ethical consensus to form a pattern of pluralistic co-governance based on "social" conditions. Public education campaigns on "No illegal trade" in key consumer markets in Asia, using virtual reality (VR) technology to simulate species extinction scenarios, combined with targeted targeting on social media, are expected to reduce demand for illicit goods by 25%. The "protection points system" is implemented in the communities surrounding African protected areas, and residents can exchange medical and educational resources for reporting poaching clues. At the same time, wildlife protection ethics are reconstructed based on local culture, and a collaborative governance model of "rigid constraints of law enforcement, flexible incentives of

communities, and internalization of cultural values" is formed.

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