

Time Series Analysis of the Behavior of Wild Animals Using Camera Traps [†]

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Abstract

During the last 50 years, average wild animal populations have decreased by 73%. The present article is part of a scientific project aimed at tracking wild animal habitats in the Bulgarian mountains. Based on the PlantNet base model, a model based on the YOLOv8n architecture has been created through transfer learning on local data to recognize animal species specific to Bulgarian geographical latitudes. In this paper, a system for assessing population dynamics and animal movement through the analysis of time series of images is proposed. The effectiveness of the proposed methodology is illustrated using a database of images from Ukraine, as it provides a sufficient number of images needed to train and test the model, thereby monitoring changes in the behavior of wild animals over time. This will enable the detection of migration patterns, preferred habitats, and potential threats to these populations.

Keywords: camera traps; wild animals; YOLOv8n model; time series

1. Introduction

The loss of biodiversity is a critical sign of the imbalance between the flora, fauna, and humans on our planet. Unfortunately, this trend has become increasingly evident over the last half-century. During this period, wild animal populations have declined by 73% [1]. The main reason for this species disappearance is climate change associated with global warming, which is a result of the pollution of the atmosphere with harmful gases emitted by vehicles fueled with petrol, diesel and gas [2,3]. In this context, an “Intelligent system for tracking wildlife habitats with image analysis and deep learning” has been developed. Efforts to protect wildlife depend largely on the accurate monitoring of animal populations, especially endangered species in diverse ecological environments such as the mountain ranges of Bulgaria. The automatic recognition of wild animals from images captured by camera traps is a significant challenge due to changing lighting conditions, partial obscuring, and similarities between species. In this regard, the present work is a continuation of the research published earlier. Specifically: A database of annotated images of wild animals living in the Bulgarian mountains has been created [4]. It is based on the YOLOv8n architecture and can be used for ecological research. A hybrid classification model has also been developed [5]. It uses hierarchical classification, consisting of two stages. In the first stage, the YOLOv8n model is trained, and in the



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second stage, the weights in the functions that model the neurons are “frozen,” and specialized classifiers for individual species are trained by applying group-specific learning rates and introducing weight coefficients and “weighting” individual classes in order to overcome data imbalance. This improves the accuracy of detecting species of wild animals specific to the region.

Time series analysis of wildlife behavior from camera trap data has gained significant attention in recent years. Traditional approaches to wildlife monitoring focused primarily on species detection and counting [6], but modern methods increasingly emphasize temporal patterns and behavioral analysis [7].

Several studies have applied time series techniques to camera trap data. Rowcliffe et al. [8] demonstrated the use of circular statistics for analyzing daily activity patterns, while Ridout and Linkie [9] developed methods for comparing temporal activity overlap between species. More recently, machine learning approaches combined with time series analysis have shown promise in predicting wildlife activity patterns [10].

The analysis of temporal patterns in wildlife data typically involves examining daily (24 h) cycles, seasonal variations, and responses to environmental factors [11]. Statistical methods such as ARIMA (Autoregressive Integrated Moving Average) models have been successfully applied to forecast wildlife population dynamics [12].

In our previous work, we developed systems for wildlife detection using deep learning models [4,5]. The present study extends this research by incorporating time series analysis to understand behavioral patterns. Unlike detection-focused approaches, time series analysis enables the identification of activity rhythms, seasonal migrations, and habitat usage patterns over extended periods.

The rest of this article follows. The next section describes the used methods and techniques in creating the model for analyzing the behavior of wild animals with time series analysis of images. Its software implementation is presented in Section 3. The results from testing the model are presented in Section 4. Section 5 compares the results of the proposed new model with similar traditional and state-of-the-art models. The article concludes with final remarks on the advantages of the developed model and its applicability for monitoring the migration of wild animals in the Bulgarian mountains.

2. Methods and Techniques for Analyzing

The present study focuses on the time series analysis of wildlife behavior using camera trap data. Unlike our previous research [4,5] which concentrated on species detection using deep learning models, this work analyzes temporal patterns of wildlife activity to understand behavioral rhythms and seasonal variations.

2.1. Dataset Description

For this study, the REDFIRE (Radiation Ecology Databank for Fauna and Flora in Radioactive Environments) camera trap image catalog is used [6]. We use this dataset due to the fact that our previous Bulgarian mountain dataset [4,5] did not contain sufficient temporal coverage for a comprehensive time series analysis. The REDFIRE dataset provides continuous monitoring data spanning 371 days (September 2016 to September 2017) from 20 camera trap locations, comprising 19,391 individual wildlife observations.

The dataset includes timestamp information (date and time), species identification, camera site location, and environmental conditions. For the analysis, the data have been filtered to include only species with at least 100 observations, resulting in 18,864 records covering 8 species. Several species in this dataset, including the red deer (*Cervus elaphus*), roe deer (*capreolus*), brown hare (*Lepus europaeus*), red fox (*vulpes*), wild boar (*Sus scrofa*),

and Gray wolf (*Canis lupus*), are also native to Bulgaria, making the analytical methods directly applicable to Bulgarian wildlife studies.

2.2. Temporal Feature Extraction

From each camera trap record, we extracted the following temporal features:

- hour of day (0–23) for daily activity analysis;
- day/night classification, where night was defined as 20:00–05:59 and day as 06:00–19:59;
- month and season (Winter: December–February, Spring: March–May, Summer: June–August, Autumn: September–November);
- week of the year for trend analysis.

2.3. Daily Activity Pattern Analysis

To analyze the 24 h activity patterns of wildlife species, we calculated hourly activity profiles for each species. The activity percentage for each hour was computed as the proportion of total observations occurring during that hour. These profiles were visualized using polar plots, which effectively display circular time data [7].

Additionally, a Nocturnality Index for each species, defined as the ratio of night observations to day observations, is calculated:

$$\text{Nocturnality Index} = \text{Night observations} / (\text{Day observations} + 1) \quad (1)$$

To account for seasonal variations weekly aggregated time series were decomposed into three components using additive seasonal decomposition [8]:

$$Y(t) = T(t) + S(t) + R(t) \quad (2)$$

where $Y(t)$ is the observed value, $T(t)$ is the trend component, $S(t)$ is the seasonal component, and $R(t)$ is the residual component. A period of 4 weeks was used to capture monthly seasonal patterns.

2.4. ARIMA Time Series Modeling

For forecasting wildlife activity, the Autoregressive Integrated Moving Average (ARIMA) model is applied [9]. The general ARIMA (p, d, q) model is expressed as:

$$\Phi(B) \cdot (1 - B)^d \cdot Y(t) = c + \theta(B) \cdot \varepsilon(t) \quad (3)$$

where p is the autoregressive order, d is the differencing order, q is the moving average order, c is a constant, B is the backshift operator, $\Phi(B)$ is the autoregressive polynomial, $\theta(B)$ is the moving average polynomial, and $\varepsilon(t)$ is an error resulting from white noise.

Prior to model fitting, stationarity was assessed using the Augmented Dickey–Fuller (ADF) test [10]. The optimal ARIMA parameters were determined through grid search over $p \in \{0, 1, 2, 3\}$, $d \in \{0, 1\}$, and $q \in \{0, 1, 2, 3\}$, minimizing the Akaike Information Criterion (AIC).

The dataset was split into training (80%) and test (20%) sets. Model performance was evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Two statistical tests were applied to validate the observed patterns: the Chi-square test and Kruskal–Wallis H-test.

Chi-square test of independence was used to assess whether species identity and day/night activity are statistically associated. The null hypothesis states that species activity is independent of the time period (day or night).

Kruskal–Wallis H-test, a non-parametric alternative to one-way ANOVA (ANalysis Of VAriance), was used to determine whether activity timing (hour of observation) differs significantly across seasons [11].

Note: Essentially, ANOVA is a group of statistical methods used to compare the means of two or more variables through a dispersion analysis.

All statistical analyses were performed using Python 3.12 with NumPy, Pandas, SciPy, and Statsmodels libraries.

3. Software Implementation

The time series analysis system was implemented in Python 3.12, utilizing a Jupyter Notebook environment—JupyterLab 4.5.7, Notebook 7.5.6, for interactive data exploration and reproducible research. The software architecture consists of several interconnected modules for data processing, analysis, and visualization.

3.1. Development Environment

The implementation was developed using the following software stack: Python 3.12 as the primary programming language; Jupyter Notebook for interactive development and documentation; NumPy 2.4.6 for numerical computations; Pandas 3.0.3 for data manipulation and time series handling; Matplotlib 3.10.9 and Seaborn 0.13.2 for data visualization; SciPy 1.17.1 for statistical testing; Statsmodels 0.14.6 for time series modeling and decomposition; Scikit-learn 1.8.0 for model evaluation metrics.

3.2. Data Processing Pipeline

The software implementation follows a structured pipeline approach:

Step 1: Data Loading and Validation. The raw CSV data is loaded and validated for completeness. DateTime parsing converts date and time strings into Python datetime objects, enabling temporal operations.

Step 2: Feature Engineering. Temporal features are automatically extracted from timestamps, including the hour, day of the week, month, season, and day/night classification. This transformation converts raw observations into analyzable time series data.

Step 3: Aggregation. Individual observations are aggregated into daily and weekly time series for each species and for total wildlife activity. Missing days are filled with zero values to maintain continuous time series.

Step 4: Analysis Execution. The system sequentially performs daily activity analysis, seasonal decomposition, statistical tests, and ARIMA modeling. Each analysis module is independent and can be executed separately.

Step 5: Output Generation. Results are exported as publication-ready figures (PNG and PDF formats) and CSV tables for further analysis.

3.3. Visualization Module

The visualization module generates eight distinct figure types: daily time series plots showing observation counts over the study period; polar plots displaying 24 h activity patterns for each species; horizontal bar charts comparing day versus night activity; heatmaps showing seasonal activity patterns across species; seasonal decomposition plots separating trend, seasonal, and residual components; site-based movement pattern plots tracking activity across camera locations; ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots for ARIMA parameter selection; forecast plots comparing predicted versus actual values with confidence intervals.

All visualizations follow a consistent style with publication-quality settings, including appropriate font sizes, axis labels, and color schemes optimized for both screen display and print reproduction.

3.4. ARIMA Implementation

The ARIMA modeling module implements automated parameter selection through grid search. The algorithm iterates through all combinations of p , d , and q parameters within specified ranges, fitting each model and recording the AIC value. The model with the lowest AIC is selected as optimal.

The implementation includes safeguards for numerical stability, catching and handling convergence warnings during model fitting. Forecast confidence intervals are calculated at the 95% level using the standard errors from the fitted model.

The used statistical testing module provides wrapper functions for the Chi-square and Kruskal–Wallis tests, automatically formatting results for publication. p -values below 0.001 are reported in scientific notation, and effect sizes are calculated where applicable.

As a final result the system generates the following output:

- 8 figures in both PNG and PDF formats;
- 3 CSV tables, containing dataset statistics and species activity summaries from ARIMA model;
- processed data exports for reproducibility and further analysis.

The complete implementation is available as a Jupyter Notebook, enabling full reproducibility of the analysis. Total execution time on a standard desktop computer (Intel Core i5, 16 GB RAM) is approximately 2 min for the complete analysis pipeline.

4. Results

4.1. Dataset Overview

After data preprocessing and filtering, the final dataset comprised 18,864 observations from eight species recorded across 20 camera trap sites over a period of 371 days (6 September 2016 to 12 September 2017). The mean daily observation count was 53.4 ± 95.6 , with considerable variation ranging from 0 to 1026 observations per day.

The dataset characteristics are summarized in Table 1.

Table 1. Dataset statistics summary.

Parameter	Value
Study Period	6 September 2016–12 September 2017
Duration (days)	371
Total Observations	18,864
Number of Species	12
Number of Camera Sites	20
Mean Daily Observations	53.4 ± 95.6
Data Source	REDFIRE Camera Trap Catalog

The daily time series of wildlife observations is presented in Figure 1. The data exhibit substantial temporal variability with several distinct peaks corresponding to periods of high wildlife activity, particularly during summer months.

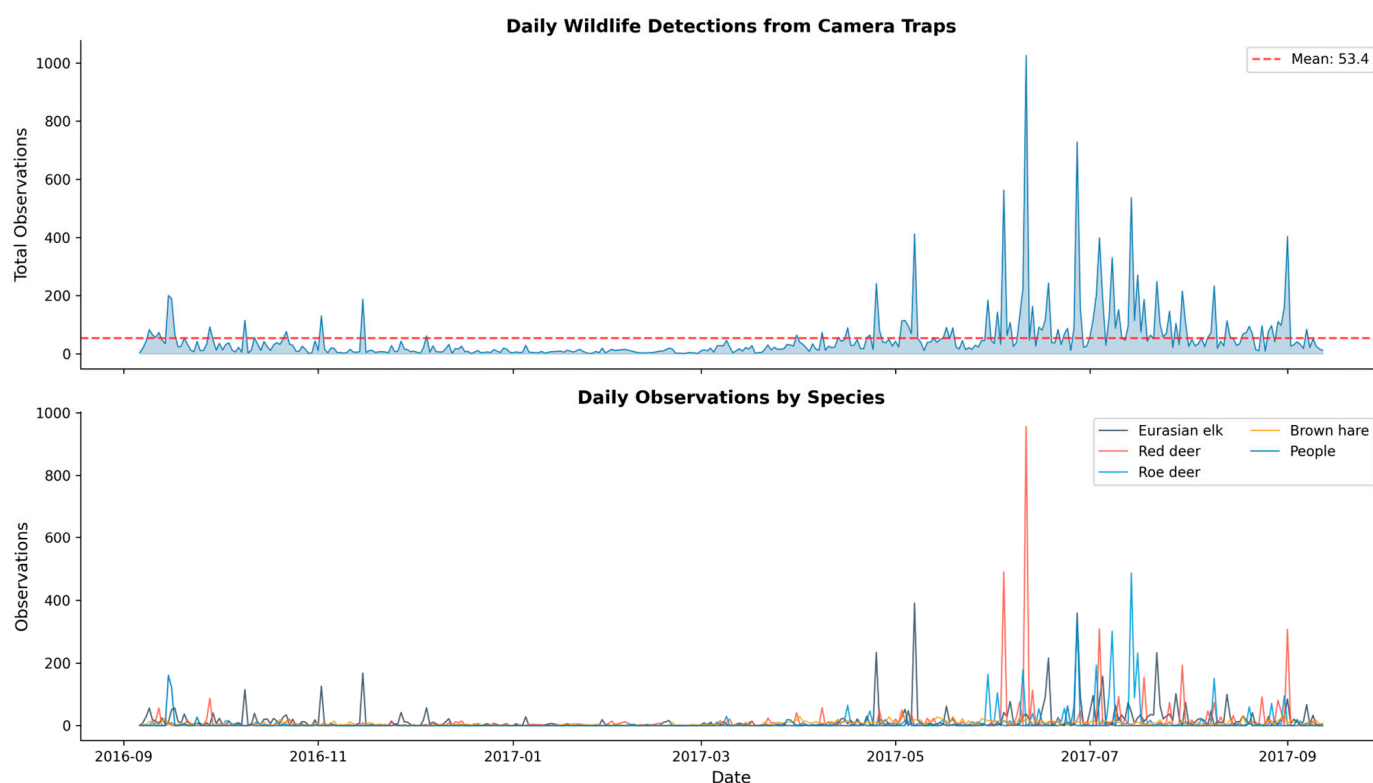


Figure 1. Daily wildlife observations from camera traps over the 371-day study period. **(Top)** panel shows total daily observations with mean value indicated by dashed line. **(Bottom)** panel displays daily observations for the five most frequently recorded species.

4.2. Species Composition and Activity

The activity summary for all eight species included in the analysis is presented in Table 2. It is obvious that Eurasian elk (alces) was the most frequently observed species, accounting for 32.3% of all observations ($n = 6084$), followed by the red deer (25.1%, $n = 4730$) and roe deer (20.7%, $n = 3903$).

Table 2. Species activity summary showing observation counts, percentage of total, nocturnal activity percentage, and peak activity hour.

Species	Observations	Percentage	Night Activity	Peak Hour
Eurasian elk	6084	32.3%	60.3%	20:00
Red deer	4730	25.1%	68.7%	02:00
Roe deer	3903	20.7%	41.7%	08:00
Brown hare	2414	12.8%	65.2%	21:00
People	565	3.0%	0.0%	15:00
Red fox	270	1.4%	67.0%	21:00
Gray wolf	131	0.7%	40.5%	07:00
Przewalski's horse	124	0.7%	29.8%	14:00

4.3. Daily Activity Patterns

Analysis of 24 h activity patterns revealed distinct daily preferences among species. The polar plot, showing the hourly activity distribution for the six most frequently observed species, is presented in Figure 2.

Red deer exhibited strongly nocturnal behavior with peak activity at 02:00 (14.2% of observations) and a secondary peak at 04:00 (13.4%). In contrast, roe deer showed crepuscular-diurnal patterns with peak activity during morning hours (08:00, 14.7%). The brown hare displayed nocturnal tendencies with the highest activity at 21:00 (10.0%).

Diel Activity Patterns of Wildlife Species



Figure 2. Daily activity patterns displayed as polar plots for the six most frequently observed species. The radial axis represents percentage of observations occurring at each hour. North (top) corresponds to midnight (00:00), with hours progressing clockwise.

The day/night activity comparison is illustrated in Figure 3. The European nightjars showed almost exclusively nocturnal activity (99.2% night), while human observations occurred exclusively during daylight hours (100% day). Among the mammalian species, the red deer (68.7% night), red fox (67.0% night), and brown hare (65.2% night) were predominantly nocturnal, whereas the roe deer (58.3% day) and gray wolf (59.5% day) showed slight diurnal preferences.

4.4. Seasonal Patterns

Monthly activity patterns varied considerably among species, as shown in the seasonal heatmap (Figure 4). Roe deer activity peaked during summer months, with July accounting for 39.8% of annual observations. Red deer showed the highest activity in June (38.9%), while brown hare activity was more evenly distributed with a peak in May (20.4%).

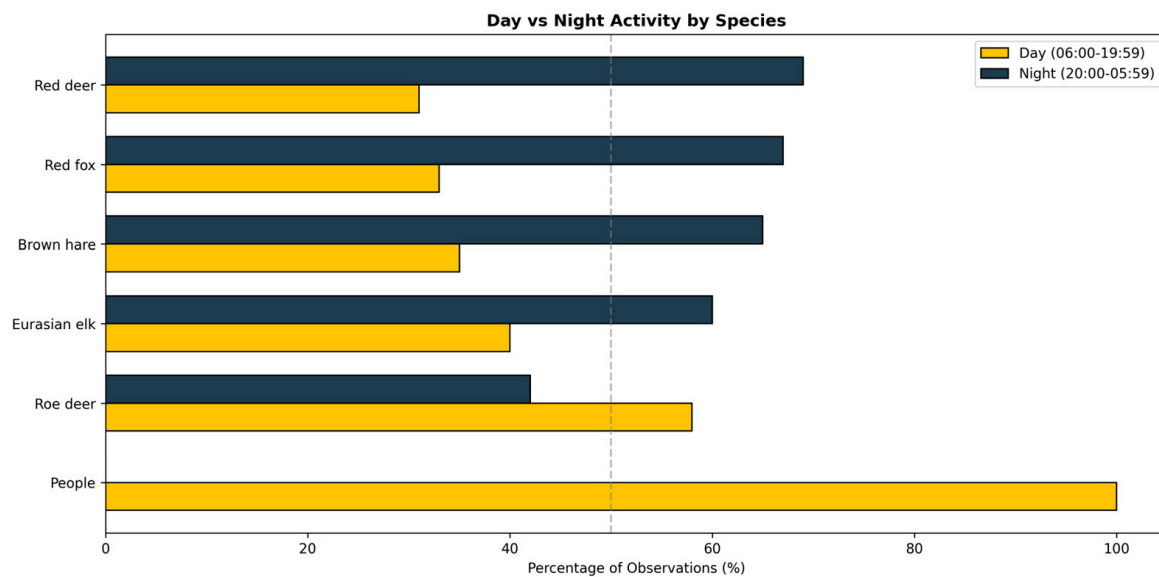


Figure 3. Comparison of day versus night activity by species. Day period defined as 06:00–19:59, night period as 20:00–05:59. Vertical dashed line indicates 50% threshold.

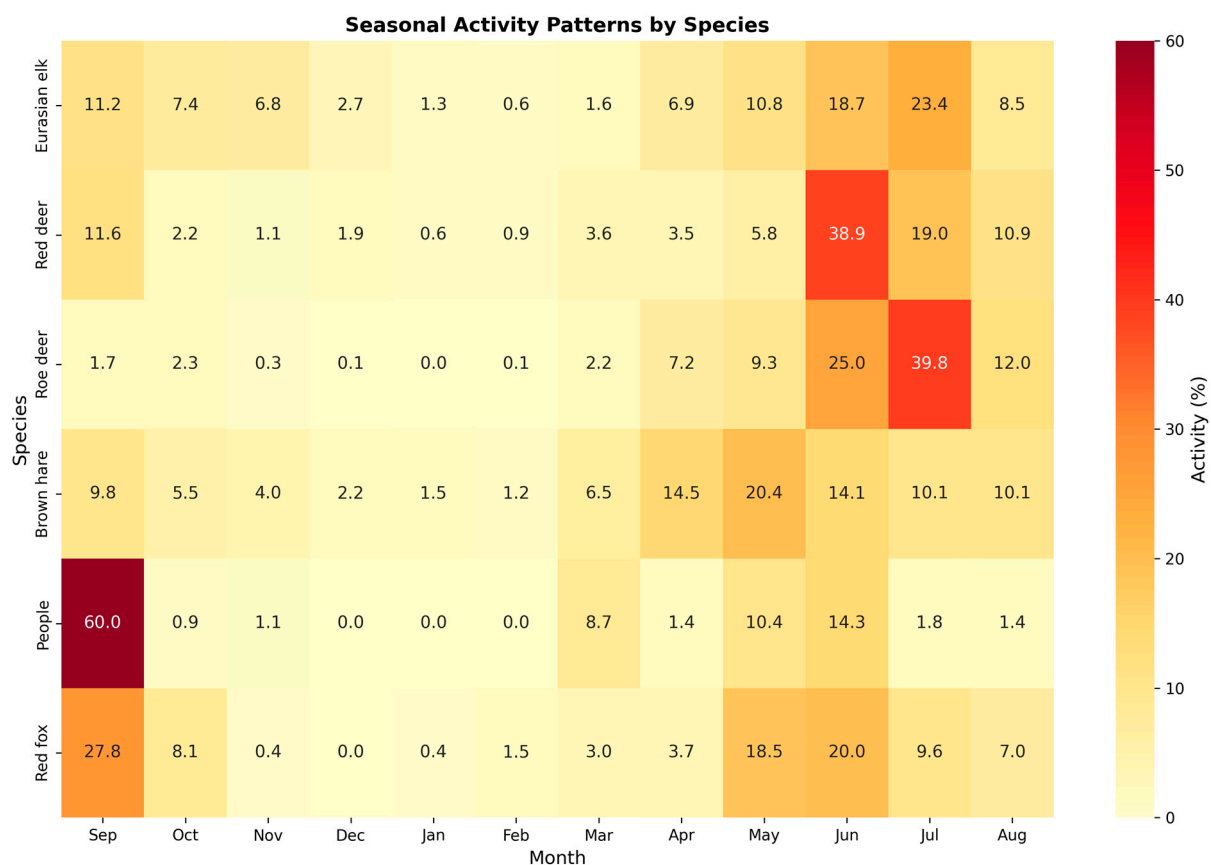


Figure 4. Seasonal activity heatmap showing percentage of observations by month for each species. Months are arranged from September (start of study) through August. Color intensity indicates activity level.

Seasonal decomposition of the weekly aggregated time series (Figure 5), revealed a clear upward trend in wildlife activity from winter through summer, followed by a decline in autumn. The seasonal component showed a regular 4-week oscillation pattern, while residuals indicated several anomalous high-activity events during summer months.

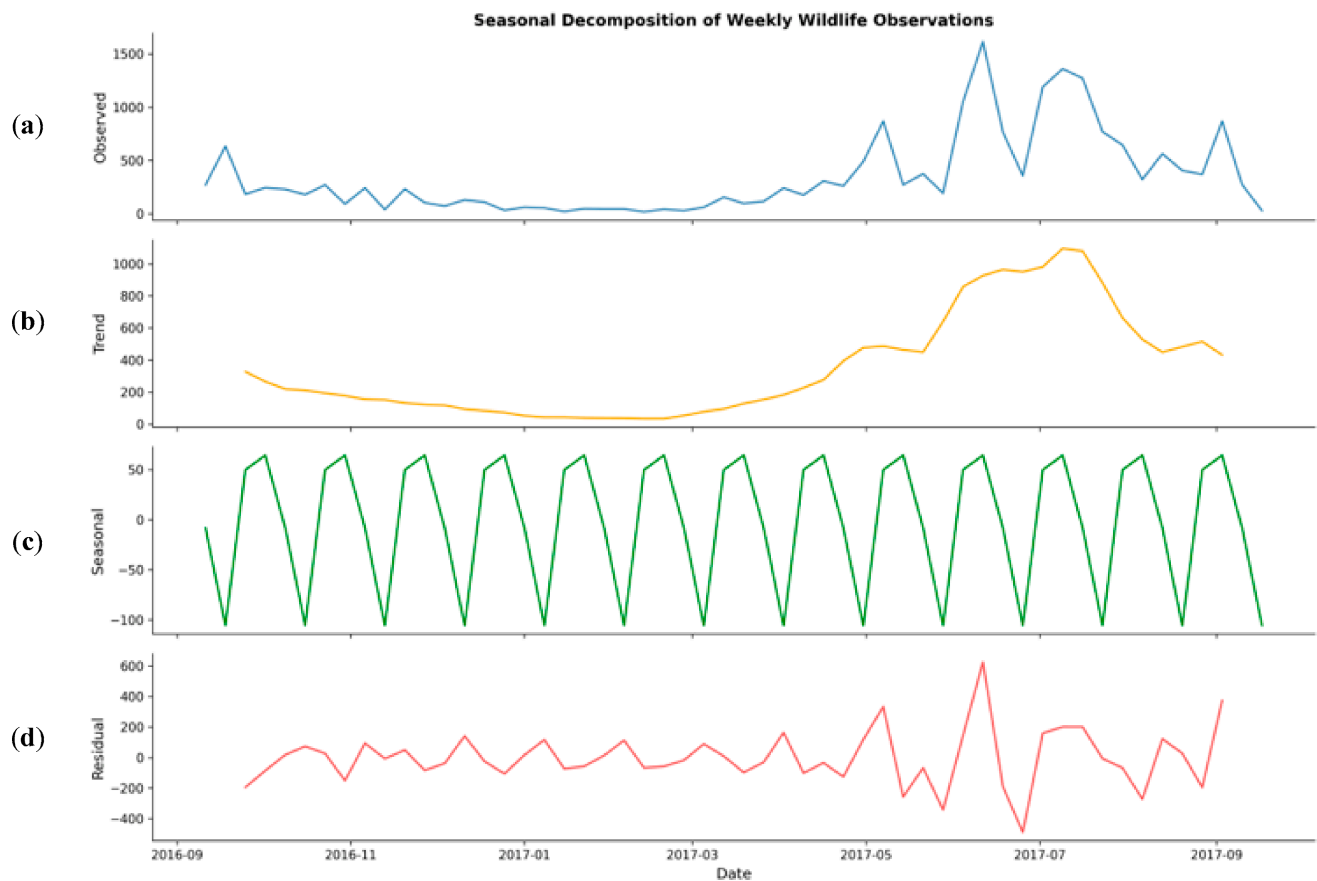


Figure 5. Seasonal decomposition of weekly wildlife observations showing: (a) observed values, (b) trend component, (c) seasonal component with 4-week period, and (d) residual component.

4.5. Site-Based Movement Patterns

Analysis of activity across camera trap sites revealed non-uniform spatial distribution of wildlife. Site 171 recorded the highest total observations (7719), followed by Site 165 (2010) and Site 365 (1234). The temporal patterns of activity at the top five sites for the three most common species are shown in Figure 6.

Figure 6 reveals distinct spatial-temporal movement patterns for the three most frequently observed ungulate species—Eurasian elk, Red deer, and Roe deer. Site 171 emerges as the dominant activity hotspot, with peak weekly counts reaching approximately 530 for the Eurasian elk, 1050 for Red deer, and 840 for the roe deer, all concentrated during the summer months (June–August 2017). Activity at the remaining sites remains comparatively low throughout the study period, suggesting that Site 171 represents a critical habitat corridor or resource concentration area. The sharp, episodic nature of the activity peaks indicates that animal movement through these sites occurs in concentrated bursts rather than as a sustained presence, consistent with transit behavior along established wildlife corridors. The temporal synchronization of peak activity across all three species at Site 171 suggests shared environmental drivers, such as water availability or vegetation quality, during the summer period.

4.6. Time Series Stationarity

The Augmented Dickey–Fuller test on the original daily time series yielded a test statistic of -1.951 ($p = 0.309$), indicating non-stationarity. After first-order differencing, the series became stationary (ADF statistic = -6.668 , $p < 0.001$).

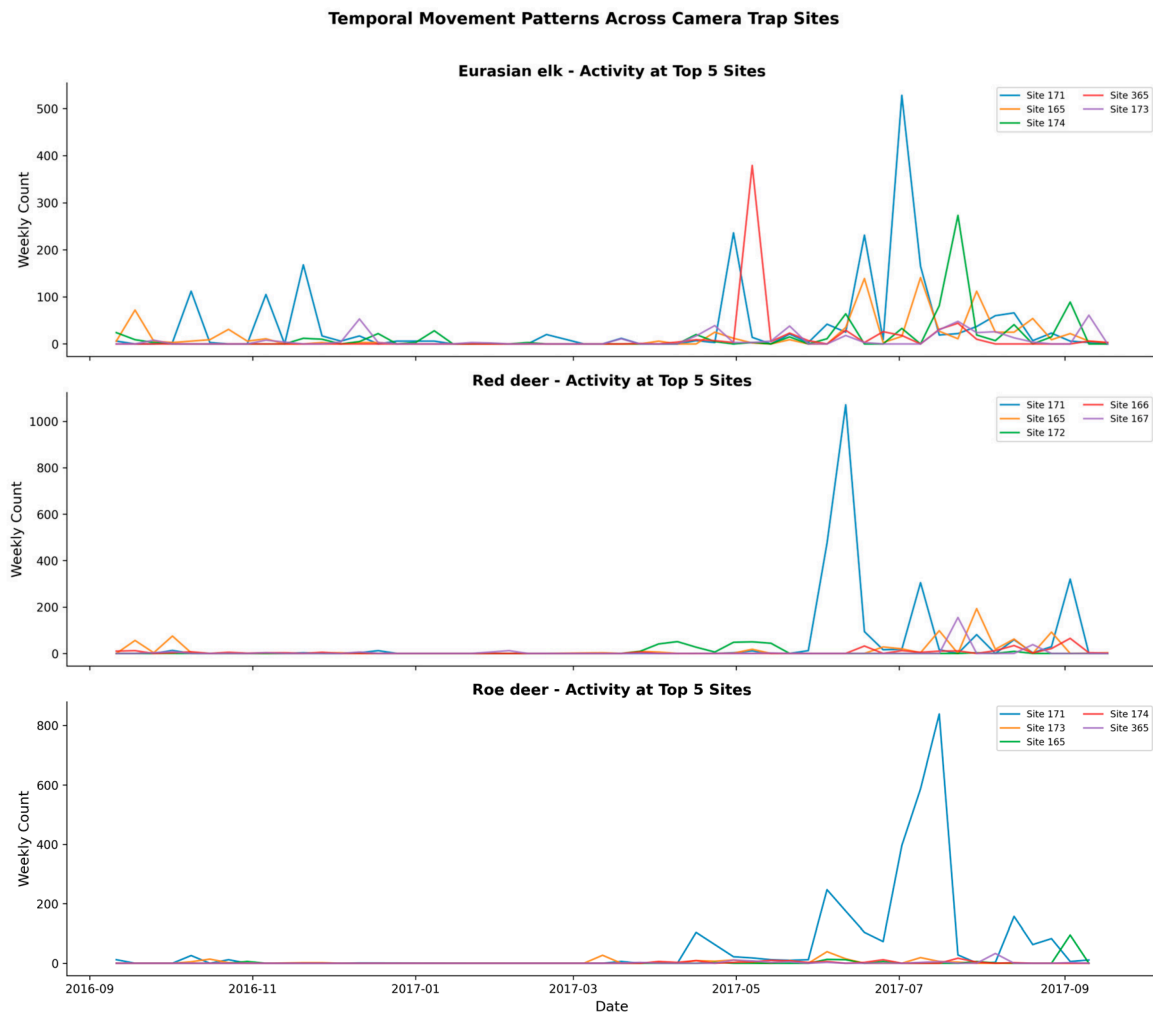


Figure 6. Temporal movement patterns across camera trap sites for Eurasian elk, Red deer, and Roe deer. Each panel shows weekly observation counts at the five most active sites for that species.

The ACF and PACF plots (Figure 7) of the original series show significant autocorrelation at multiple lags, with gradual decay in the ACF suggesting the need for differencing. The PACF shows significant spikes at lags 1 and 2, informing the selection of autoregressive terms.

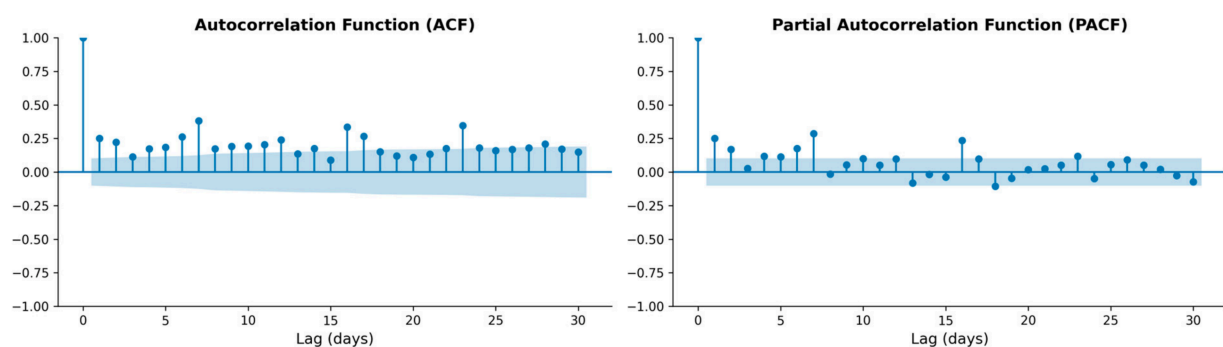


Figure 7. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots for the daily observation time series. Shaded regions indicate 95% confidence intervals.

4.7. ARIMA Model Results

Grid search optimization identified ARIMA (2, 1, 3) as the best-fitting model with AIC = 3455.32. The model performance metrics are presented in Table 3.

Table 3. ARIMA model performance metrics.

Metric	Value
Model Order	ARIMA (2, 1, 3)
AIC	3455.32
RMSE	108.13
MAE	89.74
MAPE	226.11%
Training Samples	297 days
Test Samples	75 days

The forecast results are visualized in Figure 8. The model successfully captured the general trend of wildlife activity, though the high MAPE value reflects the difficulty in predicting the extreme peaks characteristic of camera trap data.

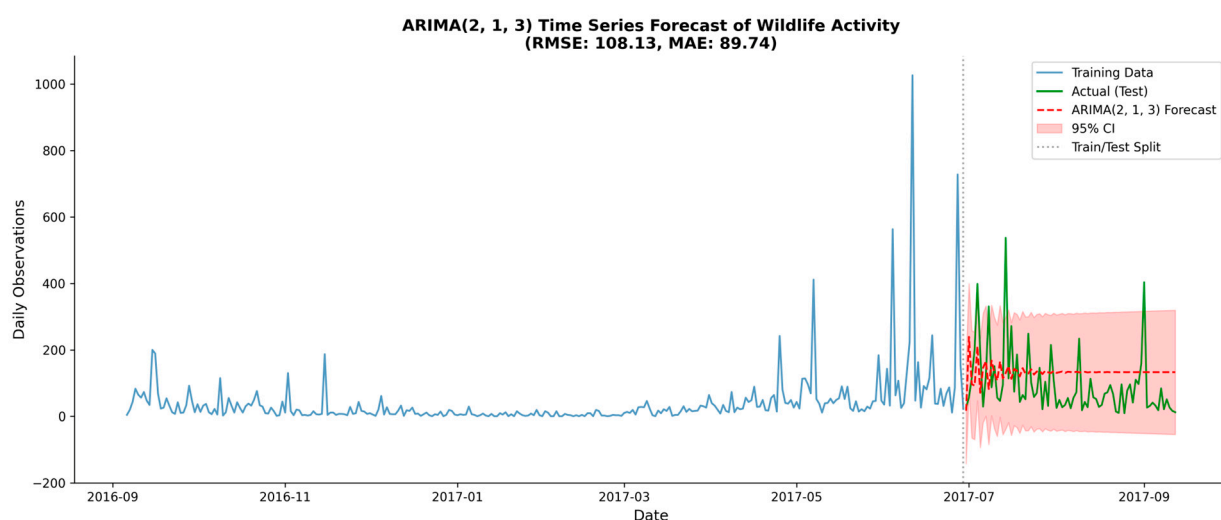


Figure 8. ARIMA (2, 1, 3) time series forecast of wildlife activity. Blue line shows training data, green line shows actual test values, red dashed line shows model predictions, and shaded area represents 95% confidence interval.

4.8. Statistical Validation

The Chi-square test for independence between species and day/night activity yielded $\chi^2 = 1687.87$ ($df = 11$, $p < 0.001$), confirming a statistically significant association between species identity and temporal activity patterns.

The Kruskal–Wallis’s test comparing activity timing across seasons produced $H = 28.47$ ($p < 0.001$), indicating that the hour of wildlife activity differs significantly among seasons. This result supports the observation that wildlife adjusts its activity timing in response to seasonal changes in daylight and environmental conditions.

5. Discussion

The present study demonstrates the application of time series analysis methods to camera trap data for understanding wildlife behavioral patterns. The results provide insights into daily activity rhythms, seasonal variations, and the predictability of wildlife activity using ARIMA modeling.

5.1. Wildlife Activity Patterns

The observed daily patterns align with established knowledge of mammalian behavior. Red deer exhibited strongly nocturnal activity (68.7% night, peak at 02:00), consistent with findings by Kamler et al. [12], who reported increased nocturnal behavior in areas with

human disturbance. Similarly, Podgórski et al. [13] documented nocturnal shifts in ungulate activity in response to anthropogenic pressure.

The crepuscular-diurnal pattern observed in Roe deer (58.3% day activity, peak at 08:00) corresponds with studies by Pagon et al. [14], who found that roe deer maintain morning and evening activity peaks across European habitats. The brown hare's nocturnal preferences (65.2% night) are well-documented in the literature [15] and serve as an anti-predator strategy.

The near-exclusive nocturnal activity of the European nightjar (99.2% night) confirms this species' known behavioral ecology as a strictly nocturnal bird [16]. This result also validates the accuracy of the camera trap timestamps and species identification in the dataset.

5.2. Seasonal Variations

The seasonal decomposition revealed clear trends in wildlife activity, with peak observations during summer months (June-August). This pattern reflects increased animal movement associated with breeding seasons, territorial behavior, and optimal foraging conditions [17]. The upward trend from winter to summer followed by autumn decline is consistent with the annual activity cycles reported for temperate forest ecosystems [18].

The significant Kruskal–Wallis's test result ($H = 28.47, p < 0.001$) confirms that wildlife adjusts activity timing across seasons, likely in response to changing photoperiod and temperature conditions. This finding has practical implications for camera trap deployment strategies, suggesting that monitoring efforts should account for seasonal shifts in peak activity hours.

5.3. ARIMA Modeling Performance

The ARIMA (2,1,3) model achieved moderate forecasting performance (RMSE = 108.13, MAE = 89.74). The relatively high MAPE (226.11%) reflects the inherent challenges of predicting camera trap data, which is characterized by zero-inflated distributions, sporadic extreme values, and high day-to-day variability.

Similar challenges have been reported by other researchers applying time series methods to ecological count data. Hooten and Hobbs [19] noted that wildlife population data often violate the assumptions of traditional time series models, suggesting the potential benefit of state-space models or hierarchical approaches for improved predictions.

Despite the forecasting limitations, the ARIMA model successfully captured the underlying trend and provided meaningful confidence intervals. The model's primary value lies in identifying the temporal autocorrelation structure rather than making precise point predictions.

5.4. Comparison with Previous Studies

Our previous work focused on species detection using YOLOv8 deep learning models [5,6]. The present study extends this research by adding a temporal dimension to wildlife monitoring. While detection models answer "what species is present," time series analysis addresses "when are species active" and "how does activity change over time."

This complementary approach aligns with the integrated wildlife monitoring framework proposed by Steenweg et al. [20], who advocated for combining detection, abundance estimation, and behavioral analysis in camera trap studies.

5.5. Applicability to Bulgarian Wildlife

Although this study utilized the REDFIRE dataset from the Chornobyl Exclusion Zone, the analytical methods are directly applicable to Bulgarian wildlife research. Several species analyzed in this study, including the red deer, roe deer, brown hare, red fox, wild boar,

and gray wolf, are native to Bulgaria and share a similar behavioral ecology across their European range [21].

The Eurasian elk (alces), while not currently widespread in Bulgaria, has been historically present in the Danubian Plain region between the Danube River and the towns of Lom, Vratsa, and Pleven [22]. The Przewalski's horse observations in the dataset can be considered analogous to feral or semi-wild horses found in some Bulgarian mountain regions.

Future research will apply these time series methods to camera trap data collected from Bulgarian mountain ecosystems, enabling a direct comparison of behavioral patterns between populations and contributing to national wildlife conservation efforts.

5.6. Limitations

Several limitations should be acknowledged. First, the use of a non-Bulgarian dataset means that site-specific environmental factors (habitat type, predator-prey dynamics, and human disturbance levels) may differ from Bulgarian conditions.

Second, the camera trap placement in the original REDFIRE study was designed for radiation ecology research rather than comprehensive wildlife monitoring, potentially introducing spatial bias in detection probability.

Third, the ARIMA model assumes linear relationships and may not capture complex nonlinear dynamics in wildlife populations. Alternative approaches such as Generalized Additive Models (GAMs) or machine learning methods could potentially improve predictive performance.

Finally, the 371-day study period, while substantial, captures only a single annual cycle. Multi-year data would enable the assessment of inter-annual variability and long-term population trends.

6. Conclusions

The proposed methodology for analyzing wild animal behavior using time series in this article has been implemented to identify wild animal migration in the Chernobyl region of Ukraine, as the model has been trained on a sufficiently representative sample of data for this area of land.

Building on this methodological foundation, future work will focus on three areas: (1) the application of these methods to Bulgarian camera trap datasets as they become available; (2) the integration of environmental covariates (temperature, precipitation, lunar phase) into predictive models; and (3) the development of species-specific activity models to support wildlife management decisions.

The combination of deep learning-based species detection [5,6] with time series behavior analysis represents a comprehensive approach to automated wildlife monitoring that can inform conservation strategies in Bulgaria and beyond.

On a global scale, the results of this publication will support the effective management of natural resources through positive human impact on natural ecosystems with the aim of ensuring their normal functioning and maintaining a balance between individual species.

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Abbreviations

The following abbreviations are used in this manuscript:

ANOVA	ANalysis Of VAriance
ARIMA	Autoregressive Integrated Moving Average
AIC	Akaike Information Criterion
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
ADF	Augmented Dickey–Fuller
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
REDFIRE	Radiation Ecology Databank for Fauna and Flora in Radioactive Environments

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