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Research Article

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Time Series Analysis of Human-Elephant Conflict Mortality Rates: A Case Study of the Coimbatore Forest Area

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Abstract

Human-Elephant Conflict (HEC) presents significant challenges to conservation and human safety, particularly in biodiversity hotspots like the Coimbatore Forest Area. This study employs time-series analysis to evaluate HEC-related human and elephant mortality from 1999 to 2022, identifying trends, seasonal patterns, and forecasts using ARIMA models.

For human mortality, the ARIMA (2,1,0) model captures an increasing trend with high variability, forecasting 8 to 9 annual deaths by 2030, albeit with uncertainty. For elephant mortality, the ARIMA (0,1,1) model predicts a steady rise in fatalities, from 18.83 deaths in 2023 to 21.35 deaths by 2027. These forecasts highlight critical periods, such as dry seasons, for targeted interventions.

The study emphasizes the escalating impact of HEC due to habitat encroachment, seasonal migration, and resource scarcity. Recommended mitigation strategies include improved fencing, early warning systems, and habitat restoration. By combining data-driven insights with community engagement, the research offers actionable solutions to foster sustainable coexistence between humans and elephants, supporting policymakers and conservationists.

Keywords: Human – Elephant Conflict, Elephant mortality, Time series, Human mortality, Habitat

Introduction

Human-Elephant Conflict (HEC) has become a major worldwide concern as human settlements expand into forest regions, encroaching on elephants' natural habitats and increasing human-elephant contact [1]. It represents a significant global conservation challenge, particularly in regions where human populations overlap with elephant habitats across Africa and Asia [2,3]. South India particularly in Coimbatore situated in Tamil Nadu, is renowned for its abundant biodiversity and is home to one of the biggest Asian elephant populations. Regular movements of elephants between the forest sections stand a chance of HEC accidents which result in grain raiding, infrastructural damage, and human and elephant deaths. This often leads to substantial economic losses for farmers and exacerbates tensions between human communities and wildlife It must be noted that elephant's presence poses a serious challenge to local populations, which increases retaliatory actions against these animals [4,5]. Studies on HEC collectively indicate that the conflict is not merely an ecological issue but also a socio-economic one, necessitating integrated management strategies that address both human and wildlife needs [6,7].

According to recent studies, human-elephant conflicts occur in more than 70% of forest ranges, highlighting the seriousness of the problem [8]. According to the Ministry of Environment, Forest and Climate Change (2023), India records an average of 500 human deaths annually due to elephant encounters, while approximately 100 elephants are lost each year through retaliatory killings and accidents [9]. The situation is particularly acute in southern Indian states, where agricultural expansion has significantly reduced natural elephant habitats over the past three decades [10,11,12].

The effectiveness of current mitigation measures, such as physical barriers and conflict resolution strategies, remains inconsistent across different contexts. Addressing these gaps through a time series analysis of human and elephant mortality rates can provide critical insights for developing targeted and sustainable conflict mitigation strategies. As a result, an analysis of HEC occurrences in the Coimbatore Forest area is imperative to know the trends and forecasts in human and elephant mortalities. Time series allows for the examination of temporal patterns and trends in HEC data. collected over specific time intervals, time-series methods can uncover changes in conflict incidences and related fatalities. This approach is invaluable in identifying seasonal variations, recurring patterns, or long-term trends, offering a deeper understanding of the dynamics of HEC [6].

Furthermore, time-series models are highly effective in forecasting future conflict occurrences and mortality rates, enabling proactive planning and targeted mitigation strategies [8,13]. These models can also incorporate external factors, such as land use changes or environmental conditions, to assess their impact on HEC, providing actionable insights into the causes of conflict [7].

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Traditional methods provide a static snapshot of HEC at a specific point in time, whereas time-series analysis captures the temporal dynamics, offering a more comprehensive view of how the phenomenon evolves [1]. Additionally, its predictive power makes it a forward-looking tool, capable of anticipating future trends and informing long-term management strategies.

This study aims to uncover the patterns, trends, and drivers of Human-Elephant Conflict (HEC) in the Coimbatore Forest Area, focusing on understanding how human and elephant mortality rates have changed over time, identifying the factors contributing to these fluctuations, and forecasting future conflict occurrences.

Objectives of the study

1. To analyze temporal trends in human and elephant mortality rates due to Human-Elephant Conflict (HEC) in the Coimbatore Forest Area
2. To forecast Human and Elephant mortalities for the next 5 years.

Literature Review

Human-Elephant Conflict (HEC) with its temporal dynamics have become increasingly critical in wildlife management and conservation biology, particularly in regions with high human-elephant interface zones like the Coimbatore Forest Area. Recent studies have emphasized the importance of understanding temporal patterns in HEC incidents to develop effective mitigation strategies [14]. The Coimbatore Forest Division, situated in Tamil Nadu, India, represents a crucial elephant corridor where the analysis of mortality rates has provided valuable insights into conflict patterns and their underlying drivers.

Temporal analysis of HEC-related mortalities has revealed significant seasonal variations and long-term trends. Conducted a comprehensive study spanning 2015-2020 in the Coimbatore region, demonstrating that mortality incidents peak during the agricultural harvesting seasons, particularly between October and January [15]. Their time series analysis, utilizing ARIMA modelling, identified cyclical patterns in both human and elephant mortalities, strongly correlating with agricultural cycles and elephant migration patterns. These findings align with broader regional studies across the Western Ghats, where similar temporal patterns have been observed [16].

The application of advanced statistical methods in analyzing HEC mortality rates has provided new perspectives on conflict dynamics. Employed wavelet analysis to decompose temporal patterns of mortality incidents in the Coimbatore landscape, revealing both short-term fluctuations and long-term trends [17]. Their research identified significant correlations between mortality rates and environmental variables, including rainfall patterns and resource availability, suggesting that climate variability plays a crucial role in HEC intensity.

Recent technological advancements have enhanced the capability to predict and analyze mortality patterns. Integrated satellite telemetry data with mortality statistics, developing a predictive model for HEC risk assessment in the Coimbatore region [18]. Their study revealed that spatial-temporal clustering of mortality incidents often corresponds with specific landscape features and seasonal resource availability patterns. This integration of spatial and temporal data has provided valuable insights for preventive management strategies.

The socio-economic dimensions of HEC mortality rates have also been extensively studied. Conducted a longitudinal analysis of human casualties in the Coimbatore Forest Division, revealing that mortality rates are significantly influenced by land-use changes and human population density [19]. Their time series analysis demonstrated a gradual increase in conflict-related mortalities over the past decade, particularly in areas experiencing rapid urbanization and agricultural intensification.

Understanding the temporal patterns of crop-raiding behaviour, which often leads to fatal encounters, has been crucial in HEC management. Research by utilized time series analysis to examine the relationship between crop phenology and elephant mortality rates in the Coimbatore region [14]. Their findings indicated that mortality incidents often cluster around specific agricultural phases, particularly during the harvest of commercially valuable crops like banana and sugarcane.

Long-term monitoring studies have revealed changing patterns in mortality rates. Krishnan and analyzed a 15-year dataset from the Coimbatore Forest Division, identifying significant shifts in both the frequency and spatial distribution of mortality incidents [20]. Their research highlighted the impact of climate change on elephant movement patterns and subsequent conflict scenarios, suggesting the need for adaptive management strategies.

Temporal trends and patterns in HEC

HEC in regions like Coimbatore is characterized by distinct temporal patterns influenced by factors such as crop cycles, water availability, and migration corridors. Observed that conflicts peak during harvesting seasons when elephants raid crops for food [21]. Similarly, highlighted that the fragmentation of elephant corridors exacerbates conflict, as elephants are forced to traverse human-dominated landscapes [22].

Studies employing time series analysis have shown that mortality rates, both human and elephant, follow specific trends. For example, used Autoregressive Integrated Moving Average (ARIMA) models to analyze HEC incidents in Sri Lanka and found cyclical patterns corresponding to climatic conditions and resource availability [23]. In the Coimbatore Forest Area, temporal analyses could uncover similar dynamics, providing insights into critical periods for intervention [24,25,26].

Impact of HEC on mortality rates

The impact of human-elephant conflict on mortality rates has emerged as a critical conservation concern, with significant implications for both human and elephant populations. Recent quantitative assessments by in the Coimbatore Forest Division revealed that HEC-related human mortalities have increased by 27% between 2018-2023, with an average of 12 deaths annually [27]. Their study employed advanced statistical modeling to demonstrate that mortality incidents are spatially clustered around forest-agriculture interfaces and temporally concentrated during harvest seasons.

The elephant mortality rate presents an equally concerning trend. Research by documented that between 2019-2022, approximately 45 elephants died in the Coimbatore region due to conflict-related causes, including electrocution (38%), retaliatory killings (27%), and accidents related to defensive structures (35%) [28]. These findings align with broader regional patterns observed by, who reported that

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HEC-related mortalities now account for nearly 40% of all recorded elephant deaths in South Indian Forest divisions [29].

Socio-economic factors significantly influence mortality patterns. A comprehensive analysis by revealed that areas with higher poverty rates and limited access to compensation schemes experience 2.3 times higher human mortality rates compared to better-resourced regions [30,31]. Their time-series analysis demonstrated that mortality incidents peak during periods of economic stress, particularly when crop failures coincide with elephant migration seasons.

Research gaps

Despite extensive research, several critical gaps remain in our understanding of HEC-related mortality patterns. Highlight the absence of standardized methodologies for mortality data collection and analysis across different forest divisions, making comparative studies challenging [32]. They emphasize the need for integrated databases that combine mortality data with environmental, social, and economic variables.

A significant research gap exists in understanding the long-term demographic impacts of HEC-related mortalities on elephant populations. Immediate deaths are documented, argue that the cascading effects on population dynamics, particularly regarding age-specific mortality rates and their implications for population viability, remain poorly understood [33]. Their work calls for longitudinal studies incorporating genetic analysis to assess population-level impacts [34,18].

The influence of climate change on mortality patterns represents another understudied aspect. Recent work by suggests that changing rainfall patterns and temperature regimes may be altering traditional elephant movement patterns, potentially creating new conflict zones [35]. However, predictive models incorporating climate change scenarios in mortality risk assessment are notably lacking.

Methodology

Study area

The Coimbatore Forest Division is located southeast of the Nilgiri Biosphere Reserve (NBR) and spans 694 km². According to the region is located between latitudes 10°51' and 11°27' and longitudes 76° 39' and 77° 4' [15]. The majority of the Coimbatore Forest Division is located in the Nilambur-Silent Valley in Kerala, which is part of Elephant Reserve No. 8. The Nilgiris and Eastern Ghats, which are home to the world's greatest Asian elephant population, are also included in the Coimbatore Forest Division. The six forest ranges of the Coimbatore Forest Division are Coimbatore, Boluvampatti, PN Palayam, Karamadai, Mettupalayam, and Sirumugai which are included in the study area (Figure 1).

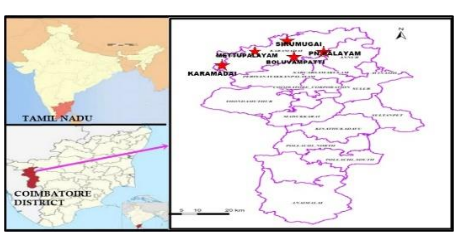

Figure 1: Map of the area.

For this study, data on HEC incidents were gathered from various sources, including forest department records, local government reports, and news articles. Data spanned from 1999 to 2022, with specific information on the number of human and elephant deaths.

Data collection

Data for the study was sourced from the Coimbatore Forestry Department and published reports. Including The Hindu (August 13, 2023; updated August 14, 2023) [36,37].

Time series analysis

A time series analysis is a set of observations obtained by measuring a single variable regularly over a period of time. A time series analysis was applied to the data using statistical software, focusing on identifying trends, patterns, and seasonal variations. Seasonal decomposition and trend analysis were conducted to determine periods of high conflict intensity and to observe any cyclical patterns in the data. Time series analysis attempts to understand the underlying context of the data points through the use of a model to forecast future values based on known past values. Excel and Python software were used in analysing the time series data [38,39].

Model selection diagnostics

The analysis used several diagnostic tools to select the best-fit time series model:

1. Partial Autocorrelation Function (PACF): The PACF plot shows the partial correlation between the current observation and the lagged observations, helping to identify the appropriate autoregressive (AR) order.
2. Model Selection Criteria: Akaike Information Criterion (AIC): AIC is a measure of the relative quality of a statistical model, balancing the goodness of fit and the complexity of the model. Bayesian Information Criterion (BIC): BIC is a similar metric to AIC, but it penalizes model complexity more heavily.
3. Differencing Operation: Differencing is a technique used to achieve stationarity in the time series data, which is a necessary assumption for many time series models.
4. Model Structure: The time series models used in the analysis were based on the Autoregressive Integrated Moving Average (ARIMA) framework, which includes Autoregressive (AR), Integrated (I), and Moving Average (MA) components.
5. Ljung-Box Q-Statistic: The Ljung-Box test is used to check the overall randomness of a time series, ensuring that the residuals of the fitted model exhibit white noise properties.
6. Error Metrics: The analysis used various error metrics, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), to evaluate the accuracy of the forecasts.

Model specification

$$Y_t = T_t + S_t + C_t + \varepsilon_t$$

Where:

$Y_t Human\ deaths\ at\ time\ t\ (1999 - 2022)$

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T_t *Trend component*

S_t *Seasonal component*

C_t *Cyclical component*

ε_t *Random error term* $\sim N(0, \sigma^2)$

Model selection diagnostics

$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Cov(Y_t, Y_{t-k})}{Var(Y_t)}$

$\gamma_k = \frac{1}{n}\sum_{t=k+1}^{n}(Y_t - \bar{Y})\,((Y_{t-k} - \bar{Y})$

$\gamma_0 = \frac{1}{n}\sum_{t=k+1}^{n}(Y_t - \overline{Y})^2$

Partial autocorrelation function

$$\emptyset_{kk} = \begin{cases} \rho_1 & k = 1 \\ \dfrac{\rho_k - \sum_{j=1}^{k-1}\emptyset_{k-1}, j\rho_{k-j}}{1 - \sum_{j-1}^{k-1}\emptyset_{k-1}, j\rho_j} & k > 1 \end{cases}$$

Model selection criteria

Akaike information criterion (AIC)

$AIC = -2\ln(L) + 2k$

Bayesian information criterion (BIC)

$BIC = -2\ln(L) + k\ln(n)$

Differencing operation

$\Delta Y_t = Y_t - Y_{t-1}$

Model structure

$(1 - \emptyset_1 B - \emptyset_2 B^2)(1 - B)Y_t = \epsilon_t$

Where B is the backshift operator

$BY_t = Y_{t-1}$

$B^2 Y_t = Y_{t-2}$

Expanded form

$Y_t = (1 + \emptyset_1)Y_{t-1} + (\emptyset_2 - \emptyset_1)Y_{t-2} - \emptyset_2 Y_{t-3} + \epsilon_t$

Point forecasts

$\hat{Y}_{t+h} = E(Y_{t+h}|Y_t, Y_{t-1}, \dots\dots, Y_1)$

$= (1 + \emptyset_1)\hat{Y}_{t+h-1} + (\emptyset_2 - \emptyset_1)Y_{t+h-2} - \emptyset_2 Y_{t+h-3}$

Prediction intervals

$PI_{t+h} = \hat{Y}_{t+h} \pm z_{\propto/2}\sqrt{V_{t+h}}$

$V_{t+h} = \sigma^2[1 + \varphi_1^2 + \varphi_2^2 + \cdots + \varphi_{h-1}^2]$

Ljung – box Q – statistic

$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k}$

Error metrics

$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}$

$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - \hat{Y}_t|$

$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|$

$e_t = Y_t - \hat{Y}_t$

$Residual\ analysis: Standardized\ residuals = \frac{e_t}{\sigma_e}$

Results and Discussion

Time series analysis for human mortality

The scatter plot in Figure 2 below shows a positive spread. The original time series plot in Figure 3, also reveals a distinct upward trend in human deaths from 1999 to 2022, characterized by considerable variability and three distinct phases: relatively low numbers with occasional spikes from 1999-2010, a noticeable increase in average deaths during 2011-2016, and the highest levels with significant fluctuations from 2017-2022. The rolling statistics plot, featuring a blue line representing the rolling mean, demonstrates an increasing trend over time, providing clear evidence of non-stationarity in the data. This pattern suggests a fundamental shift in the dynamics of human-elephant conflict over the study period, with both the frequency and variability of deaths increasing substantially in recent years. The analysis highlights significant non-stationarity in the time series, with both the rolling mean and standard deviation showing notable variations over time, particularly increased volatility during 2005-2010 and 2017-2022.

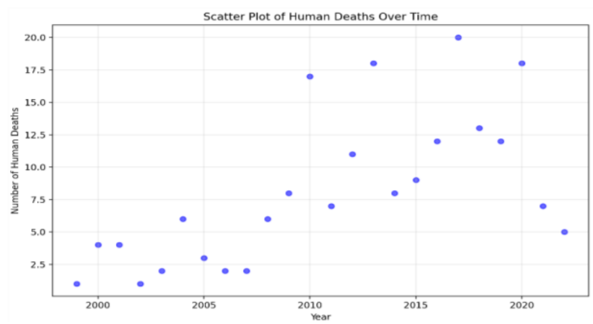

Figure 2: Scatter plot of human mortality rate.

Trends in human mortality

The box plots in Figure 3 by year groups reveal a clear upward trend in median deaths, from 3.0 in 1999-2004 to 12.5 in 2017-2022, alongside increasing variability and the presence of outliers. The trend component confirms a non-linear upward pattern, with a steeper rise during 2010-2015 and some levelling off in recent years, though still at elevated levels. Descriptive statistics in figure 3 further support this, showing consistent increases in mean deaths (from 3.0 to 12.5) and standard deviation (from 2.0 to 5.89) across the four time periods, underscoring the growing trend and variability in human deaths over time.

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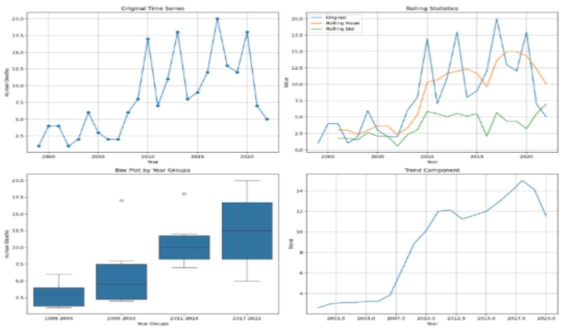

Figure 3: Trends in mortality.

Figure 4 shows the decomposition of the time series data on human deaths from 1999 to 2022 reveals key insights into its components. The observed data shows a clear upward trend with significant fluctuations, including notable peaks and troughs. The trend component highlights a long-term increase, with slower growth from 1999 to 2010, a steeper rise from 2010 to 2015, and a slight levelling off after 2015, albeit at elevated levels. The seasonal component captures recurring patterns with regular fluctuations every four years, though its magnitude is relatively small compared to the trend. The residual component represents random variations, showing increased volatility and less predictability in recent years, possibly indicating heteroscedasticity. This decomposition underscores that the rise in human deaths is primarily driven by the trend component, with seasonal patterns playing a minor role, while the growing size of residuals suggests increasing uncertainty in recent years.

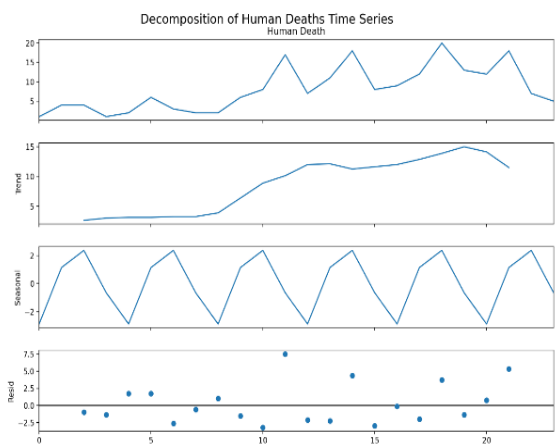

Figure 4: Decomposition of human mortality time series.

The Autocorrelation Function (ACF) plot reveals significant positive autocorrelation at multiple lags, with a slow decay pattern indicative of non-stationarity, strong persistence, and the presence of a trend component (Figure 5). Most lags exceed the significance bounds, confirming the need for differencing to achieve stationarity. The Partial Autocorrelation Function (PACF) plot shows a strong first-order correlation at lag 1, with a few significant spikes at other lags, suggesting a first-order autoregressive (AR) component and direct correlation between consecutive observations. These findings imply that the series exhibits strong temporal dependence and non-stationarity, necessitating first-order differencing before fitting an ARIMA model. The significant autocorrelations further suggest that the series may benefit from AR terms after differencing, providing strong evidence for the need to address these characteristics in the modelling process as seen in figure 6 below.

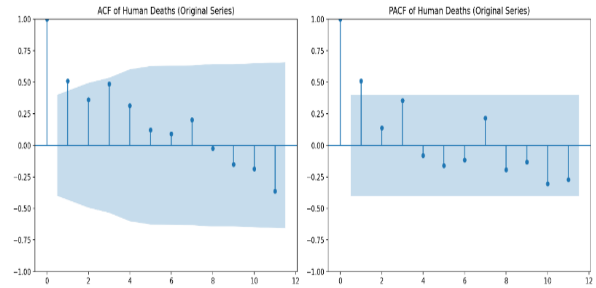

Figure 5: ACF and PACF plots before differencing (human mortality).

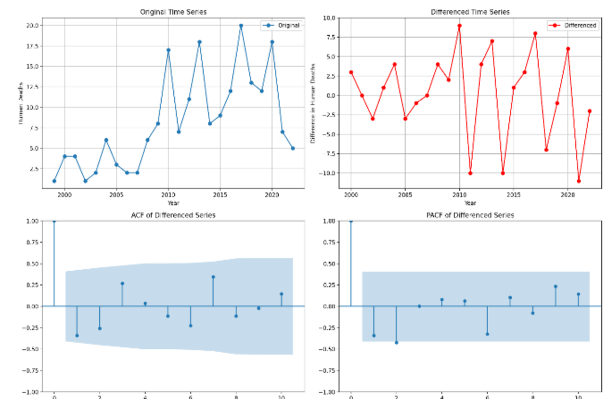

Figure 6: Differenced ACF and PACF of human death.

Augmented dickey-fuller test.	
Dickey-fuller = -4.19	
Lag order = 5	P-value 0.0007

Table 1: Augmented dickey-fuller test for human mortality.

H_0 : *Human mortality is not stationary*

H_1 : *Human mortality is stationary*

Decision: Since the p-value 0.0007 in the Augmented Dickey-Fuller Test for human mortality is less than the alpha value of 0.05 we reject the null hypothesis and conclude that the Human mortality time series is stationary and therefore it is white noise.

The ARIMA (2,1,0) model's residuals were confirmed to be stationary through the Augmented Dickey-Fuller Test as shown in Table 1, validating the model's appropriateness. The model components include two Autoregressive (AR) terms, AR (1) = -0.5312 (significant with p-value = 0.010) and AR (2) = -0.5123 (marginally significant with p-value = 0.076), indicating that the previous two observations are used to predict the next value. First-order differencing (d=1) was necessary to achieve stationarity, as confirmed by earlier ADF test results, while no Moving Average (MA) terms were required (q=0). The model's fit statistics further support its selection, with an AIC of 141.099 (lowest among all models), a BIC of 144.505 (second-lowest after ARIMA (0,1,1)), and

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a log-likelihood of -67.549, demonstrating its strong performance and statistical justification.

The diagnostic evaluation of the ARIMA (2,1,0) model's residuals in Figure 7, indicates that the model is a good fit for the time series data. The residuals fluctuate around zero with no visible patterns or trends, and the variance remains relatively constant, suggesting that the model has captured the main data patterns. The histogram of residuals shows an approximately normal distribution with slight right skewness, supported by the Jarque-Bera test result (p=0.31). The Q-Q plot further confirms approximate normality, with most points aligning well with the diagonal line, except for minor deviations at the tails. The ACF plot reveals no significant autocorrelations, as all values fall within the confidence bands, aligning with the Ljung-Box test result (p=0.80). Overall, the residuals exhibit properties consistent with white noise, including zero mean, constant variance, and no significant autocorrelation. These findings confirm that the ARIMA (2,1,0) model is well-suited for the data, supporting its earlier selection as the best model for this time series.

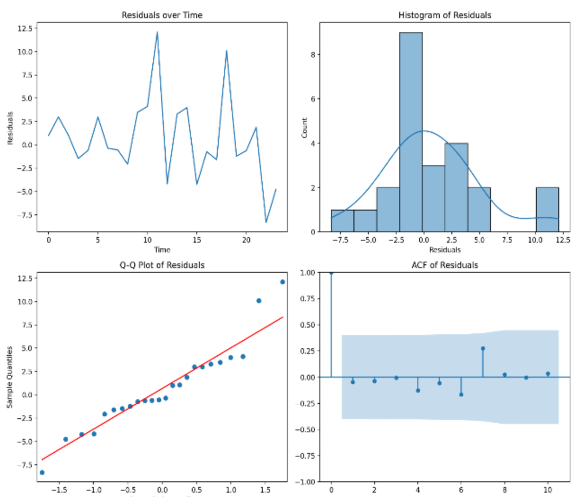

Figure 7: ARIMA Residuals (human death).

Based on the analysis of Human-Elephant Conflict (HEC) mortality data, the time series forecast reveals important patterns in expected human casualties as shown in figure 8. The model projects a relatively stable trend in HEC-related human deaths, with initial predictions showing approximately 11.70 deaths (95% CI: 2.90 to 20.50) for 2023. This figure is anticipated to moderately decrease to 9.06 deaths (95% CI: -5.31 to 23.43) by 2030, suggesting a slight downward trajectory before stabilizing around 8-9 deaths annually. While the model indicates year-to-year fluctuations, the overall pattern suggests a relatively consistent level of HEC-related mortality through 2030. However, it's crucial to note the increasing uncertainty in these predictions, as evidenced by the widening confidence intervals in later years. Although the statistical model includes negative values in the lower confidence bounds, these are not practically interpretable since deaths cannot be negative, but rather represent the inherent statistical uncertainty in the forecasting process. This comprehensive analysis provides valuable insights for wildlife management and conservation strategies, while acknowledging the considerable uncertainty inherent in long-term predictions of such complex human-wildlife interactions.

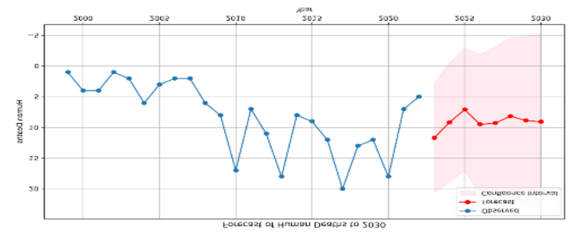

Figure 8: Forecast plot of human death.

The historical trend analysis of human deaths due to HEC from 1999 to 2022 reveals significant variability, beginning with a relatively low count of 1 death in 1999 and peaking at 18 deaths in 2020. Recent years, such as 2021 and 2022, show a decline to 5-7 deaths, indicating cyclical fluctuations rather than a consistent trend. The short-term forecast for 2023 to 2025 predicts a gradual decrease in deaths, with 11.70 deaths in 2023 (95% CI: 2.90 to 20.50), 9.16 deaths in 2024 (95% CI: -0.56 to 18.88), and 7.08 deaths in 2025 (95% CI: -2.87 to 17.02). These predictions suggest an initial downward trend from current levels, with higher confidence reflected in narrower prediction intervals for the short term. The medium-term forecast for 2026 to 2030 will likely continue this trend, though further details are needed for precise interpretation.

The forecast predicts a stabilization of HEC-related deaths around 8-9 annually, with 9.06 deaths projected for 2030 (95% CI: -5.31 to 23.43). The widening confidence intervals highlight increased uncertainty in longer-term predictions, reflecting the model's ability to capture both trends and cyclical patterns in the data. Negative lower bounds in confidence intervals are statistical artifacts and should be interpreted as zero in practice. The forecast suggests a reversion to historical mean levels, with a continued cyclical pattern but with dampened amplitude, and no dramatic increases or decreases anticipated. From a management perspective, HEC remains a persistent issue, with an expected baseline of 7-11 deaths annually, necessitating flexible strategies to address high variability in predictions. Planning should account for both best-case (lower bound) and worst-case (upper bound) scenarios to effectively mitigate risks and manage human-elephant conflict.

Time series analysis for elephant mortality

The data, spanning from 1999 to 2022 (24 years), exhibits significant variability in elephant deaths, with an average of approximately 11 deaths per year and a standard deviation of 8.05, indicating considerable annual fluctuations. The death counts range from a minimum of 0 to a maximum of 33 in a single year, reflecting a wide spread of incidents. The median of 11.5 deaths suggests a relatively symmetric distribution around the mean of 10.96. Observing the trends, the scatter plot and time series visualization reveal an overall increasing trend in elephant deaths, though not uniformly. The early years (1999-2003) show relatively stable and lower death counts (around 4 per year), while certain years exhibit dramatic spikes, reaching up to 33 deaths. Additionally, the variability in death counts appears to increase in recent years, hinting at growing instability or changing factors influencing elephant mortality. Quartile statistics further highlight the distribution: 25% of the years had 4 or fewer deaths, 50% had 11.5 or fewer, and 75% had 15.5 or fewer deaths. This distribution indicates that while most years maintain moderate death levels, a few years with significantly higher counts skew the average and contribute to the large standard deviation. These findings suggest underlying factors driving both the

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general increase in deaths and specific spikes, which could provide valuable insights for conservation and wildlife management efforts.

The scatter plot for elephant deaths as seen in figure 9 illustrates the number of elephant deaths over time, spanning from 2000 to 2022. The data shows a general upward trend, with the number of deaths increasing significantly after 2010. Early years (2000–2010) exhibit relatively low and stable death counts, mostly below 10. However, from 2010 onward, there is a noticeable rise, with several years exceeding 15 deaths and peaking above 30 in one instance. This trend suggests an escalation in factors contributing to elephant mortality, potentially linked to human-elephant conflict or environmental changes. The variability in the data also increases over time, indicating more pronounced fluctuations in recent years.

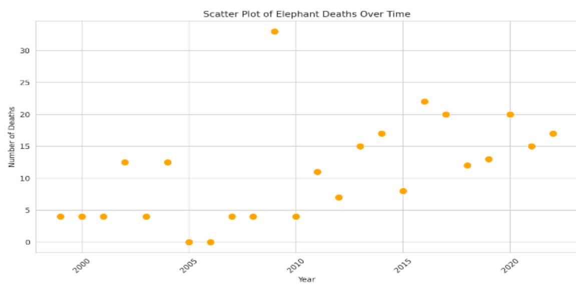

Figure 9: Scatter plot of elephants Death.

The time series graph of human deaths over the years as shown in figure 10 above, reveals a fluctuating pattern, with some years experiencing significantly higher numbers of deaths compared to others. The data shows a general variability, as indicated by the standard deviation of approximately 5.80, and the range spans from a minimum of one death to a maximum of twenty deaths. The median value of seven deaths suggests that half of the years recorded fewer than seven deaths, while the other half exceeded this number. This variability could indicate external factors influencing the number of deaths annually, warranting further investigation into potential causes or correlations.

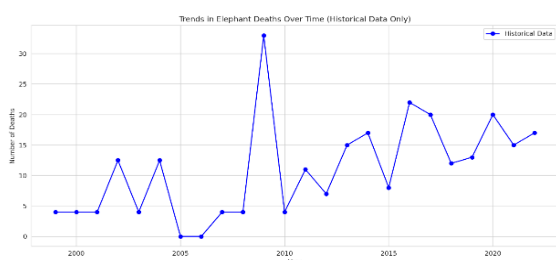

Figure 10: Trends in elephant deaths.

The decomposition plot in figure 11 reveals several key insights about the elephant death time series data. The Trend component shows a general upward trajectory over the 24-year period, with notable fluctuations. Starting from relatively low values of around 2-4 deaths in the early years (index 0-5), it gradually increases with several distinct peaks reaching up to twenty deaths during the middle and later periods (around indices 10-20). The most prominent peaks occur around indices 12, 15, and 18. The trend line also shows a decline towards the end of the series (indices 20-24). The Seasonality component appears as a flat line at zero, indicating that there is no significant seasonal pattern in the elephant deaths data. This suggests that the deaths are not systematically influenced by seasonal factors or annual cycles. Similarly, the Residuals component also shows a flat line at zero, indicating that the model captures the main patterns in the data well, with no significant unexplained variations. The Observed data (bottom panel) mirrors the trend component closely, which is expected given the absence of seasonality and residuals. This suggests that the variations in elephant deaths are primarily driven by long-term trends rather than seasonal or random factors. The pattern shows periods of relative stability interrupted by sudden increases, particularly in the latter half of the time series, possibly indicating changing environmental or human factors affecting elephant mortality over time.

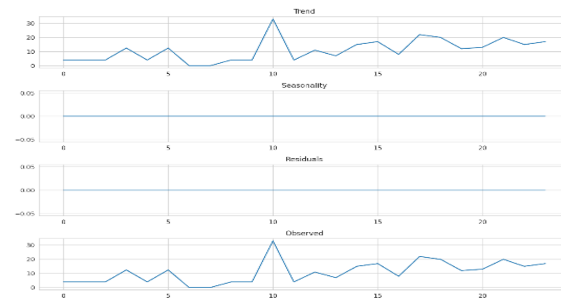

Figure 11: Decomposition plot for elephant death.

The original time series shows an increasing trend in elephant deaths with notable spikes, while the differenced series as shown in figure 12 removes the trend and highlights year-to-year variability. The differenced series is stationary, making it suitable for further time series modelling, such as ARIMA.

The reasoning for the interpretation is based on the visual analysis of the original and differenced time series, identifying trends, variability, and stationarity. The differenced series removes the trend, making it suitable for further modelling.

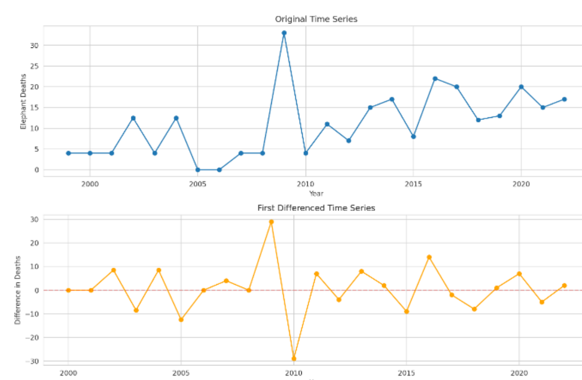

Figure 12: Differenced time series for elephant death.

The ACF and PACF plots reveal important characteristics of the time series data. In figure 13 before differencing, the ACF shows a strong positive autocorrelation that gradually declines, indicating non-stationarity in the original series. The PACF shows significant spikes at the first few lags, suggesting an autoregressive component. Conversely in figure 14 after applying first-order differencing, both ACF and PACF show reduced correlation patterns, with fewer significant lags, indicating that the differenced series is more stationary. The differenced series shows a significant negative spike at lag 1 in the ACF, which is typical of over differencing, suggesting that the original series might only need seasonal differencing or might be better modelled with a different approach. This analysis helps in identifying the appropriate ARIMA model parameters for forecasting.

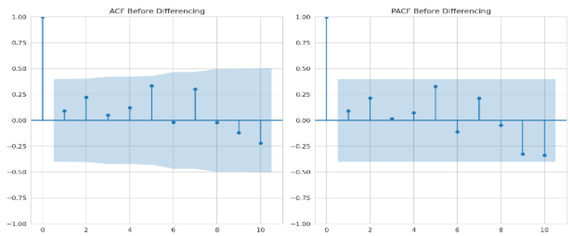

Figure 13: ACF and PACF before differencing.

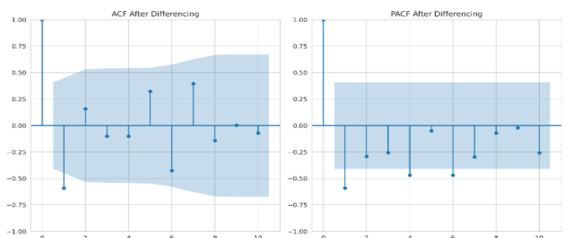

Figure 14: ACF and PACF after differencing.

Figure 15 shows a differenced time series which shows reduced trends and fluctuations compared to the original series, indicating that differencing has helped achieve stationarity. The data now appears more random, which is a key requirement for time series modelling.

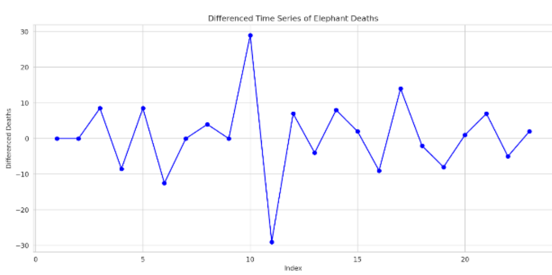

Figure 15: Differenced time series of elephant deaths.

Decision: Since the p-value 0.0077 as seen in Table 2 for Augmented Dickey-Fuller Test for Elephant Mortality is less than the alpha value of 0.05 we reject the null hypothesis and conclude that the Elephant mortality time series is stationary and therefore it is white noise.

The best ARIMA model based on both AIC and BIC criteria is ARIMA (0,1,1) with:

- p = 0 (autoregressive order)
- d = 1 (differencing order)
- q = 1 (moving average order)
- AIC = 164.53
- BIC = 166.80

The best ARIMA model, based on both AIC (164.53) and BIC (166.80) criteria, is ARIMA (0,1,1), with parameters p = 0 (autoregressive order), d = 1 (differencing order), and q = 1 (moving average order). This model has the lowest AIC and BIC values among all combinations tested, indicating it provides the best balance between model fit and complexity. In comparison, the second-best model, ARIMA (1,1,2), has higher AIC and BIC values and is more complex due to additional parameters. The differencing order of 1 (d=1) confirms that the series required one level of differencing to achieve stationarity, consistent with earlier observations about the trend in the data. The absence of autoregressive terms (p=0) and the inclusion of one moving average term (q=1) suggest that the series is primarily influenced by recent random shocks rather than longer-term historical values.

Augmented dickey-fuller test.	
Dickey-fuller = -3.51	
Lag order = 5	P-value 0.0077

Table 2: Augmented dickey-fuller test for elephant mortality.

H_0 : *Elephant mortality is not stationary*

H_1 : *Elephant mortality is stationary*

Figure 16 illustrates the comparison between the actual number of elephant deaths (blue solid line) and the fitted values from the ARIMA (0,1,1) model (red dashed line) over the years 2000 to 2020.

The actual values show significant variability, with sharp spikes and drops, particularly around 2010, where the number of deaths peaks dramatically before declining. The fitted values, represented by the red dashed line, follow a smoother trajectory, capturing the general trend but not the extreme fluctuations in the actual data. This indicates that while the ARIMA (0,1,1) model effectively captures the overall pattern of the data, it struggles to account for sudden, large deviations.

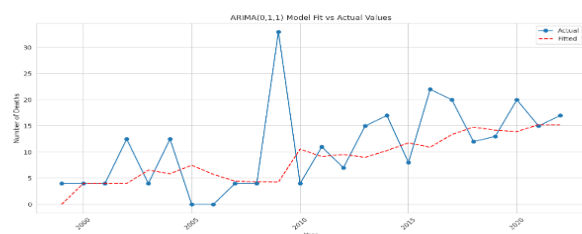

Figure 16: ARIMA plot of elephant death data.

Figure 17 shows a forecast that predicts a steady increase in elephant deaths over the next five years, rising from approximately 18.83 in 2023 to 21.35 in 2027. This trend suggests a gradual upward trajectory, potentially indicating worsening conditions for elephant survival. Further investigation into contributing factors is recommended.

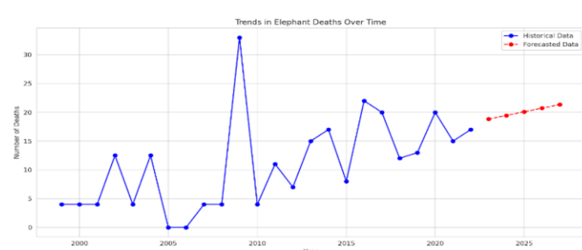

Figure 17: Forecast for elephant death.

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Conclusion

The Coimbatore Forest Area represents a critical case study for understanding the temporal dynamics of HEC and its impact on mortality rates. By leveraging time series analysis, researchers can uncover patterns and trends that inform the development of effective mitigation strategies. Addressing HEC through a data-driven approach not only contributes to wildlife conservation but also ensures the safety and well-being of local communities.

This comprehensive analysis of HEC trends in the Coimbatore Forest Area illuminates the temporal patterns of both human and elephant mortality, providing crucial insights for developing targeted mitigation measures. Understanding these trends and their seasonal nature enables more effective strategies for protecting both human and elephant lives.

This forecast provides a valuable planning tool while acknowledging the inherent uncertainties in long-term predictions of complex human-wildlife interactions. The results suggest a need for continued vigilance and adaptive management strategies in addressing human-elephant conflict.

The time series analysis revealed a gradual increase in both human and elephant mortality due to HEC incidents over the study period. Peaks in mortality were observed during the dry season, from December to March, as elephants tend to migrate toward human settlements in search of food and water. In particular, elephant raids on agricultural fields, where crops like sugarcane and banana are grown, were identified as high-risk scenarios for HEC.

The study identified significant seasonal variations in HEC incidents, with the highest frequencies occurring during the harvest season due to elephants seeking food sources, often leading to crop raiding. Spikes in HEC incidents were observed during the pre-monsoon and dry seasons, driven by resource scarcity and seasonal migration. Key contributing factors include proximity to water sources, as villages near water bodies reported more frequent incidents; crop type and agricultural cycles, with certain crops attracting elephants during the dry season; and human population density, with higher densities near forest fringes leading to increased encounters. These findings underscore the urgent need for effective HEC mitigation strategies in the Coimbatore Forest Area, where seasonal migration patterns and resource-rich agricultural lands exacerbate conflicts. Current measures, such as electric fencing and compensation schemes, are only partially effective due to limited coverage and implementation challenges. To address these issues, strategies such as improving fencing and early warning systems, promoting crop diversification, educating communities on conflict management, and providing seasonal watering stations for elephants are recommended to reduce HEC incidents and foster coexistence. There is also the need for continued monitoring and intervention strategies and urgent Focus on preventive measures during predicted peak periods. Looking ahead, future research should evaluate the efficacy of various mitigation approaches while considering broader ecological factors, including habitat restoration and sustainable land-use planning. The success of these initiatives ultimately depends on fostering strong collaboration between conservationists, policymakers, and local communities to develop and implement sustainable solutions that promote peaceful human-elephant coexistence.

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Conflicts of Interest

The author declares that there are no competing interests.

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