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Research on the Use of Photo Trap Cameras in Estimating the Size of Large Mammalian Populations

SUMMARY

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Contents

CHAPTER 1 – INTRODUCTION

The estimation of game population sizes is a major concern for all stakeholders involved in species management and conservation. Studies on large mammal population estimates focus on determining their size as accurately as possible, along with relevant population indices such as density and abundance of individuals within a given territory. Other parameters of interest in population estimates include age structure, sex ratio, health status, hybridization rate, and reproduction rate.

Wildlife diversity and population studies are essential for assessing the condition of populations in their existing environments (Ancrenaz et al., 2012). Regularly updating data on animal population densities and interspecific interactions is crucial for evaluating spatiotemporal variations in populations (Ouché et al., 2012).

The equation for population estimation includes multiple variables depending on the research objective. Key variables in this equation include territory (surveyed area and its structure), human resources involved, available financial resources, technology, and time allocated to obtain results.

The main goal of conservation and wildlife management, as outlined in *Analysis and Management of Animal Populations* (Byron Williams, 2002), is to create an algorithm that integrates all parameter values from the estimation equation with population modeling systems and theoretical management decisions into a unified and cohesive framework.

Data on mammalian species distribution and density, as well as other population attributes, are critical for biodiversity management and conservation. Estimating population size within a specific habitat is essential for understanding species characteristics and provides valuable indicators for their sustainability (Varman & Sukumar, 1995).

As a result, population estimation activities support and guide decision-making processes, ensuring sustainability for all species and their vital elements in both quantitative and qualitative aspects.

Estimating population density and monitoring trends in large carnivore populations is a complex task, posing significant challenges for researchers and wildlife managers (Linnell et al., 1998). Due to these challenges, various methods have been developed for estimating population sizes and monitoring their distribution. Unlike other species groups, no globally recognized standard methods exist for large carnivore population estimation (Linnell et al., 1998).

Scientific, technological, and societal advancements have enabled progress in wildlife research, both in fundamental and applied aspects, addressing challenges arising from the unsustainable exploitation of natural resources.

Research methods are diverse and complex, generally selected based on the study environment, target species, study objectives, and inherent constraints such as available human and financial resources (Lee White & Ann Edwards, n.d.).

Population estimation methods have evolved significantly over time. Initially, full censuses of individuals in small areas were used to assess food resources. As society and the need for broader knowledge expanded, sampling-based estimation methods and index-based estimation techniques emerged (O. Ionescu, 2011).

The scientific foundation of large mammal population estimation was established with the adoption of the "sampling" concept. Research focused on estimating large mammal populations, both nationally and internationally, has adopted various methodologies, including standardized sample plot placement, different sample plot sizes and shapes, and varying sampling percentages, depending on established outcome indicators, desired precision, available time, and financial and human resources.

The first images of mammals were officially published in 1906 when *National Geographic* featured 74 photographs taken by George Shiras, considered the father of wildlife photography. The first "camera trap" was used between 1878 and 1884 in the United States by British photographer Eadweard James Muybridge.

Later, F. Chapman (1927) used a similar system of image trap cameras and cable systems to capture wildlife photographs on Barro Colorado Island, Panama. These pioneers popularized automated cameras among the American Hunting Brotherhood (Sanderson & Trolle, 2005), leading to the expansion of the global camera trap market (Meek et al., 2012). The functionality of photo trap cameras has evolved significantly, undergoing continuous improvements (Shiras, 1906, 1913; Guiler, 1985) until reaching modern models (Rovero et al., 2013).

The first commercial photo trap cameras appeared in the United States under the Xenon brand in 1980, using a white flash and consisting of two separate components: the camera and an infrared beam system that triggered the camera when interrupted by passing animals. Two decades later, integrated units with motion sensors, infrared beams, and high-performance optical devices emerged.

Most modern camera traps operate using a passive infrared sensor (PIR), which detects movement by identifying infrared radiation emitted by animals. All animals emit a heat signature in the infrared spectrum, and PIR sensors detect these differences, triggering the camera (Meek et al., 2012).

Today, a wide range of camera trap brands and models are available, with new features introduced each year, varying significantly in characteristics and specifications (Cutler & Swann, 1999; Swann et al., 2011).

The number of scientific publications in ecology, biology, zoology, and veterinary sciences featuring keywords such as "camera trap," "infrared triggered camera," "trail camera," "automatic camera," "photo trap," and "remotely triggered camera" has increased from less than 0.5% in the early 1990s to nearly 3% in 2013 (Rovero et al., 2013).

The first studies using camera traps for large mammal conservation emerged in the 1990s, focusing on tigers (*Panthera tigris*) (Griffiths & Schaik, 1993; Karanth, 1995). A significant portion of conservation and research projects focus on managing protected species, requiring long-term spatial and temporal monitoring (Trolliet et al., 2014). Many current studies employing camera traps aim to estimate population densities (Kalle et al., 2011; Garrote et al., 2021; Oliveira-Santos et al., 2013) or simply confirm species presence in a given area (Gil-Sánchez et al., 2011; Gray et al., 2012; Liu et al., 2012).

Data analysis methods for camera trap studies are continuously evolving. Various population estimation methods without individual recognition are currently used, including:

- Time to Event Model (MTE) (Moeller, 2017)
- Random Encounter Model (REM) (Rowcliffe et al., 2008)
- Spatial Counts (SC) (Chandler & Andrew Royle, 2013; Evans & Rittenhouse, 2018; Howe et al., 2017)
- Random Encounter and Staying Time (REST) (Nakashima et al., 2018)
- A recent model considering species' space use (Luo et al., 2020; Palencia et al., 2022)

Most of these methods analyze encounter frequency but use different approaches. Some researchers estimate abundance within a clearly defined model area, accounting for the time and location of animal detections (Chandler & Andrew Royle, 2013). Others estimate density within the collective field of view (FOV) of cameras, assuming representativeness for the sampling framework (Rowcliffe et al., 2008).

A deeper theoretical comparison of unmarked population estimation methods was provided by Gilbert et al. (2020). However, an empirical comparison under field conditions is still lacking and remains in high demand (Palencia et al., 2022).

CHAPTER 3

RESEARCH METHOD AND MATERIALS

3.1 Research Location

The research conducted to estimate large mammal populations using camera trap methodology was carried out within the Rovina Exploitation perimeter in Hunedoara County and the Crasna and Valea Mare forested hydrographic basins in Prahova County (Figure 1).

The Rovina study area is located within hunting grounds number 9, named Rovina, and number 8, named După Piatră. Hunting ground number 9, Rovina, is managed by the Hunedoara County Hunters and Sport Fishermen Association (AJVPS Hunedoara), while hunting ground number 8, După Piatră, is managed by "AVPS Căprioara Vișca." Administratively, the study area falls within the jurisdiction of Bucureșci commune, covering a total area of 2,767.75 hectares.

The Crasna and Valea Mare hydrographic basins, covering approximately 5,600 hectares, are entirely included in hunting ground number 27, named Teleajen, managed by Transilvania University of Brașov. Administratively, the study area is located within the territorial units (U.A.T.) of Izvoarele and Măneciu.

The total area of the two basins is mainly covered by forest vegetation. The agricultural lands within these basins consist of pastures and orchards.

Research Site

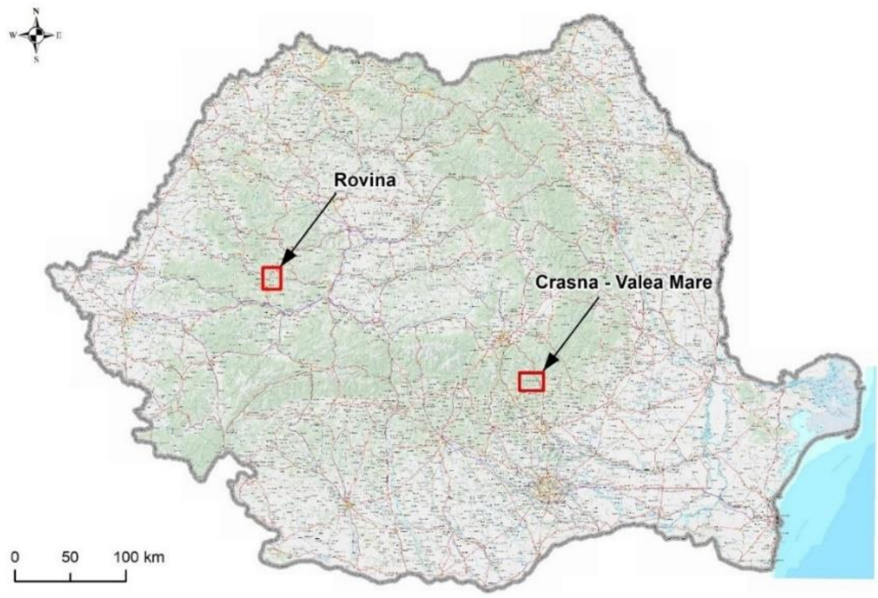

Figure 1. Location of the research areas

3.2 Establishing Comparative Estimation Methods for Large Mammal Populations in the Study Areas

3.2.1 Analyzed Fauna Species

The research within this doctoral thesis focused on large mammal species of hunting interest with high hunting and conservation value. In the Rovina area, due to the smaller research surface and the sampling scheme (500x500m), species of secondary hunting interest (e.g., roe deer) were also considered, as their daily activity range allowed for an integrated approach to estimation methods.

The species listed in Table 1, detailed in Appendix 1, were the subject of the doctoral research, with their densities estimated using different analytical methods to ensure calibration and obtain integrated results.

Table 1. Species included in the research

No.	Species
1	Wolf (*Canis lupus L.*)
2	Lynx (*Lynx lynx L.*)
3	Bear (*Ursus arctos L.*)
4	Red Deer (*Cervus elaphus L.*)
5	Wild Boar (*Sus scrofa L.*)
6	Roe Deer (*Capreolus capreolus L.*)

3.2.2 Sampling

For this doctoral research, population parameter estimation of the targeted game species was conducted using image capture (photo-trap camera) methods. Although advanced statistical methods for field data collection have significantly evolved (Burnham et al., 1980), estimating population sizes using a single technique introduces uncertainties and may lead to varied interpretations of the results. Thus, results obtained through image capture methods were compared with those obtained via presence sign analysis and direct species observation.

Differences in size between the two research areas and the species' ethology, combined with the need for comparative analysis of estimation methods, required different approaches in sampling grid size.

In the first phase of the study, a 500x500-meter grid was established in the Rovina area (Figure 2), while a 2000x2000-meter grid was used in the Crasna-Valea Mare area (Figure 3). Each transect was identified using a code based on grid intersection numbers to ensure data collection clarity and transparency. A maximum of 19 transects were determined in the Rovina area and 7 transects in the Crasna-Valea Mare area.

During the initial research phase, 16 transects in the Rovina area and 7 transects in the Crasna-Valea Mare area were surveyed to collect species presence indicators.

Research site sampling Rovina

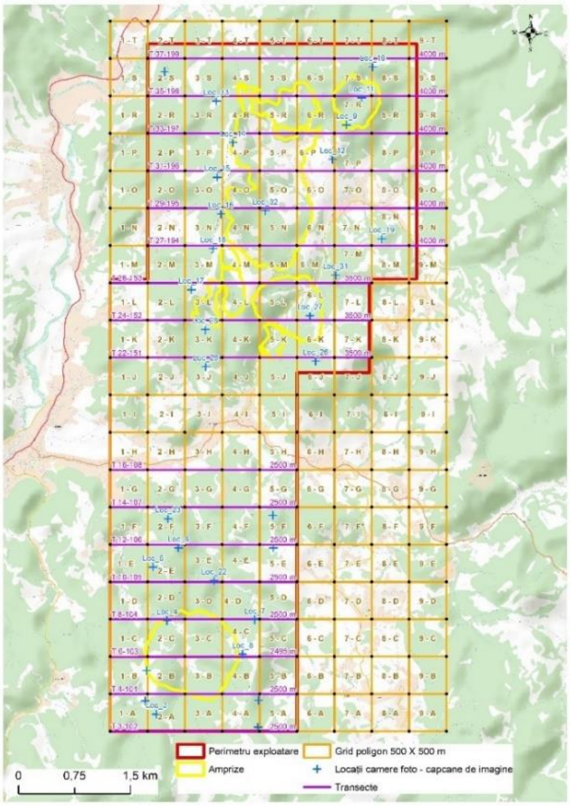

Figure 2. Sampling grid in the Rovina research

Research site sampling Crasna-Valea Mare

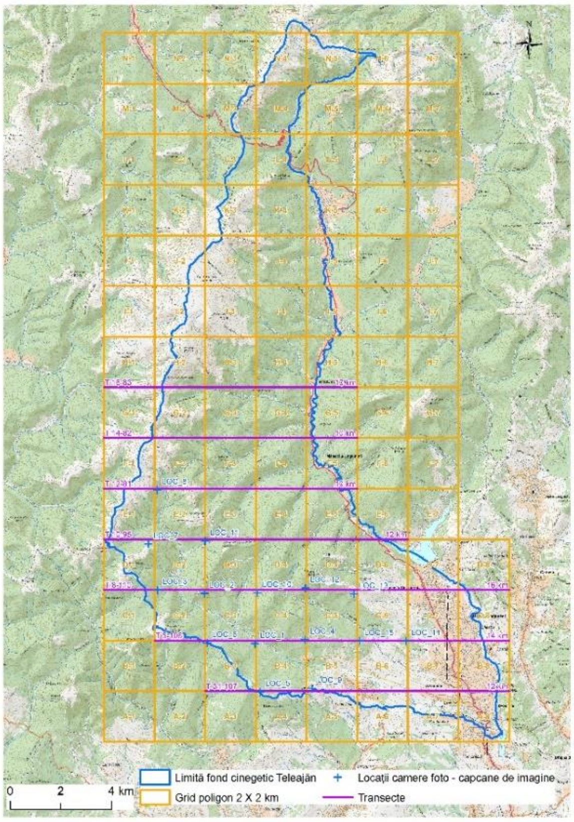

Figure 3. Sampling grid in the Crasna-Valea Mare

Transect surveys in the Rovina area took place in March under conditions that facilitated easy track identification, while those in the Crasna-Valea Mare area were conducted in March-April on an intermittent snow layer and soft ground.

In the second research phase, two camera traps were installed at each transect in the Rovina area. Camera trap installation points were pre-selected based on desktop analysis, prioritizing the highest-density locations of species presence signs within each transect.

For the Crasna-Valea Mare area, a different approach was used. At each grid intersection point, within a circular sample plot with a 130-meter radius centered on the grid intersection, at least two and at most three cameras were installed in locations with optimal visibility and lighting conditions, ensuring proper image capture and functionality of solar-powered equipment.

In the Rovina area, cameras were installed individually, with one camera per point, whereas in the Crasna-Valea Mare area, cameras were grouped: 2 cameras at 9 locations and 3 cameras at 6 locations. At sites with 2 or 3 cameras, installation ensured overlapping capture fields. Image capture periods differed between the two locations: October-December for Rovina and January-February for Crasna-Valea Mare, considering visibility and solar energy requirements for Bolly and Reolink cameras equipped with solar panels.

For the reference method, field data collection followed the guidelines in Annex 1 of Law 407/2006 for red deer, roe deer, and wild boar, as per Order 2847/2022 of the Ministry of Environment, Waters, and Forests. For protected species (bear, wolf, lynx) from Annex 2 of Law 407/2006, data collection was conducted following official Ministry directives (No. 147714/2022 and 50300/2023).

For red deer, roe deer, and wild boar, data collection involved both direct and indirect methods. Direct data collection took place from September to October within the research area: 7 rutting sites for red deer and 6 feeding points for wild boar. Indirect data collection was conducted in February by surveying 4 ridges and 4 valleys, each 7-15 km in length, as sample plots (Figure 4).

For wolf, lynx, and bear, data collection occurred year-round, focusing on presence signs, reproductive units, and direct observations. Data collection for wolf and lynx was conducted in February along the same ridges and valleys surveyed for red deer. Bear data collection was conducted via direct observation at feeding points for wild boar and cervids and indirectly through presence signs throughout the year.

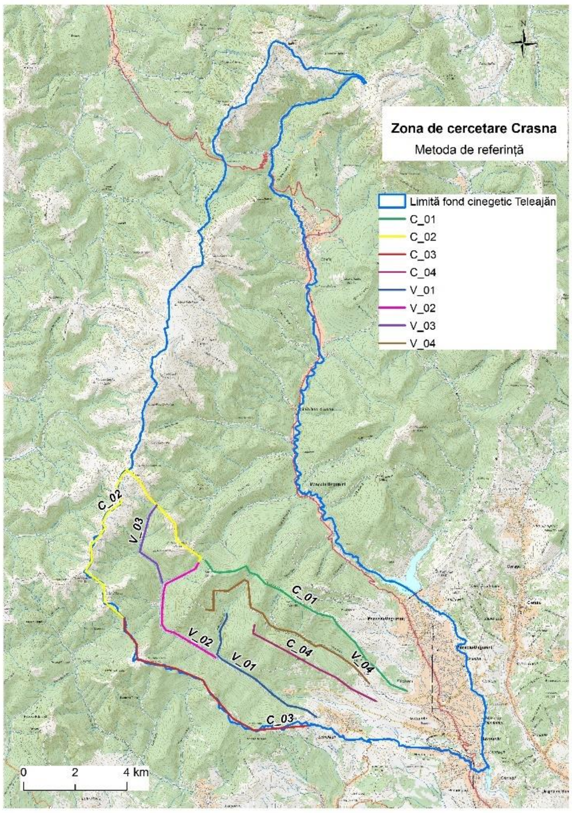

Figure 4. Sample plots for reference methods

3.2.3 Equipment Used

For the Rovina area, 32 ForestCam LS 870 camera traps were used. For the Crasna-Valea Mare area, 36 photo-trap cameras were deployed, including 15 ForestCam LS870 cameras, 15 Reolink cameras, and 6 Bolly cameras.

GPS devices used for field data collection were Trimble Juno S8. Data were downloaded using an HP Legion laptop. Field images were captured using mobile phone cameras from Samsung and Apple. Fieldwork transportation was provided by 4x4 vehicles, including Dacia Duster and Nissan Navara.

3.2.4. Data Collection Method from the Field

The installation of camera trap cameras was carried out by a team consisting of two operators, with the local capture perimeter chosen based on micro-orography elements (e.g., hunting trails) and support elements for the cameras. The camera trap cameras were placed in areas with maximum visibility and a very high probability of image capture. The installation was done on trees, secured with straps or screws, at variable heights ranging from 2.5 meters to 3 meters. The installation height was primarily dictated by the risk of the cameras being destroyed by bears and, secondly, by the potential for theft. For each installation point, a file was created in the GPS used, which mainly included the location number, coordinates, installation date, date of card change, number of cameras installed, guidance details, habitat details, etc.

Data collection from the cameras was done by changing the cards, downloading the images from these cards into a database, and for Forest Cam cameras, based on activity and energy consumption, the batteries were changed. For other camera models, where necessary, solar panels were repositioned to optimize battery charging. Data download was done in JPG File and MP4 File formats, using Windows 11 Pro extensions.

Data collection on transects was done using a Trimble Juno 38 GPS for each presence sign, an image was recorded, and the position was noted with the GPS. A file was created for each transect based on the identification code, with the data later being downloaded at the office using the Trimble GPS Pathfinder Office software. The data uploaded into the GPS for each recorded point described the species, presence sign name, quantity, habitat type, and, where applicable, the estimated number of individuals, either directly or indirectly.

Data collection using the reference method was carried out for the Crasna-Valea Mare research area, similar to the methodology applied in research at the Tinca Forest District (Bihor County) by traversing the evaluation trails during the periods recommended by the previously mentioned regulations. The data collection forms and summaries attached to the instructions and addresses from public authorities regarding the evaluation/estimation of populations of species of game or protected fauna were completed.

For red deer, data was collected directly and indirectly: directly - by listening to the calls of red deer in September; and indirectly - by reading tracks in the snow in February. For direct data collection, field visits were made 3 consecutive days, both in the morning and evening. An Observation Sheet type 2.0 was completed for each observation point, and at the end of the action, Summary Sheet type 2.1 was completed.

For roe deer, direct data was collected in July, during the rutting period, and indirect data was collected in February by reading snow tracks. For direct data collection, field visits were made 3 consecutive days, at dawn and sunset, and for each observation point, Observation Sheet type 3.0 was completed. At the end of the action, Summary Sheet 3.1 was completed.

Indirect data collection for both red deer and roe deer was done by walking the ridges and valleys previously established during the office phase, and the observation sheets type 2.2 and Summary Sheet 2.3 for red deer were completed, as well as Observation Sheet type 3.2 and Summary Sheet 3.3 for roe deer.

For wild boar, data was collected directly in February through observations at feeding points and indirectly by reading tracks in the snow. For each feeding point, Field Sheet type 5.0 was completed, and at the end of the action, Summary Sheet 5.1 was completed.

For bear, wolf, and lynx, indirect data collection was done by recording signs of presence by walking the ridges and valleys previously established in the office phase, in conjunction with the cervid evaluation activity. For bear, the data was collected directly through observations at feeding points for wild boar and cervids. For each day of observation, the Observation Sheet Annex 1A to letter 50300/2023 was completed, and all the data from the observation sheets was recorded in the Summary Sheet 2A from the same Ministry of Environment, Waters, and Forests letter.

3.2.5. Data Analysis and Interpretation Method

The data collected as part of the doctoral thesis were analyzed integrally to obtain results that would allow calibrations and methodological comparisons both within the studied areas and between the two zones studied, Rovina and Crasna-Valea Mare.

The analysis of the data collected at the transect level regarding species presence signs had two approaches. The first approach involved establishing correlations between species presence signs and forest habitat conditions, characterized by the quantifiable and structural elements from the forestry management plans. The second approach involved transforming them into probability densities, from points to continuous surfaces.

Thus, for the Crasna-Valea Mare area, a multivariate analysis was applied to data regarding the presence of game species (presence signs), correlated with various characteristics of the forest stands in the forest fund for understanding the interdependence of wildlife with its habitat. In this regard, a correlation matrix was used to highlight the relationships between multiple variables, followed by a Principal Component Analysis (PCA), a method recognized for its efficiency in reducing the dimension of complex data sets.

Information related to the forest fund was extracted from the forestry management database, specifically from the Forestry Management Plan of the forests where the observations on wildlife species presence were made. These data are essential as they characterize ecological and environmental conditions for species and reflect a range of interspecific relationships. In the analyzed data set, a scale of values was used to indicate the importance of variables, where a value of 1 denotes minimal importance, and higher values indicate corresponding importance. Several relevant elements were reviewed, including:

1. Presence of fauna through observations (Pz_fauna), where a value of 1 indicates minimal importance, and n indicates maximum importance;
2. Terrain altitude (ALT), where a value of 0 indicates minimal importance, and n indicates maximum importance;
3. Forest category (Cat_Pad), where value 1 (Conifers) indicates minimal importance, and 2 (Broadleaf) indicates maximum importance;
4. Production subunit (SUP), where Regular forest (A) has value 1, Protective forests (M) have value 2, and Gardened forest has value 3;

5. Terrain exposure (EXPOZITIE), with values: N, NE, NV have value 1; V has value 2; E, SE, SV have value 3, and S has value 4.
6. Terrain slope (INC), where the importance of values is determined based on the recorded value; for smaller slopes, the importance is higher, and vice versa.
7. Current forest type character (CRT_PAD), which characterizes the naturalness of forest ecosystems, with values: 1 - artificial forests, 2 - derived forests, and 3 - natural forests.
8. Litter (LITIERA), which characterizes the thickness of the leaf layer, with a value of 1 for minimum and 5 for maximum.
9. Stand structure (STR) has the following values: 1 - even-aged stand, 2 - relatively even-aged, 3 - relatively multi-aged stand, and 4 - multi-aged stand.
10. Stand consistency, expressed by crown closure degree (DNS), with values characterized by minimal importance for minimal values (1.0 and 0.9) and maximum for values 0.1 and 0.2.
11. Stand age (VRT), where small values have maximum importance and large values have minimal importance.
12. Works executed within the management unit (LCR_EXT), with the following values: 0 - no works, 1 - accidental works, 2 - thinning, 3 - clearing and cleaning, and 4 - semi-gardening and progressive cutting.
13. Main species in the stand (SP_PRINC_ARB), with values 1 - Fir and Spruce; 2 - Alder and Birch; 3 - Beech; and 4 - Hornbeam.
14. Stand volume (VOLUM), where a minimum value represents minimal importance, and a maximum value represents maximum importance.

The data analysis was performed according to the following stages and methods: To reduce the dimensionality of the data sets and obtain a more detailed visualization of relationships between variables, Principal Component Analysis (PCA) was used (Mudrov & Proch, 2005); (Greenacre et al., 2022). This method allowed for identifying the principal components that explain the most variance in the data, providing a clearer perspective on the structure of the data and correlations between variables.

The analysis was conducted using specific packages in the R programming environment via the R Studio application (R Core Team, 2025). The packages used include:

1. **corrr** (Kuhn, 2020): This package allowed for exploring correlations between variables, providing a solid foundation for understanding the relationships between species presence and stand characteristics.

2. **ggcorrplot** (Kassambara, 2022): This package was used for graphical visualization of correlation matrices, facilitating the visual interpretation of relationships between variables.

3. **FactoMineR** (Lê et al., 2008): This package was essential for performing factorial analysis and PCA, allowing data dimensionality reduction and identification of principal components.

4. **factoextra** (Kassambara & Mundt, 2020): This package was used to extract and visualize results from multivariate analyses, offering a clear graphical representation of principal components and data structure.

Specifically, PCA was applied to identify patterns and relationships between species presence and environmental variables. The use of R Studio (R Core Team 2019) allowed for efficient data management and integrated interpretation of complex data, providing the necessary tools for obtaining valuable insights.

For quantitative analysis of data collected at the transect level regarding species presence signs, ArcGIS geospatial analysis method was used, correlated with Kernel Density Estimation (KDE) for probability density estimation (species presence points gradually distributed over areas with continuous values reflecting their relative density in a specific territory).

For transforming species presence point data into polygon data, representing continuous surfaces, KDE was used for the two research areas (Rovina and Crasna - Valea Mare). The KDE method provides a non-parametric estimate of the underlying intensity function (Waller and Gotway, 2004). This method is widely used in various scientific fields, such as vegetation fire studies to identify fire occurrence patterns (Lorent et al., 2015; Lorent et al., 2018); wildlife ecology (Fleming & Calabrese, 2017); (FIEBERG, 2007), or crime incident analysis (Levine & Associates, 2013), ensuring a comprehensive representation of the analyzed area.

For applying the KDE method, field data (presence signs) collected on transects in the research zones were used, including the coordinates of the presence signs, the time of their collection, habitat type, and quantitative estimates. Through KDE, a continuous density was obtained starting from the fixed species presence points.

In KDE density analysis, bandwidth selection is crucial, often more important than choosing the kernel function (Kuter et al., 2011). This parameter determines the influence of each point in estimating density (distance of kernel influence around the point). The optimal bandwidth was determined by calculating the average distances to the N-th closest neighbor using the Calculate Distance Band from Neighbor Count algorithm in ArcGIS. This algorithm returns the minimum, maximum, and average distances to the N-th closest neighbor (N is an input parameter) for a set of entities. After several tests, the optimal value of neighboring points was identified by visual inspection and by considering 10%-20% of the total points in the study area for each species, proportional to their daily activity radius.

To treat observations consistently across different concentrations, a normal distribution kernel function with a fixed bandwidth was used, ensuring a standardized data management process for each research zone.

The mathematical equation underlying the KDE method for establishing probability density with two variables is:

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K \left\{ \frac{(x - X_i)}{h} \right\}$$

Where:

n - number of points (presence signs);

h - smoothing parameter (bandwidth);

K - kernel density function;

x - coordinate vector of the location where the function is estimated;

xi - coordinates of the points (presence signs).

The Kernel Density Estimation (KDE) method was used to transform species presence points into continuous surfaces with values reflecting their relative density in a specific territory. This method allows for estimating the spatial distribution of species based on a set of georeferenced points obtained from field data collected by traversing transects.

By applying KDE, each presence point is used to generate an influence area with a kernel function, gradually distributing density around each point, based on a search radius (bandwidth). The result is a probability density map of species presence points, with areas of higher point density represented by higher values, and areas with low presence or absence represented by lower values. Density probability maps were generated for each species and research area.

Data analysis from the cameras was carried out using two methods, both used in situations where individual identification of species captured in images is not possible.

The first method, the Random Encounter Method (REM), used in the data analysis of the doctoral thesis, calculates the density of the studied species based on the principle that individuals are captured randomly over a time interval and at a certain distance.

The second method, the N-mixture Method, used for data processing, has the ability to estimate species density based on the number of images captured and the detection probability. Thus, we used the REM and N-mixture methods to estimate the number of individuals in the studied area and correlated these estimates with the results of the reference method.

For managing and organizing images captured by camera traps, the "DigiKam" application was used, which, through the tools it provides, allowed the organization into distinct folders as well as labeling the captured images by species and number of individuals.

For the use of the processed metadata in R programming, the "imageRename" function was used to label the images based on their metadata. Later, with the "createSpeciesFolders" function, distinct folders were created and the images were organized into these folders.

The creation of the database used by the analysis functions in the R programming environment was done with the "recordTable" function. This organized database allowed data processing and the application of analysis methods.

The REM method uses images of animals captured by camera traps without the need for individual identification of the animals (Rowcliffe et al., 2008).

The REM method uses the following equation:

$$D = \frac{y}{t} \cdot \frac{\pi}{v \cdot r \cdot (2 + \theta)}$$

Where:
y - the number of records;
t - total survey effort;
v - daily activity radius;
r - camera detection radius;
θ - camera detection zone angle.

The number of records was considered to be the number of individuals in the captured images. The number of image captures used was determined by the total number of captures made at 120-second intervals.

The daily activity radius was determined using the procedure described by P. Palencia et al. (2021). Thus, the "trappingmotion" package from R (Palencia et al., 2022; Rowcliffe, 2019) was used to calculate the daily activity radius. For calculation between detections, the "dayrange" function was used, as well as the Haversine algorithm to calculate the distances between detections. To estimate the detection radius and angle, the procedure mentioned by J. M. Rowcliffe et al. (2011) was applied, using the Distance Sampling method to analyze the positions of individuals in the captured images. Errors in the activity radius, as well as the radius and angle of camera detection, were taken into account when calculating densities. The general variance of the density estimates was calculated using the delta method (Seber, 1982) and the R package "emdbook" (Bolker, 2019), as well as the R "camtools" functions.

The N-mixture method is accessible and relatively simple, relying on the use of relatively inexpensive camera traps within an appropriate sample, image sorting, animal identification, counting, and analysis of repeated records in an algorithm (Grant M. Harris et al., 2024).

For applying the N-mixture method, the R package 'unmarked' (Fiske & Chandler, 2011) was used, which is suitable for hierarchical models of abundance and detection of animals using camera traps deployed in a sample.

For data processing, using the "umf_abundance" function, a structured data framework was created, which includes identification history, altitude, and habitat type for each camera. The "pcount" function from the "unmarked" package was used to model the abundance of a species using the N-mixture model. This allowed the estimation of the actual number of animals in the studied area, considering imperfect detectability (the fact that not all animals present were detected by the camera traps).

The advantages of the REM method, besides not requiring individual identification, include its use in vast habitats and the fact that it does not require extremely rigorous data, thus reducing logistical effort. The limitation of the method is that the daily activity radius used in the calculation may be subject to errors.

The N-mixture method is based on detection probability, and the advantage is that by repeating the sampling, it corrects for detection errors. Like the REM method, it does not require individual identification and, in addition, can be applied to incomplete data (such as camera malfunction), with errors corrected through statistical modeling. The limitation of this method is related to logistics, where precision reflects the number of sampling repetitions, and it is also sensitive to changes in population sizes during the sampling repetitions.

Data analysis collected indirectly through the reference method was done by overlaying the temporal and spatial data collected from the 3 ridges and 4 valleys. At the end of each observation day, the data from the Observation Sheets were queried to avoid double counting, and the final data were recorded in standardized spreadsheets. The analysis of the directly collected data for each species was done through spatial and temporal comparison of records and individual recognition of individuals or herds. The data recorded in the Observation Sheets by observers at each observation point were analyzed integrally by the work teams, and the results were summarized daily in the standard spreadsheets.

The final data obtained through the processing of primary data collected throughout the year, directly or indirectly, during field trips, were harmonized and integrated into a database for the species of bear, wolf, and lynx.

Chapter 4

RESULTS AND DISCUSSIONS

4.1. Correlation Matrix and Principal Component Analysis for the Crasna-Valea Mare Research Area

4.1.1. Correlation Matrix and Principal Component Analysis for Red Deer

A) Results of using the correlation matrix for red deer (Cervus elaphus L.)

The correlation matrix analysis (Figure 5) for red deer (Pz_fauna) highlighted relationships between the species' presence and the studied forest characteristics. It is observed that the presence of cervids seems to be slightly influenced by certain environmental factors; however, these influences are not significant.

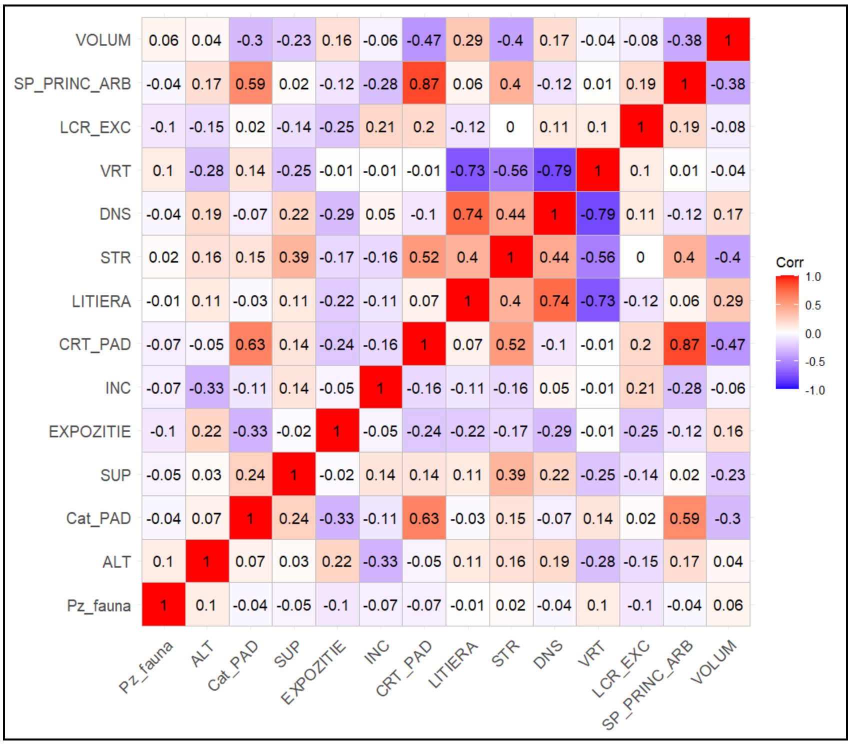

Figure 5. Correlation matrix for red deer in the Crasna-Valea Mare area

In conclusion, the presence of the red deer species (Cervus elaphus L.) is somewhat influenced by factors such as altitude (ALT), exposure (EXPOZITIE), and terrain slope (INC), as well as forest structure (VOLUM, DNS). These results suggest that the species is adaptable and can tolerate a variety of environmental conditions, with a slight preference for certain habitat characteristics.

Interpretation of PCA Analysis for Red Deer (Cervus elaphus L.)

b*) Results of using Principal Component Analysis (PCA) for red deer*

The Principal Component Analysis (PCA) method was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of red deer (Pz_fauna). The results of the PCA method are presented graphically in Figure 6.

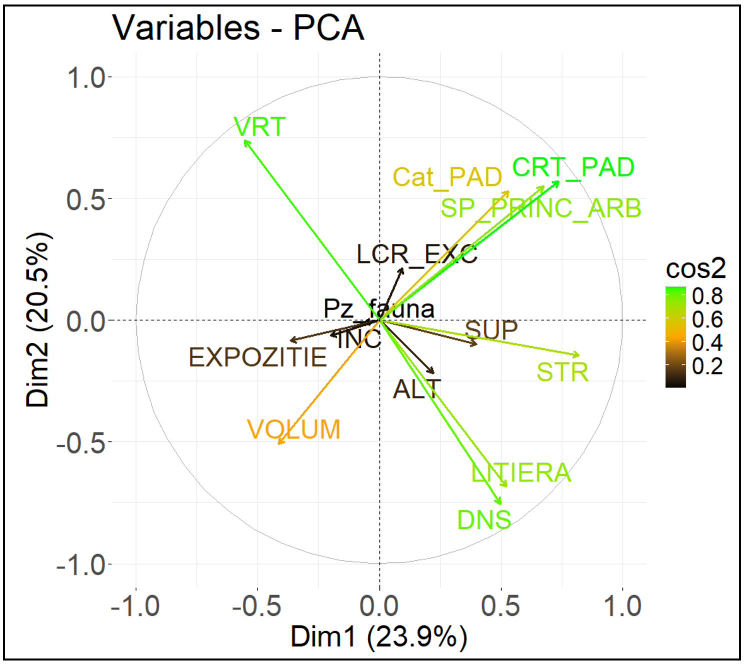

Figure 6. Principal Component Analysis for red deer in the Crasna-Valea Mare area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain the largest part of the variance in the data, with 23.9% and 20.5% of the total variance, respectively. Together, these two dimensions account for 44.4% of the total variance, indicating that they capture a significant portion of the information from the dataset. The subsequent dimensions, from Dim.3 to Dim.14, explain progressively less variance, each adding between 12.0% and 0.5% to the total variance. Cumulatively, all 14 dimensions explain 100% of the total variance.

In conclusion, the PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant portion of the variance in the data, with important contributions from variables such as CRT_PAD, STR, and DNS. The presence of cervids (Pz_fauna) is not strongly correlated with the first two principal components, suggesting that other factors, possibly not included in the analysis, may influence the species' distribution. Additionally, altitude (ALT) and density (DNS) seem to have a stronger influence on the subsequent components, indicating that these variables could play a more significant role in structuring the cervid habitat.

4.1.2. Correlation Matrix and Principal Component Analysis for Wild Boar

A) Results of using the correlation matrix for wild boar (Sus scrofa)

For wild boar, the correlation matrix analysis (Figure 7) for the species (Pz_fauna) highlighted relationships between the species' presence and the studied forest characteristics. The presence of wild boar seems to be slightly influenced by certain environmental factors, but the impact of these influences is minor/insignificant.

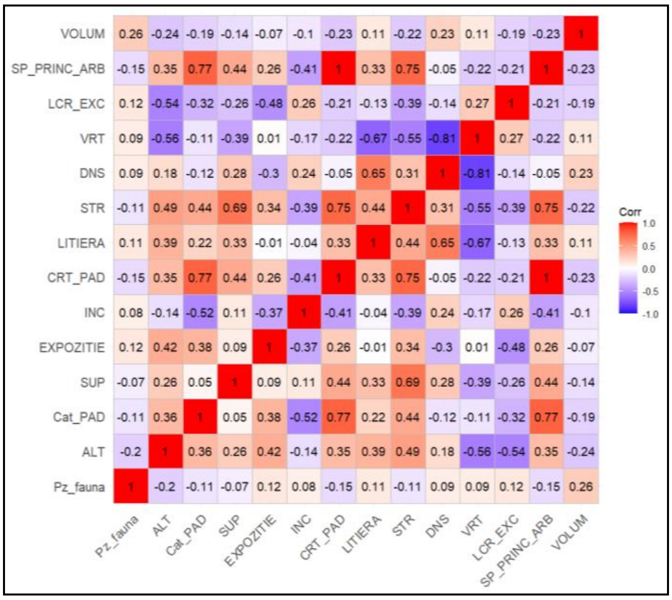

Figure 7. Correlation matrix for wild boar in the Crasna-Valea Mare area

Based on the results above, it can be said that the presence of the wild boar (Sus scrofa L.) is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only minor influences come from vegetation volume and forest density, but these are very weak. The preference for lower altitude areas is an observable factor, but it is not significant. In conclusion, the presence of wild boar (Sus scrofa) is somewhat influenced by forest volume and density, but these influences are minor. Other factors, possibly not included in the analysis, may play a more important role in the species' distribution.

Interpretation of PCA Analysis for Wild Boar (Sus scrofa L.)

B) Results of using Principal Component Analysis (PCA) for wild boar (Sus scrofa L.)

The Principal Component Analysis (PCA) method was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of wild boar (Pz_fauna). The PCA results are presented graphically in Figure 8.

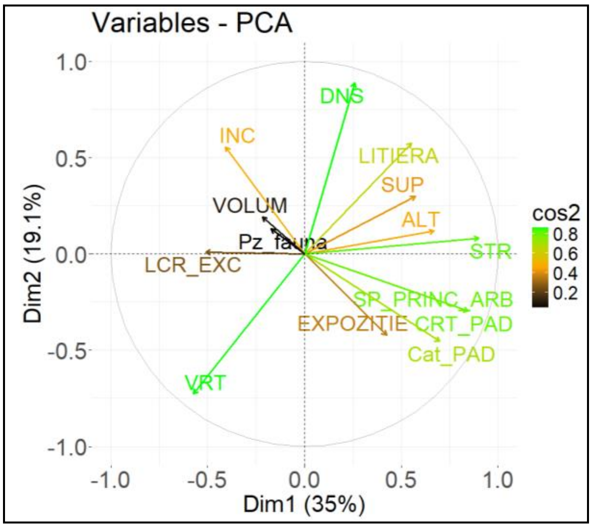

Figure 8. Principal Component Analysis for wild boar in the Crasna-Valea Mare area

Eigenvalues and Explained Variance

The PCA graphical analysis begins with the fact that Dim 1 always represents the direction in which the data have the highest variability (the vectors of the original variables are found in this direction), and Dim 2 is perpendicular to Dim 1 and explains the largest portion of the remaining variation. The first two dimensions, Dim.1 and Dim.2, explain the largest portion of the variance in the data, with 35.0% and 19.1% of the total variance, respectively. Together, these two dimensions account for 54.1% of the total variance, indicating that they capture a significant portion of the information from the dataset. The subsequent dimensions, from Dim.3 to Dim.14, explain progressively less variance, each adding between 11.1% and 0.0% to the total variance. Cumulatively, all 14 dimensions explain 100% of the total variance.

In conclusion, the PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant portion of the variance in the data, with important contributions from variables such as CRT_PAD, STR, and DNS. The presence of wild boar (Pz_fauna) is not strongly correlated with the first two principal components, suggesting that other factors, possibly not included in the analysis, may influence the species' distribution.

4.1.3. Correlation Matrix and Principal Component Analysis for Wolf

A) Results of using the correlation matrix for wolf (Canis lupus)

For the wolf, the correlation matrix analysis (Figure 9) for the species (Pz_fauna) highlighted relationships between the species' presence and the studied forest characteristics. The presence of the wolf seems to be slightly influenced by certain environmental factors.

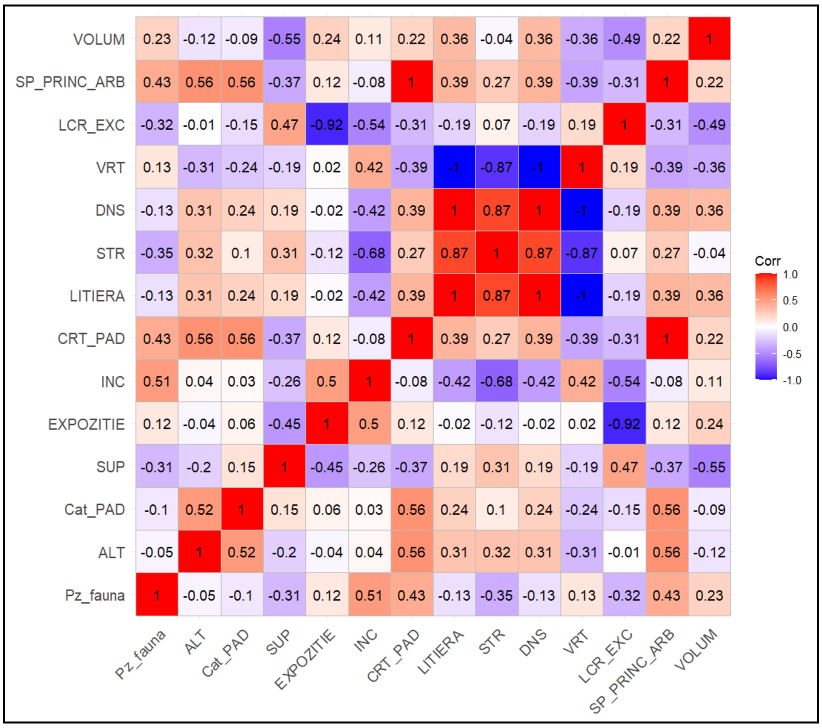

Figure 9. Correlation matrix for wolf in the Crasna-Valea Mare area

The presence of the wolf (Canis lupus L.) is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only minor influences come from terrain slope and vegetation volume, but these are moderate or weak. The preference for areas with more pronounced slope is an observable factor, but it is not significant.

In conclusion, the presence of the wolf (Canis lupus L.) is somewhat influenced by terrain slope and vegetation volume, but these influences are moderate or weak. Other factors, possibly not included in the analysis, may play a more important role in the species' distribution.

Interpretation of PCA Analysis for Wolf (Canis lupus L.)

B) Results of using Principal Component Analysis (PCA) for wolf (Canis lupus L.)

The Principal Component Analysis (PCA) method was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of wolf (Pz_fauna). The PCA results are presented graphically in Figure 10.

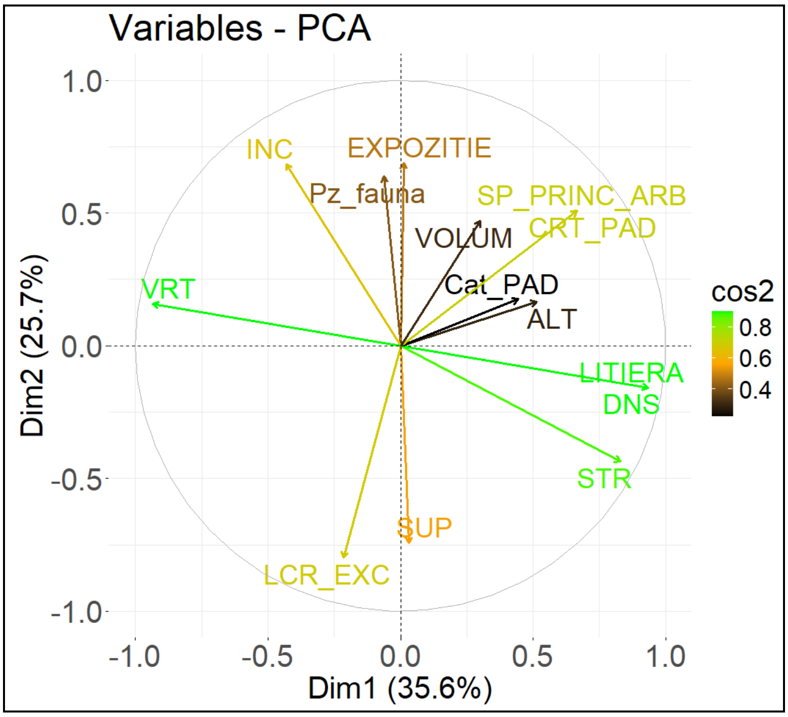

Figure 10. Principal Component Analysis for wolf in the Crasna-Valea Mare area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain the largest portion of the variance in the data, with 35.6% and 25.7% of the total variance, respectively. Together, these two dimensions account for 61.3% of the total variance, indicating that they capture a significant portion of the information from the dataset. The subsequent dimensions, from Dim.3 to Dim.10, explain progressively less variance, each adding between 14.2% and 0.0% to the total variance. Cumulatively, all 10 dimensions explain 100% of the total variance.

In conclusion, the PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant portion of the variance in the data, with important contributions from variables such as CRT_PAD, STR, DNS, and LITIERA. The presence of the wolf (Pz_fauna) is not strongly correlated with the first two principal components, suggesting that other factors, possibly not included in the analysis, may influence the species' distribution.

4.1.4. Correlation Matrix and Principal Component Analysis for the Lynx

A) Results of the Correlation Matrix for the Lynx Species (Lynx lynx L.)

For the lynx, the analysis of the correlation matrix (Figure 11) for the species (Pz_fauna) revealed relationships between the presence of this species and the characteristics of the studied forest. The presence of lynx individuals seems to be influenced to a small extent by certain environmental factors, although these influences are not strong.

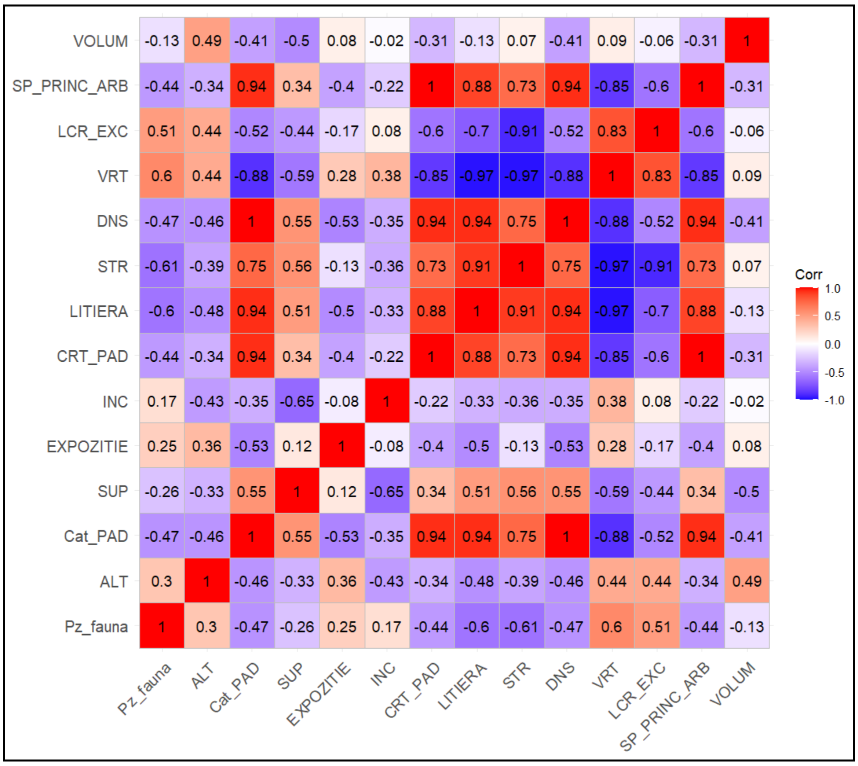

Figure 11. Correlation Matrix for the Lynx in the Crasna-Valea Mare Area

The presence of lynx individuals is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only significant influences come from the age of the forest and vegetation density, with moderate correlations. A preference for higher altitude areas is a slightly observable factor but is not significant.

In conclusion, the presence of lynx individuals (Lynx lynx L.) is influenced to some extent by the age of the forest and vegetation density, but these influences are moderate. Other factors, possibly not included in the analysis, could play a more important role in the distribution of this species.

Interpretation of PCA Analysis for the Lynx (Lynx lynx L.)

B) Results of the Principal Component Analysis (PCA) for the Lynx (Lynx lynx L.)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of the lynx species (Pz_fauna). The PCA results are shown graphically in Figure 12.

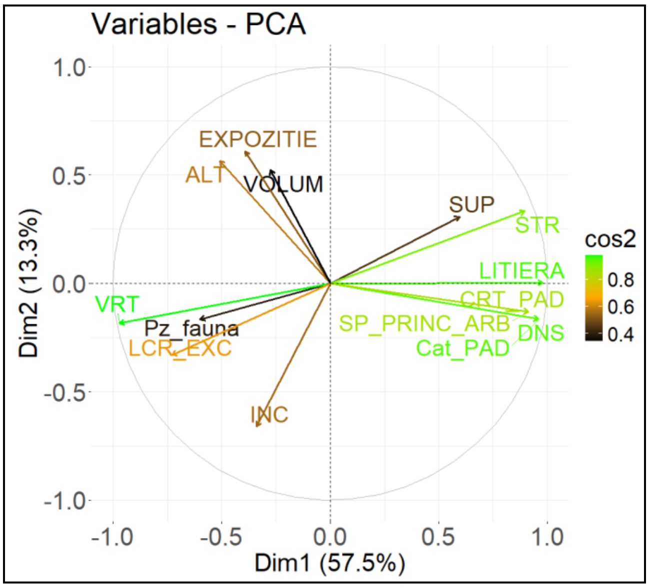

Figure 12. Principal Component Analysis for the Lynx in the Crasna-Valea Mare Area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain most of the variance in the data, with 57.5% and 13.3% of the total variance, respectively. Together, these two dimensions account for 70.9% of the total variance, indicating that they capture a significant part of the information from the dataset. Subsequent dimensions, from Dim.3 to Dim.6, progressively explain less variance, each adding between 11.1% and 3.1% to the total variance. Together, all six dimensions explain 100% of the total variance.

The PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant part of the variance in the data, with important contributions from variables such as Cat_PAD, DNS, LITIERA, and STR. The presence of lynx individuals (Pz_fauna) has a moderate influence on the first principal component, suggesting that this variable is relevant for understanding the distribution of the species.

In conclusion, PCA provided a comprehensive perspective on the relationships between environmental variables and the presence of lynx individuals, highlighting the importance of certain factors in shaping the species' habitat.

4.1.5. Correlation Matrix and Principal Component Analysis for the Brown Bear

A) Results of the Correlation Matrix for the Brown Bear Species (Ursus arctos L.)

For the brown bear, the analysis of the correlation matrix (Figure 13) for the species (Pz_fauna) revealed relationships between the presence of this species and the characteristics of the studied forest. The presence of the brown bear seems to be influenced to a small extent by certain environmental factors, although these influences are not strong.

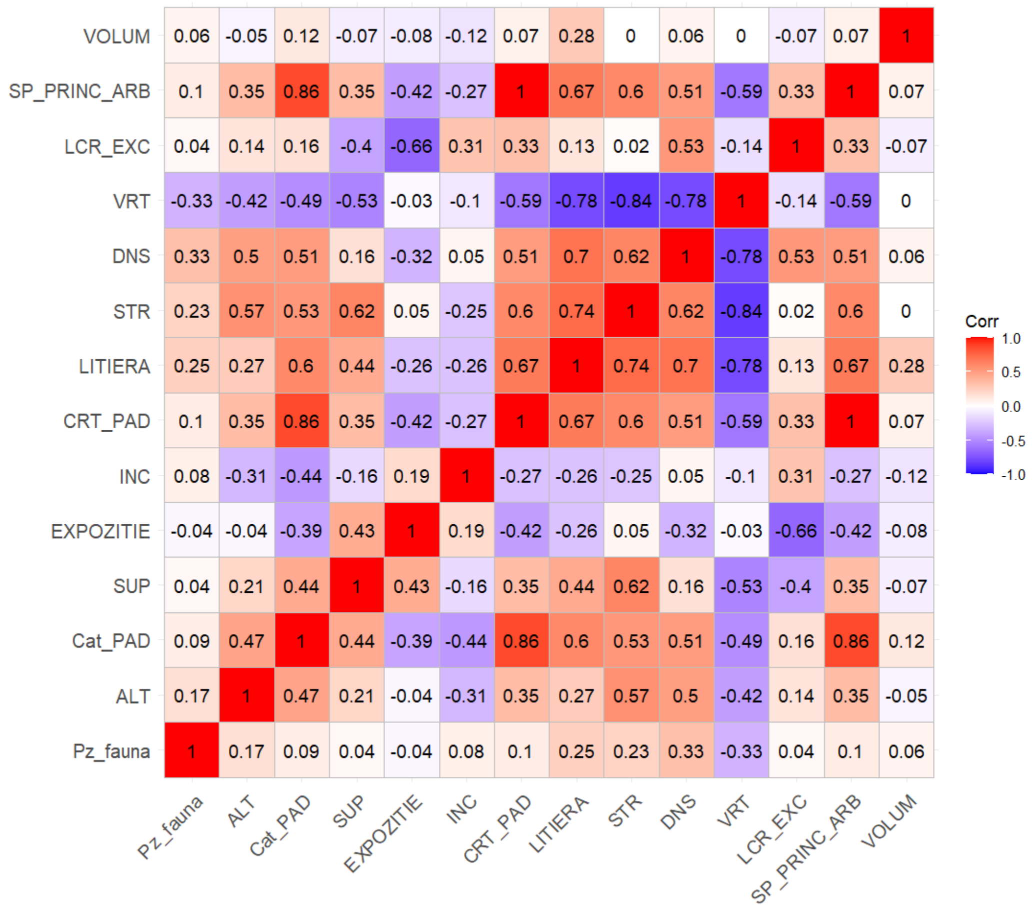

Figure 13. Correlation Matrix for the Brown Bear in the Crasna-Valea Mare Area

In conclusion, the presence of the brown bear (Ursus arctos L.) is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only minor influences come from vegetation density and forest age, but these are weak. A preference for areas with higher density is a slightly observable factor but is not significant.

Interpretation of PCA Analysis for the Brown Bear (Ursus arctos L.)

B) Results of the Principal Component Analysis (PCA) for the Brown Bear (Ursus arctos L.)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of the brown bear species (Pz_fauna). The PCA results are shown graphically in Figure 14.

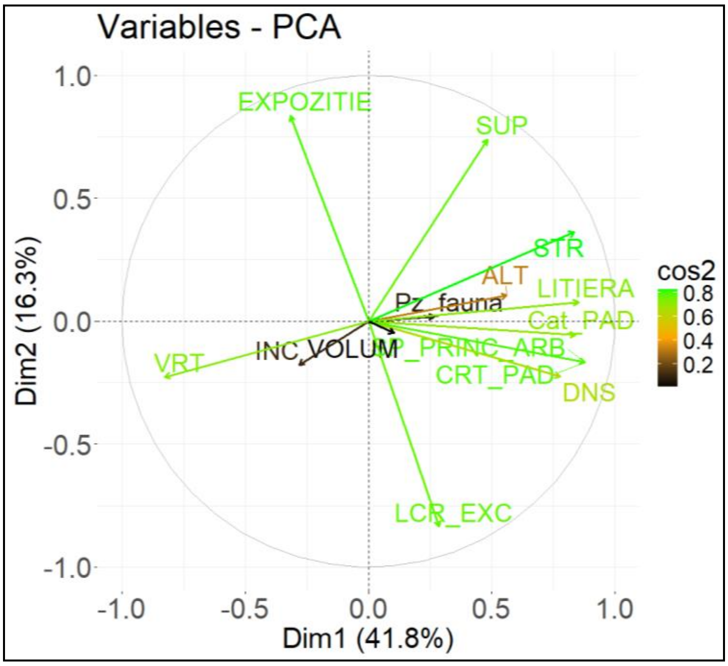

Figure 14. Principal Component Analysis for the Brown Bear in the Crasna-Valea Mare Area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain most of the variance in the data, with 41.8% and 16.3% of the total variance, respectively. Together, these two dimensions account for 58.1% of the total variance, indicating that they capture a significant part of the information from the dataset. Subsequent dimensions, from Dim.3 to Dim.14, progressively explain less variance, each adding between 11.9% and 0.0% to the total variance. Together, all fourteen dimensions explain 100% of the total variance.

In conclusion, the PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant part of the variance in the data, with important contributions from variables such as CRT_PAD, LITIERA, STR, and DNS. The presence of the brown bear (Pz_fauna) has a reduced influence on the first principal component, suggesting that this variable is not strongly correlated with the first principal components.

4.1.6. Correlation Matrix and Principal Component Analysis for the Roe Deer

A) Results of the Correlation Matrix for the Roe Deer Species (Capreolus capreolus L.)

For the roe deer, the analysis of the correlation matrix (Figure 15) for the species (Pz_fauna) revealed relationships between the presence of this species and the characteristics of the studied forest. The presence of the roe deer seems to be influenced to a small extent by certain environmental factors, although these influences are not strong.

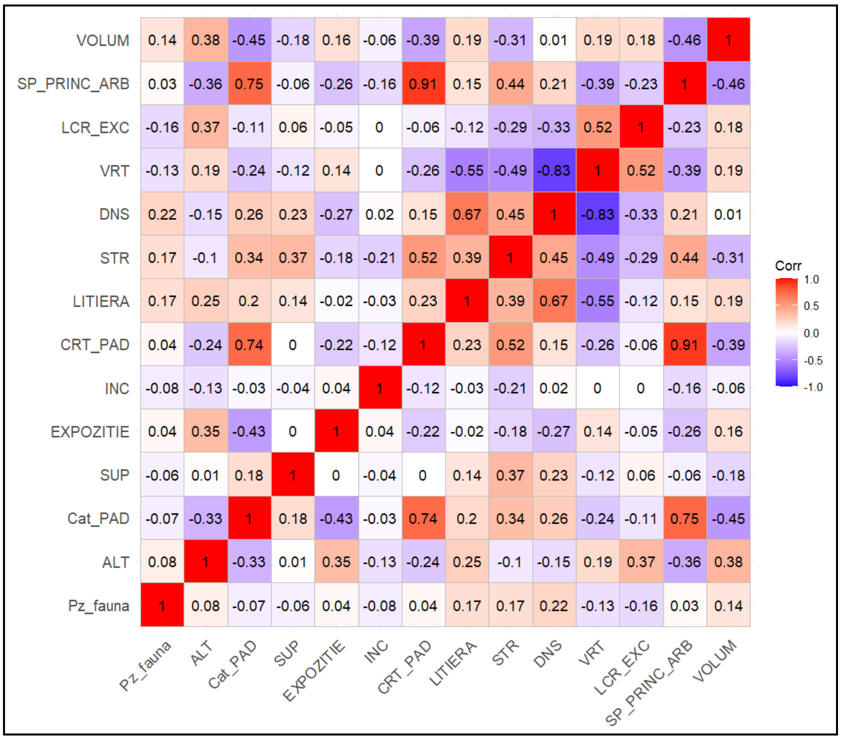

Figure 15. Correlation Matrix for the Roe Deer in the Crasna-Valea Mare Area

In conclusion, the presence of the roe deer (Capreolus capreolus L.) is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only minor influences come from vegetation volume and forest density, but these are weak. A preference for areas with higher density is a slightly observable factor but is not significant.

Interpretation of PCA Analysis for the Roe Deer (Capreolus capreolus L.)

B) Results of the Principal Component Analysis (PCA) for the Roe Deer (Capreolus capreolus L.)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and identify significant patterns and relationships between environmental variables and the presence of the roe deer species (Pz_fauna). The PCA results are shown graphically in Figure 16.

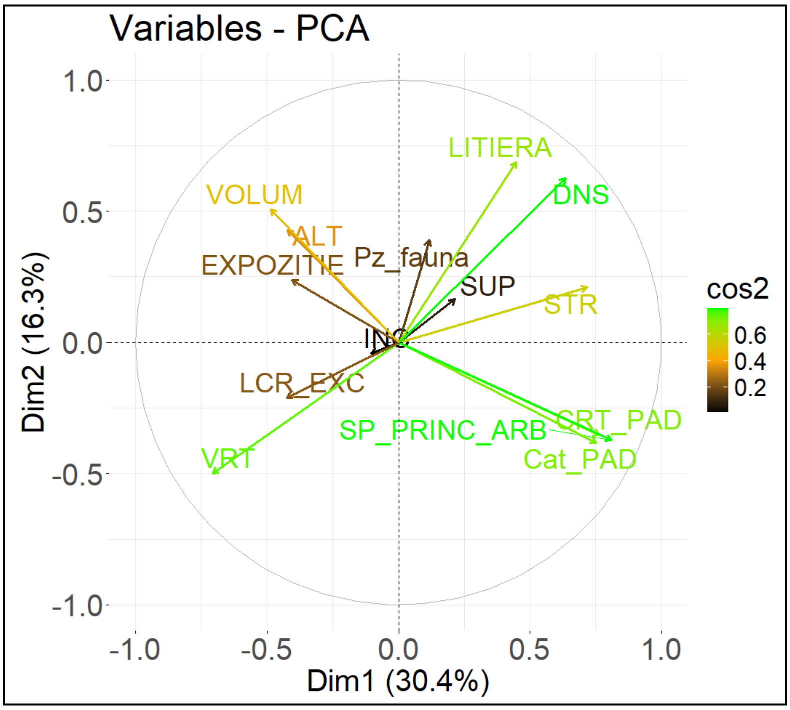

Figure 16. Principal Component Analysis for the Roe Deer in the Crasna-Valea Mare Area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain most of the variance in the data, with 30.4% and 16.3% of the total variance, respectively. Together, these two dimensions account for 46.7% of the total variance, indicating that they capture a significant part of the information from the dataset. Subsequent dimensions, from Dim.3 to Dim.14, progressively explain less variance, each adding between 10.5% and 0.3% to the total variance. Together, all fourteen dimensions explain 100% of the total variance.

In conclusion, PCA provided a comprehensive perspective on the relationships between environmental variables and the presence of the roe deer, highlighting the importance of certain factors in shaping the species' habitat.

4.2. Correlation Matrix and Principal Component Analysis for the Rovina Research Area

4.2.1. Correlation Matrix and Principal Component Analysis for Roe Deer

B) Results of Principal Component Analysis (PCA) for Roe Deer (Capreolus capreolus L.)

For roe deer, the correlation matrix analysis (Figure 17) for the species (Pz_fauna) in the Rovina area highlighted relationships between the presence of this species and the characteristics of the studied forest. The presence of roe deer appears to be slightly influenced by certain environmental factors, although these influences are not strong.

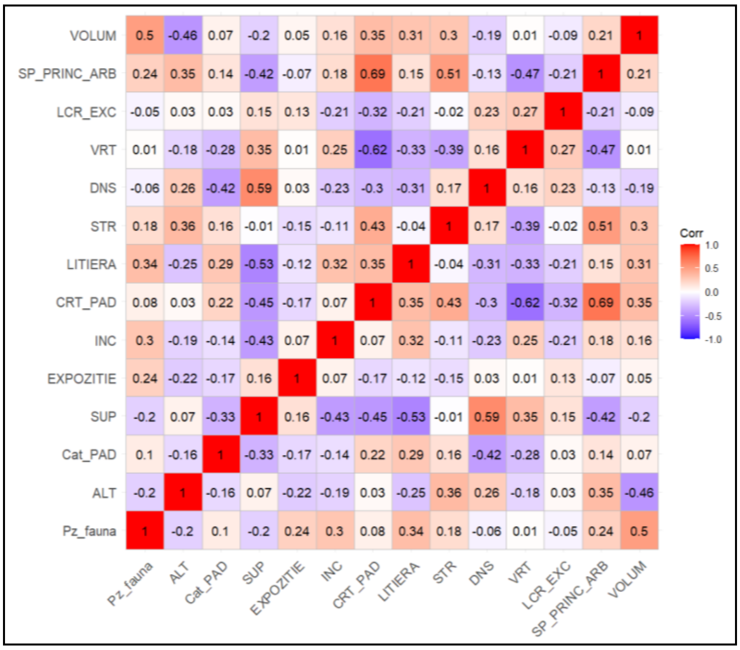

Figure 17. Correlation matrix for roe deer in the Rovina area in the Crasna-Valea Mare region

The presence of roe deer in the Rovina area is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only significant influences come from vegetation volume and terrain slope, with moderate correlations. A preference for areas with a higher volume of vegetation is a slightly observable factor, but it is not significant.

In conclusion, the presence of roe deer in the Rovina area is somewhat influenced by vegetation volume and terrain slope, but these influences are moderate. Other factors, possibly not included in the analysis, could play a more important role in the distribution of this species.

Interpretation of PCA for Roe Deer (Capreolus capreolus L.)

B) Results of Principal Component Analysis (PCA) for Wild Boar (Sus scrofa)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and to identify significant patterns and relationships between environmental variables and the presence of roe deer (Pz_fauna) in the Rovina area. The results of the PCA are presented graphically in Figure 18.

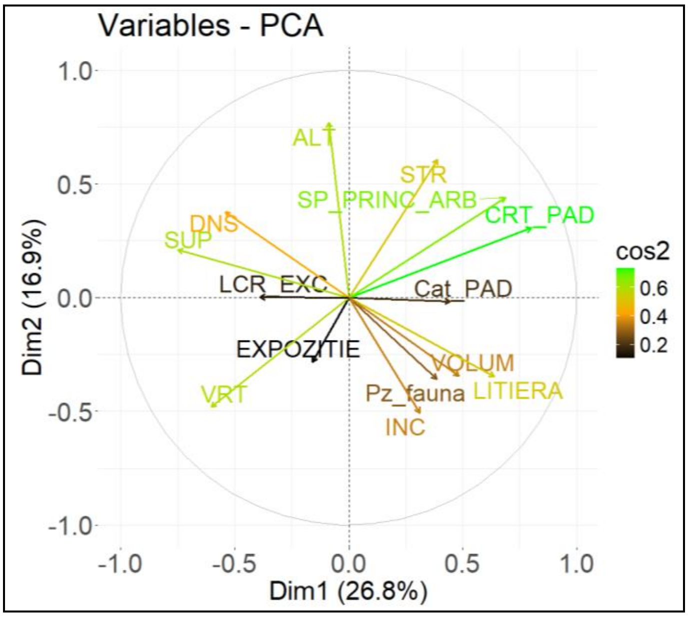

Figure 18. Principal Component Analysis for roe deer in the Rovina area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain the largest portion of the variance in the data, with 26.8% and 16.9% of the total variance, respectively. Together, these two dimensions account for 43.7% of the total variance, indicating that they capture a significant part of the information in the dataset. The subsequent dimensions, from Dim.3 to Dim.14, explain progressively less variance, each adding between 11.6% and 0.6% to the total variance. Cumulatively, all 14 dimensions explain 100% of the total variance.

In conclusion, PCA provided a comprehensive view of the relationships between environmental variables and the presence of roe deer, highlighting the importance of certain factors in structuring the species' habitat in this area.

4.2.2. Correlation Matrix and Principal Component Analysis for Wild Boar

A) Results of the Correlation Matrix Analysis for Wild Boar (Sus scrofa)

For wild boar, the correlation matrix analysis (Figure 19) for the species (Pz_fauna) highlighted relationships between the presence of this species and the characteristics of the studied forest. The presence of wild boar appears to be slightly influenced by certain environmental factors, although these influences are not strong.

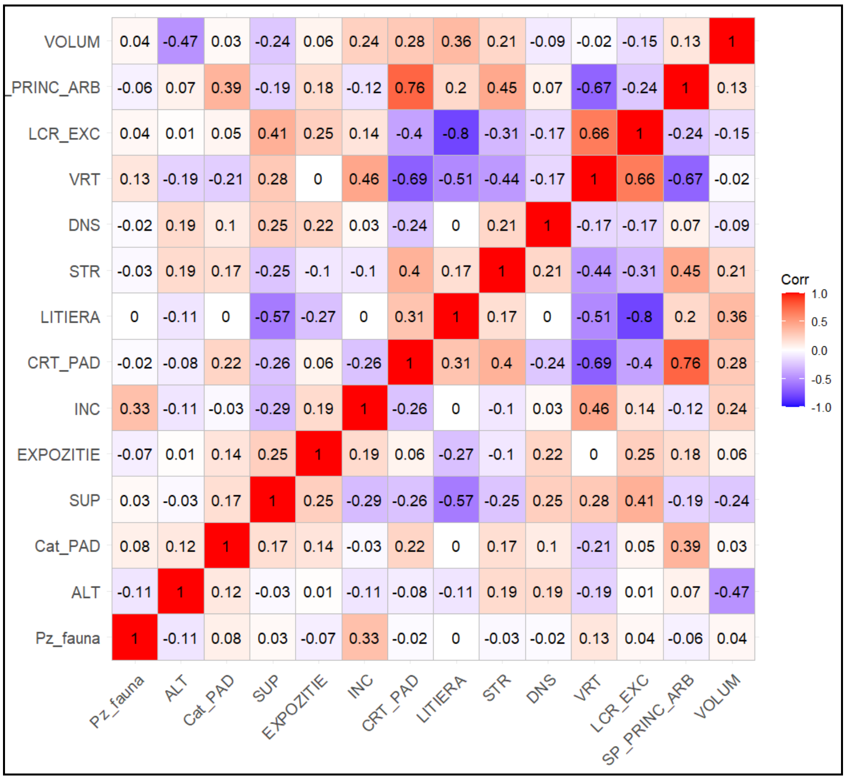

Figure 19. Correlation matrix for wild boar in the Rovina area

The presence of wild boar is not strongly correlated with most of the forest characteristics analyzed in this correlation matrix. The only minor influences come from terrain slope, but this is moderate. A preference for areas with a more pronounced slope is a slightly observable factor, but it is not significant.

In conclusion, the presence of wild boar is somewhat influenced by terrain slope, but this influence is moderate. Other factors, possibly not included in the analysis, could play a more important role in the distribution of this species.

Interpretation of PCA for Wild Boar (Sus scrofa)

B) Results of Principal Component Analysis (PCA) for Wild Boar (Sus scrofa)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the data and to identify significant patterns and relationships between environmental variables and the presence of wild boar (Pz_fauna). The results of the PCA are presented graphically in Figure 20.

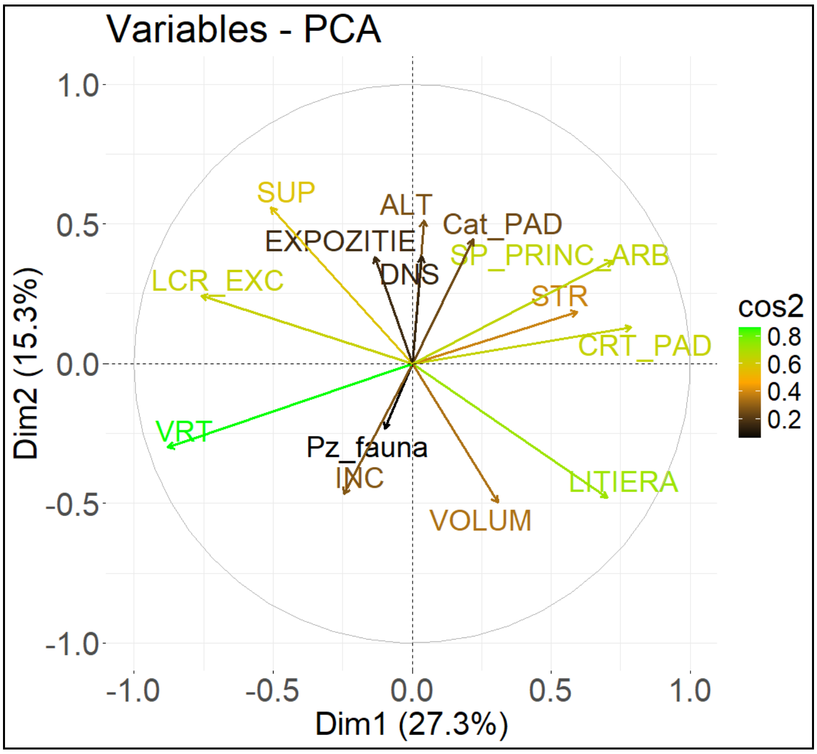

Figure 20. Principal Component Analysis for wild boar in the Rovina area

Eigenvalues and Explained Variance

The first two dimensions, Dim.1 and Dim.2, explain the largest portion of the variance in the data, with 27.3% and 15.3% of the total variance, respectively. Together, these two dimensions account for 42.6% of the total variance, indicating that they capture a significant part of the information in the dataset. The subsequent dimensions, from Dim.3 to Dim.14, explain progressively less variance, each adding between 12.0% and 0.5% to the total variance. Cumulatively, all 14 dimensions explain 100% of the total variance.

PCA analysis highlighted that the first two principal components (Dim.1 and Dim.2) explain a significant part of the variance in the data, with important contributions from variables such as CRT_PAD, LITIERA, SUP, and EXPOZITIE. The presence of wild boars (Pz_fauna) has a reduced influence on the first principal component, suggesting that this variable is not strongly correlated with the first principal components.

In conclusion, PCA provided a comprehensive view of the relationships between environmental variables and the presence of wild boar, highlighting the importance of certain factors in structuring the species' habitat.

4.3. Probability Density using the Kernel Density Estimation (KDE) Method for the Crasna-Valea Mare Research Area

For the red deer (Cervus elaphus L.), the probability density (Figure 21) provides a view of the spatial distribution of the species in the research area, calculated based on the signs of presence.

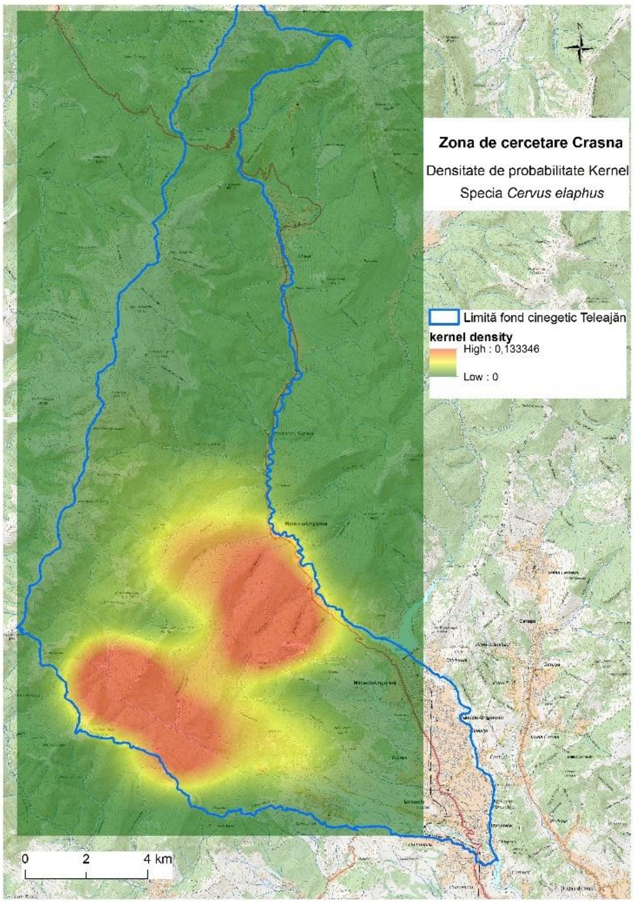

Figure 21. Probability density for red deer in the Crasna area

The red areas with high density represent areas with a high concentration of red deer, favored by the habitat conditions. Two important presence areas are identified: the northeastern and the southwestern areas. Food sources generated by regeneration treatments, as well as shelter conditions provided by rocky areas and thickets, are the main elements characterizing these high-density areas.

The yellow areas with moderate density represent transition zones and secondary habitats. It can be observed that the red deer population in the two studied basins prefers a specific communication area in the central zone. The green areas in the Crasna-Valea Mare research area represent areas with sporadic presence, generally limited by habitat conditions and human presence.

For the wild boar (Sus scrofa L.), the probability density (Figure 22) suggests grouping into three distinct zones with very low connectivity.

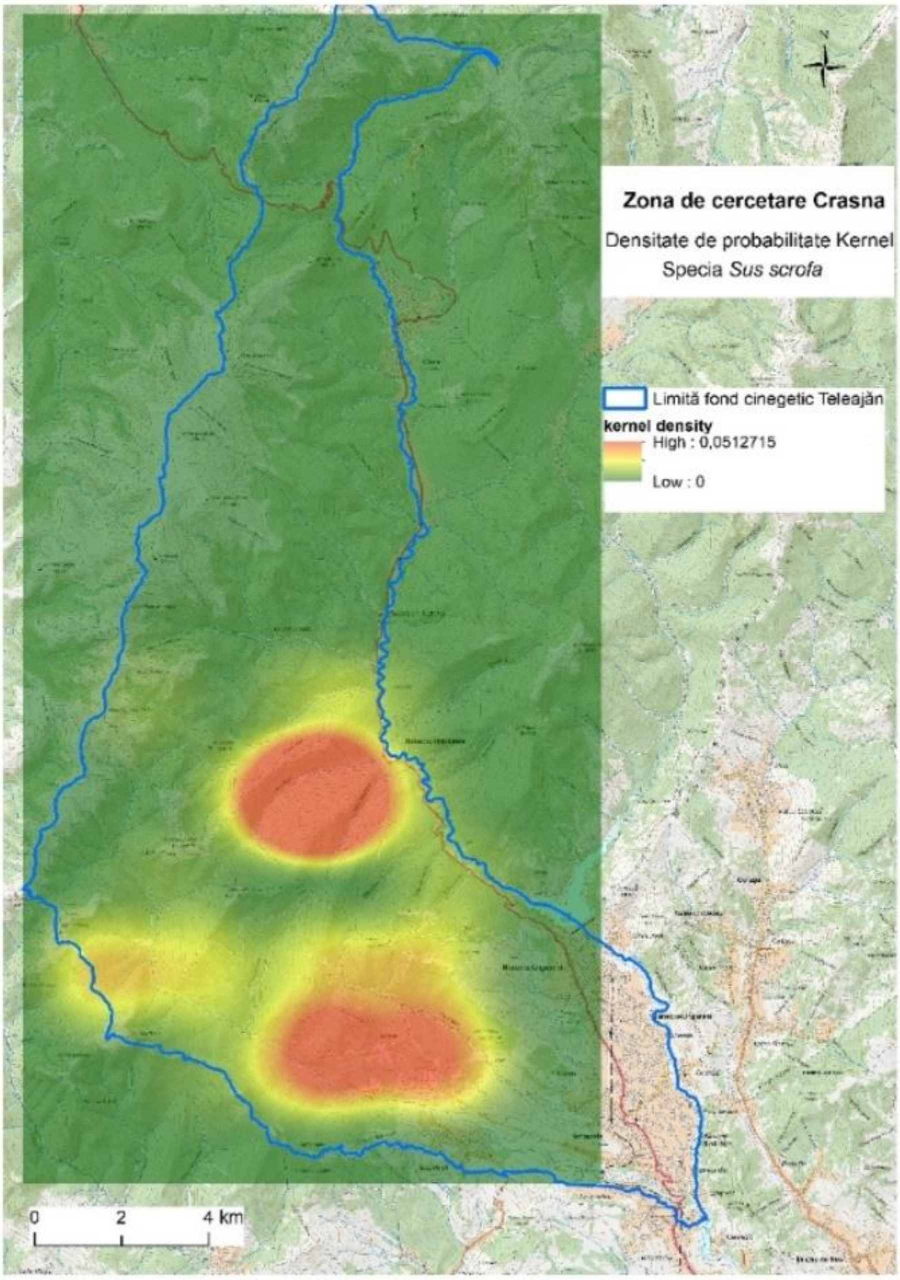

Figure 22. Probability density for wild boar in the Crasna area

The red areas with high density are distinctly distributed across the research area, represented graphically in the northeast, central, and western parts. Wild boar tend to group in areas with the best habitat conditions, providing both food sources and shelter. The grouping into almost three distinct zones provides an explanation for the species' behavior in the current African swine fever (ASF) hotspot conditions. The isolation of remaining wild boar populations is one of the conclusions that can be drawn from this graphical representation related to the species' behavior.

For the wolf (Canis lupus), the probability density (Figure 23) confirms predator-prey relationships.

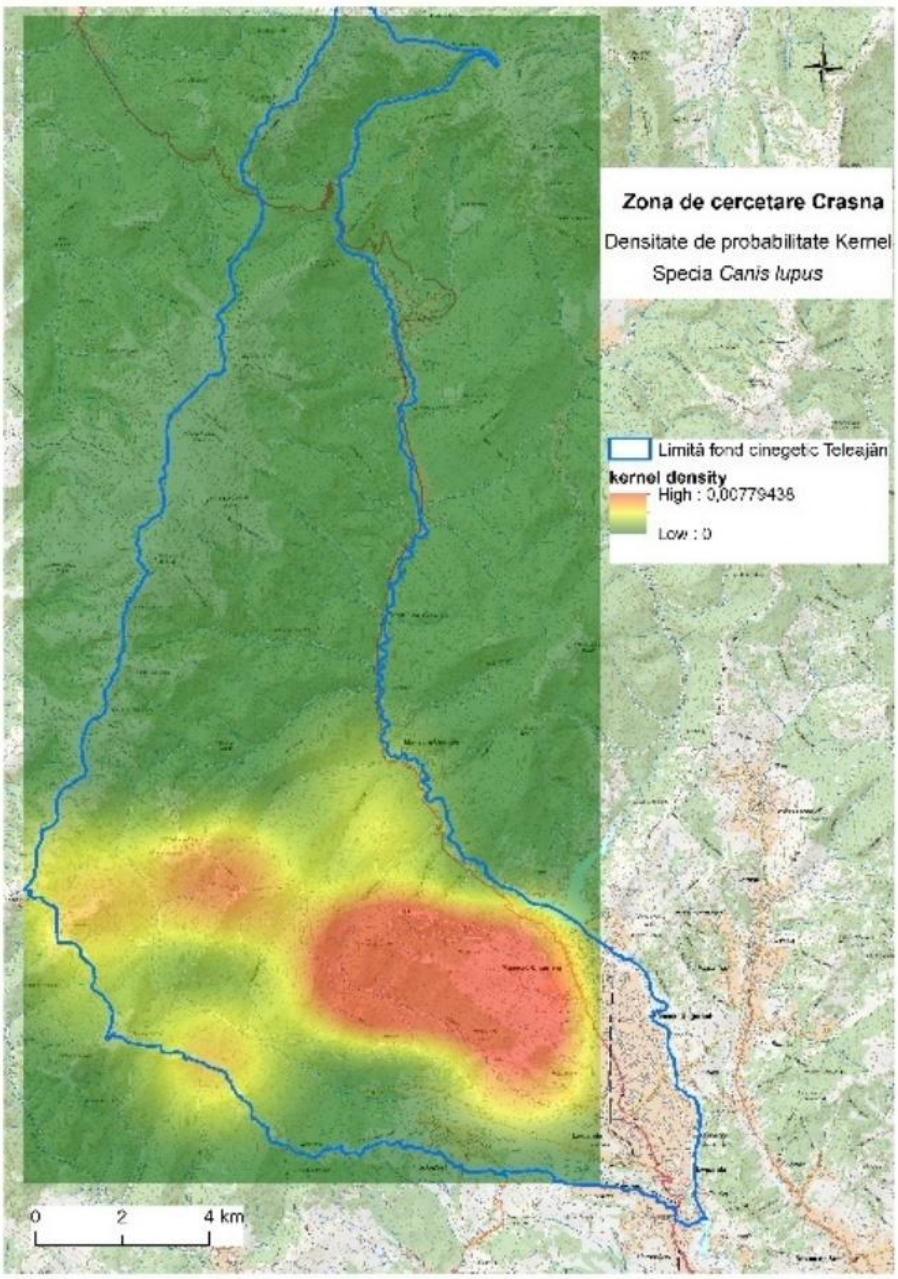

Figure 23. Probability density for wolf in the Crasna area

The overlap of the red zones, partially or fully, with those of the red deer and wild boar suggests a healthy ecosystem, with moderate relationships and pressures between predators and prey species. Another aspect that can be highlighted is the relationship between the species and human activity, including grazing and the management of stray dogs. From the graphical representation, it is evident that the species has a higher density in the border area of Măneciu locality and the national road DN1A, near parking areas and stray dogs.

For the lynx (Lynx lynx), the probability density (Figure 24) confirms field observations.

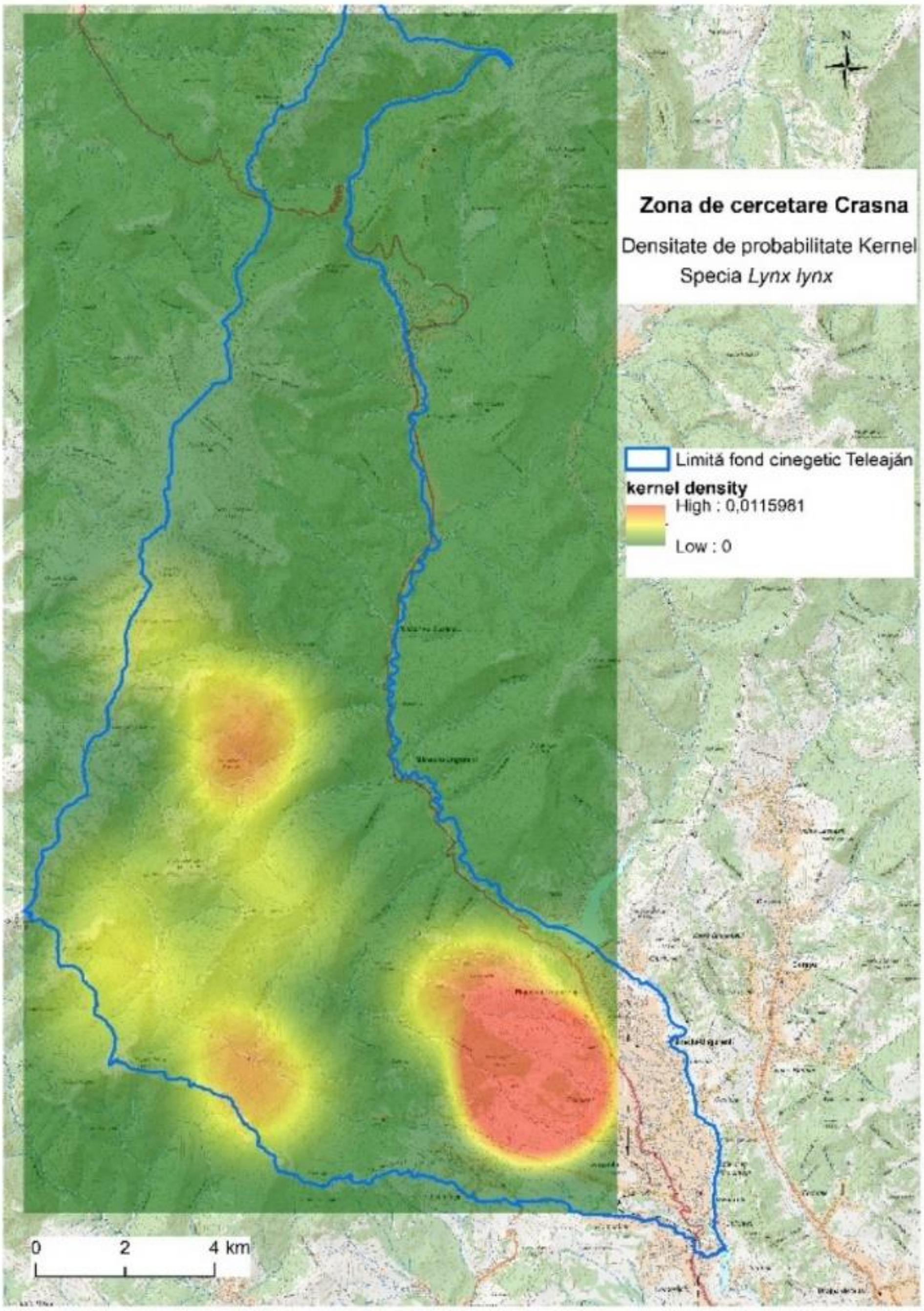

Figure 24. Probability density for lynx in the Crasna area

The pronounced red area in the southeast is the activity zone of a juvenile female, with typical prey habitats such as hares and mice, characterized by pastures and forests in age classes I and II. The other red areas with high density reflect the territory of an adult individual, while the yellow zones complete these territories by confirming moderate presences.

For the brown bear (Ursus arctos), the probability density (Figure 25) reflects the high density of the species in the research area.

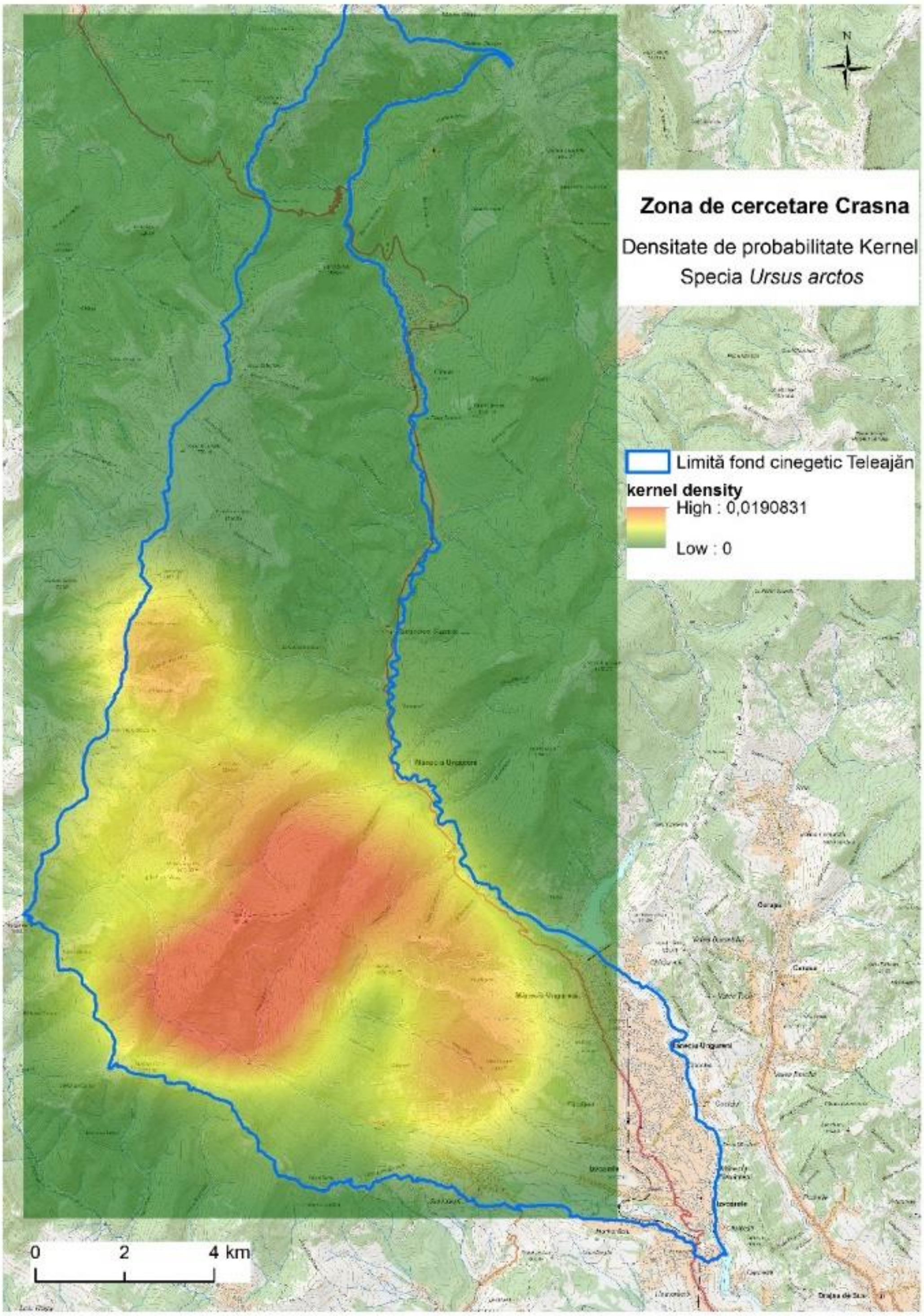

Figure 25. Probability density for brown bear in the Crasna area

The pronounced red zone, with high density, in the central part of the studied perimeter is characterized by areas favorable for the species, such as rocky areas, thickets, and forests in advanced age classes with regeneration works. The yellow zones with moderate presence cover almost the entire studied area, while the green zones, when compared to the other species analyzed, have the smallest distribution.

4.4. Density Estimation Using the Kernel Density Estimation (KDE) Method for the Rovina Research Area

For the Rovina research area, the probability density analysis was conducted for two species with significant presence in the area, the roe deer (Figure 26) and the wild boar (Figure 27), while red deer, brown bear, wolf, and lynx have only sporadic presence during certain periods of the year.

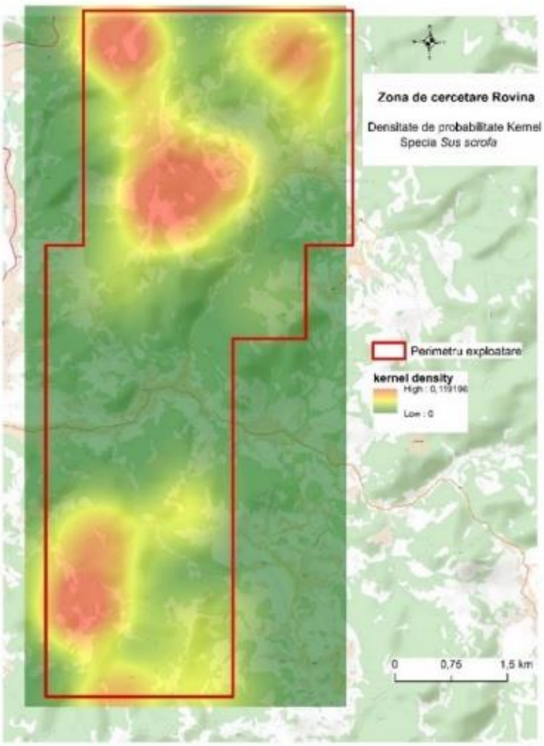

Figure 26. Probability density for roe deer in the Rovina area

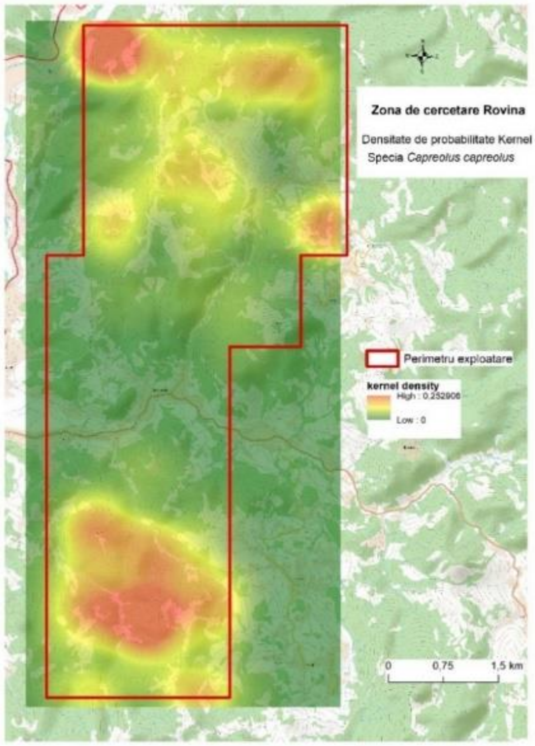

Figure 27. Probability density for wild boar in the Rovina area

An integrated analysis of the distribution of red zones for the two species reveals an overlap of high-density areas, reflecting preferences for the same habitat conditions. Fragmented thicket forests, pasture zones, and former forested village hearths form preferred habitats for both species. Additionally, it can be observed that anthropogenic activity specific to the Apuseni Mountains limits the presence of these two species, despite favorable habitat conditions for both the roe deer and wild boar.

The results obtained from processing the presence signs of the species collected along transects using the KDE method for probability density estimation confirm the results obtained through multicriteria analysis and principal component analysis (PCA). The correlations identified and confirmed by these methods reveal that intra- and interspecific relationships at the ecosystem level are functional, and the densities of the species are in balance.

4.5. Abundance and Density Estimates for the Studied Species Based on Images Recorded by Camera Traps

4.5.1 Abundance Estimates

The data collected by the camera traps were processed using the “camtrapR” package in R programming. The total survey effort was calculated using the “cameraOperation” function (Figure 28). For the Crasna-Valea Mare area, the total effort was 665 days, while for the Rovina area it was 1555 days.

```r
#create camera operation matrix
camop_no_problem <- cameraOperation(CTtable = camtraps,
                                    stationCol = "Station",
                                    setupCol = "Setup_date",
                                    retrievalCol = "Retrieval_date",
                                    hasProblems = FALSE,
                                    dateFormat = dateFormat)
```

Figure 28. The “cameraOperation” function in R

The result of applying the “cameraOperation” function is the matrix (Figure 29) on which the camera operation graph by locations was generated (Figure 30).

```
> camop_no_problem
       2025-01-03 2025-01-04 2025-01-05 2025-01-06 2025-01-07 2025-01-08 2025-01-09 2025-01-10 2025-01-11 2025-01-12 2025-01-13
LOC_1          NA        0.5        1.0        1.0        1.0          1          1        1.0        1.0          1          1
LOC_2          NA        0.5        1.0        1.0        1.0          1          1        1.0        1.0          1          1
LOC_3          NA        0.5        1.0        1.0        1.0          1          1        1.0        1.0          1          1
LOC_4          NA        0.5        1.0        1.0        1.0          1          1        1.0        1.0          1          1
LOC_5          NA         NA         NA         NA        0.5          1          1        1.0        1.0          1          1
LOC_6         0.5        1.0        1.0        1.0        1.0          1          1        1.0        1.0          1          1
LOC_7          NA         NA        0.5        1.0        1.0          1          1        1.0        1.0          1          1
LOC_8          NA         NA        0.5        1.0        1.0          1          1        1.0        1.0          1          1
LOC_9          NA         NA         NA        0.5        1.0          1          1        1.0        1.0          1          1
LOC_10         NA         NA        0.5        1.0        1.0          1          1        1.0        1.0          1          1
LOC_11         NA         NA         NA         NA        0.5          1          1        1.0        1.0          1          1
LOC_12         NA         NA         NA         NA        0.5          1          1        1.0        1.0          1          1
LOC_13         NA         NA         NA         NA        0.5          1          1        1.0        1.0          1          1
LOC_14         NA         NA         NA         NA         NA         NA         NA        0.5        1.0          1          1
LOC_15         NA         NA         NA         NA         NA         NA         NA         NA        0.5          1          1
```

Figure 29. Camera operation history matrix

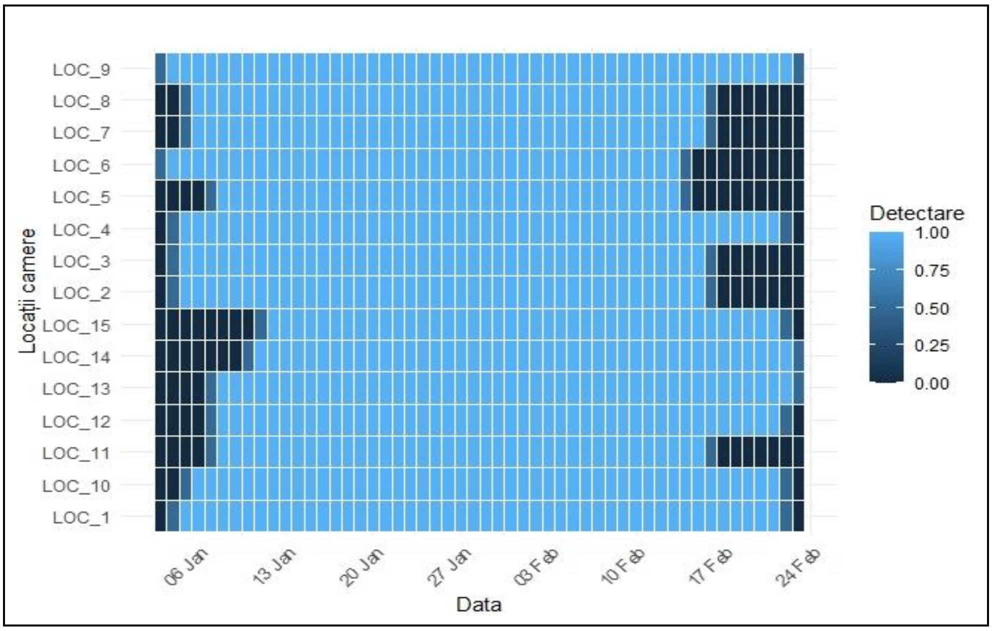

Figure 30. Camera operation histogram for the Crasna-Valea Mare area

Based on these data, a cumulative total of camera operation days was made, which defines the total survey effort for the studied area. The total survey effort was calculated by summing all the operation days of the cameras across all locations and is defined as the total trap days. For locations where multiple cameras were installed, only the period during which cameras were operational at each location was considered for calculating the survey effort. More specifically, a single camera was theoretically considered, and overlapping images were not combined.

Analysis of the species captured in the images recorded by the camera traps shows a higher capture yield for red deer (55%) in the Crasna-Valea Mare area and for wild boar (75.77%) in the Rovina area. In the Crasna-Valea Mare area, the presence of wild boar on camera traps, at a rate of 29%, reflects a drastic reduction in the population due to the impact of African swine fever (ASF).

The relative abundance index (RAI) (Table 2) was calculated using the following formula (Arroyo-Arce et al., 2017):

$$RAI = \frac{NIS * 100}{EA}$$

Where:
NIS = Number of species images (number of images captured with the target species)
100 = Standardization index, to allow comparison with other studies
EA = Survey effort (number of camera operation days)

Analyzing the relative abundance index (RAI) data, which allows us to compare the ratio between species, we can observe that the representative populations for the two areas are red deer for Crasna-Valea Mare and wild boar for the Rovina area, with an index of approximately 14. The index for the wolf, approximately 3.16, is of interest and may be correlated with constant and high activity in the Crasna-Valea Mare area, especially considering the size of the cervid herds observed directly or through snow tracks, which does not exceed a maximum of 7 individuals.

Table 2. Relative Abundance Index for the Monitored Species

Species	RAI	
	Crasna-Valea	Rovina
Red Deer	14.44	
Wild Boar	7.82	13,5
Roe Deer	-	5,53
Brown	1.05	0,06
Wolf	3.16	-
Lynx	0.6	-

For applying the REM and N-mixture methods to analyze data collected by camera traps, it was necessary to create a matrix using the "detectionHistory" function (Figure 31).

```
#creare matrice efort capturare și istoric detecție
DetHist2 <- detectionHistory(recordTable = recordTableSample,
                             camOp = camop_no_problem,
                             stationCol = "Station",
                             speciesCol = "Species",
                             recordDateTimeCol = "DateTimeOriginal",
                             species = "cerb",    # se schimba specia
                             timeZone = "Europe/Bucharest", #
                             occasionLength = 1,
                             day1 = "station",
                             includeEffort = TRUE,
                             scaleEffort = FALSE)
```

Figure 31. The "detectionHistory" function in R

The result obtained is a double matrix containing, in the first part "DetHist2," the number of individuals captured in the images, and in the second part "$effort," the number of days of operation per location.

Analysis of data collected by camera traps was handled separately for the two areas, Crasna-Valea Mare and Rovina. To apply the two analysis methods for the Crasna-Valea Mare area, field data were grouped into four distinct groups. Group 1 included only images captured by ForestCam cameras. Group 2 included images captured by both ForestCam and Bolly cameras. It is worth noting that only six locations had paired ForestCam and Bolly cameras installed. For this group, only the images collected by the Bolly cameras were used at the six locations. Group 3 analyzed images captured by both ForestCam and Bolly cameras, with the stipulation that overlapping images were not combined. Group 4 treated only the video data recorded by Reolink cameras.

Based on the analysis of data from Group 3, activity graphs were created for the studied species. Below is an example for red deer.

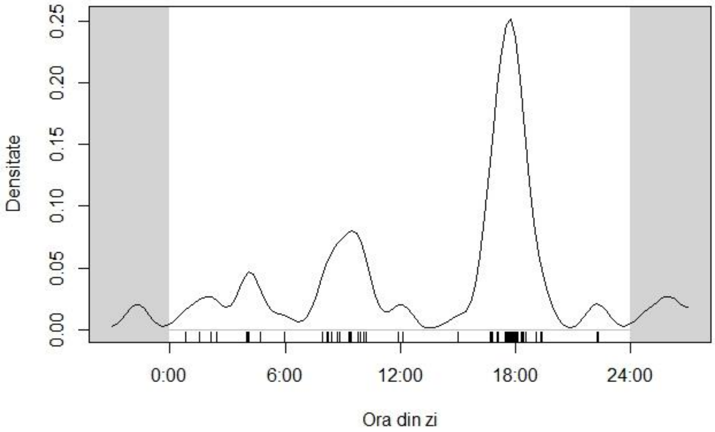

Figure 32. Daily activity report for red deer in the Crasna-Valea Mare area

For the red deer (Figure 32), a high activity level can be observed around 6 p.m., specifically during the evening, as the individuals move to feeding and watering points. Also noteworthy is the activity level in the early part of the day, centered around 9 a.m., which could be subject to future studies, possibly a result of nocturnal predator activity that reduces feeding times.

In general, from the perspective of detections for the ForestCam and Bolly camera models, we observe, according to the cumulative detection representation (Figure 33), that in the research area there is one location with no species recorded (Loc_8) and two locations where a maximum of four species from the monitored group were recorded (Loc_5 and Loc_13). There are also two locations where three species were recorded (Loc_2 and Loc_10), while the remaining locations recorded two or only one species.

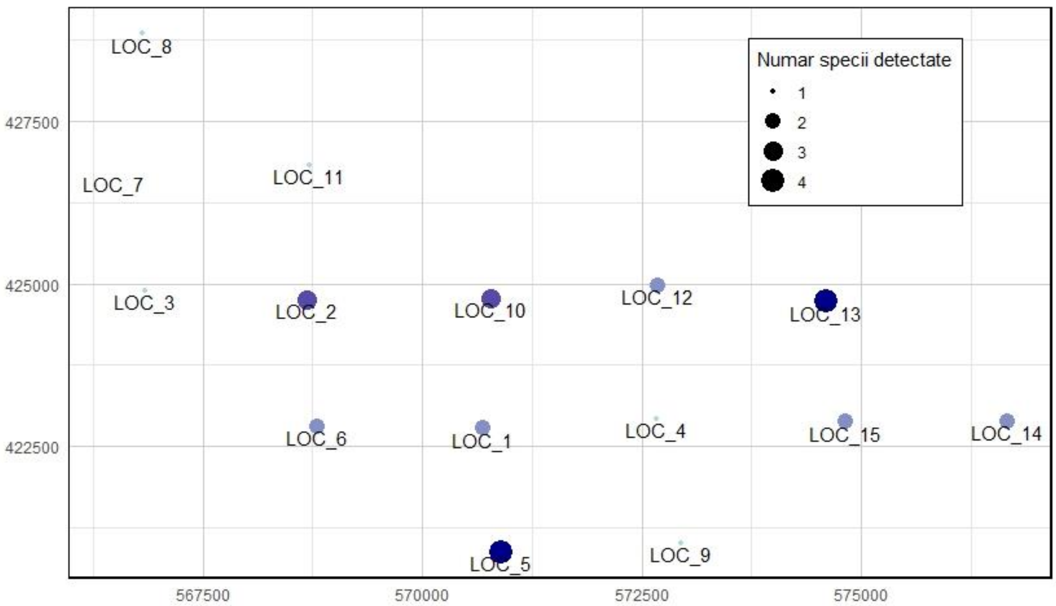

Figure 33. Frequency of detections by location for all species in the Crasna-Valea Mare area

4.5.2 Density Estimates by Species Using the REM Method

The REM method was applied in the R programming environment using the "RStudio" interface to facilitate data processing. The data were analyzed for the Crasna-Valea Mare area for species including red deer, wild boar, wolf, bear, and lynx for the four data groups presented earlier, and for the Rovina area, the analysis was conducted for wild boar and roe deer species.

The results of the analysis are summarized in Table 3, and Figure 34 shows the model for the "script" used to process the data using the REM method.

Table 3. Species Density via the REM Method – Crasna-Valea Mare Area

Species/Group	Group_1 (ForestCam)		Group_2 (ForestCam/Bolly)		Group_3 (ForestCam&Bolly)		Group_4 (Reolink_Ranger)	
	Density ex/100ha	Est. ex.	Density ex/100ha	Est. ex.	Density ex/100ha	Est. ex.	Density ex/100ha.	Est. ex.
Red Deer	0.393	22	0.383	21	0.458	26	0.037	2
Wild Boar	0.357	20	0.348	19	0.429	24	0.064	4
Wolf	0.107	6	0.105	6	0.104	6	0.048	3
Red Deer	0.117	6	0.113	6	0.129	7	0.032	2
Wild Boar			0.016	1	0.383	1	0	0

```r
##### MODEL RME ####

# Numar total de detectari din matricea de detectare
y <- sum(DetHist2$detection_history, na.rm = TRUE) #numar total de detectari

# Timp total de monitorizare (suma tuturor zilelor in care camerele au fost active)
T <- sum(DetHist2$effort, na.rm = TRUE)  # timp total de monitorizare (zile-camera)

v <- 9832 #raza zilnica de deplasare a speciei (metri/zi)

# Parametrii camerei
theta <- 52 * (pi/180) # Unghiul de detectare in radiani         110
r <- 20      # Distanta (raza) maxima de detectare in metri 10metri



# Calculăm densitatea cu formula REM
D <- (y / T) * (pi / (v * r * (2 + theta)))

D_km2 <- D * 1e6
D_km2

(D_km2 * 5600) / 100
```

Figure 34 Model "script" for using the REM method in R

For the analysis of data regarding the efficiency of the image trap cameras used, the quantitative results obtained by the REM method are graphically represented in Figure 35.

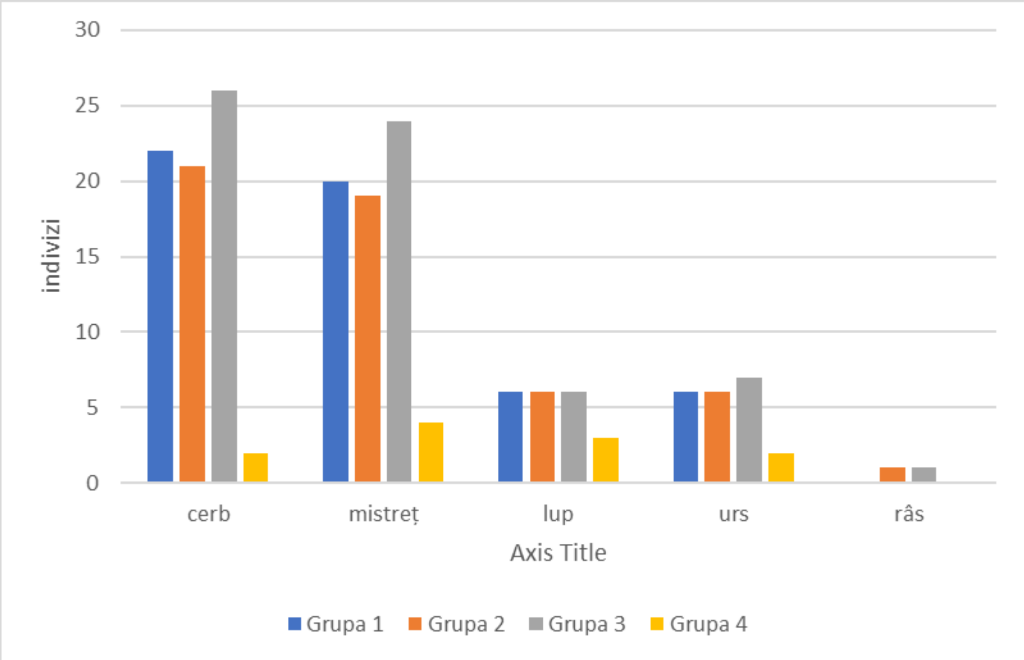

Figure 35 Species densities obtained through the REM method in the Crasna-Valea Mare area

Analyzing the species density graph (Figure 35), the following observations were made:

- The densities for the species in Group 1 are roughly equal to those in Group 2, which suggests that both camera types, ForestCam and Bolly, have similar capture efficiency.
- The results from Group 3 show an increased efficiency when using paired cameras at each location.
- The results obtained by processing the video-recorded data from Reolink cameras are significantly lower than those from the ForestCam and Bolly cameras, and in addition, no records of lynx were captured.
- For Group 1, no density calculation could be made for lynx because there was only one record from the ForestCam camera at location LOC_02. This aspect prevented the calculation of the "v" parameter (daily activity range).

For the Rovina area, the density estimates using the REM method were 0.42 ex./ km^2 for wild boar and 0.44 ex./ km^2 for roe deer. Compared to the reference method densities of 1.47 ex./ km^2 for wild boar and 2.1 ex./ km^2 for roe deer, the results from using the REM method are much lower.

4.5.3 Species Density Estimates Using the N-mixture Method

The N-mixture method was applied to the data recorded in the Crasna-Valea Mare area in the same way as the REM method, using the four analysis groups. The results are summarized in Table 4, and Figure 36 shows the model for the "script" used to process the data using the N-mixture method.

```r
##### MODEL N-mixture ####

#creare obiect
umf_abundance <- unmarkedFramePCount(
  y = DetHist2$detection_history, #matricea de detectare
  siteCovs = site_covariates,
  obsCovs = list(effort = DetHist2$effort)
)


# Aplicăm modelul N-mixture
mod_abundance <- pcount(
  formula = ~ effort ~ elevation + treecover,  # Detectare ~ Efort, Abundență ~ Altitudine + Treecover
  data = umf_abundance,
  K = 10
)



summary(mod_abundance)

sink("D:\\Folder_lucru\\R_test\\MIREA\\LUCRU_II\\mod_abundance.txt")
summary(mod_abundance)
sink()

# Facem predicția abundenței pe fiecare locație
predicted_abundance <- predict(mod_abundance, type = "state")    #"det" - arata probabilitatea de detectare
sum(predicted_abundance$Predicted)

write.xlsx(predicted_abundance,"D:\\Folder_lucru\\R_test\\MIREA\\LUCRU_II\\predicted_abundance.xlsx", overwrite = TRUE)

# Adăugăm la tabel
site_covariates$Estimated_Abundance <- predicted_abundance$Predicted
write.xlsx(site_covariates,"D:\\Folder_lucru\\R_test\\MIREA\\LUCRU_II\\site_covariates_predicted.xlsx", overwrite = TRUE)

print(site_covariates)
```

Figure 36 Model "script" for using the N-mixture method

The results for each species obtained by applying the "script" (see Annex 2) are displayed in Figures 37 and 38.

```
Abundance (log-scale):
             Estimate       SE     z  P(>|z|)
(Intercept)   3.30178 0.874713  3.77 0.000160
elevation    -0.00271 0.000806 -3.36 0.000788
treecoverB   -1.96082 0.779945 -2.51 0.011935

Detection (logit-scale):
             Estimate   SE     z P(>|z|)
(Intercept)     -4.67 1.93 -2.42  0.0154
effort           2.28 1.94  1.17  0.2402

AIC: 453.3686
Number of sites: 15
optim convergence code: 0
optim iterations: 57
Bootstrap iterations: 0
```

Figure 37 Model displaying the results of abundance estimation by species

The calculation model results presented above include:

- "SE" is the standard error,
- "z" reflects the ratio between Estimate and SE, indicating the degree of deviation,
- "P" is the probability; if P<0.05, there is a relationship between the variable and the response, while if P>0.05, the relationship is statistically insignificant.

	Intervalul de încredere al abundenței			
	Predicted	SE	lower	upper
Loc_1	3.47608997	1.1452385	1.82243776	6.63024099
Loc_2	1.55237818	0.36671663	0.97705521	2.46647067
Loc_3	1.3670407	0.3292666	0.85262941	2.19180837
Loc_4	0.36627882	0.27659313	0.08337433	1.60913047
Loc_5	0.25216685	0.18757991	0.05868172	1.08361036
Loc_6	0.24083312	0.17908907	0.05607162	1.03440194
Loc_7	0.1147673	0.08880738	0.02518577	0.52297531
Loc_8	0.95913843	0.2701183	0.55228192	1.66571907
Loc_9	0.42618797	0.3257348	0.09528602	1.90622075
Loc_10	1.77720713	0.4228192	1.11487671	2.83301747
Loc_11	1.33416073	0.3234187	0.82959347	2.14561097
Loc_12	1.4706229	0.34923456	0.92334323	2.34228361
Loc_13	1.93790275	0.46998312	1.20475098	3.11721437
Loc_14	4.74454092	1.89624712	2.16767971	10.3846839
Loc_15	0.46598285	0.35921689	0.10284795	2.11127221

Figure 38 Display model for confidence interval of estimates

In addition to the standard error, Figure 38 includes the confidence interval for the prediction at each location.

Table 4. Species Density via the N-mixture Method – Crasna-Valea Mare Area

Species/Group	**Group_1 (ForestCam)**		**Group_2 (ForestCam/Bolly)**		**Group_3 (ForestCam&Bolly)**		**Group_4 (Reolink_Ranger)**	
	Density ex/100ha	Est. ex.	Density ex/100ha	Est. ex.	Density ex/100ha	Est. ex.	Density ex/100ha	Est. ex.
Red Deer	0.016	43	0.008	21	0.012	34	0.002	6
Wild Boar	0.011	30	0.012	32	0.005	15	0.003	7
Wolf	0.004	10	0.002	6	0.002	6	0.001	4
Bear	0.002	5	0.002	6	0.003	7	0.003	9
Lynx	0.002	5	0.001	4	0.001	4	0.000	0

For the analysis of data regarding the efficiency of the image trap cameras used, the quantitative results obtained by the N-mixture method are graphically represented in Figure 39.

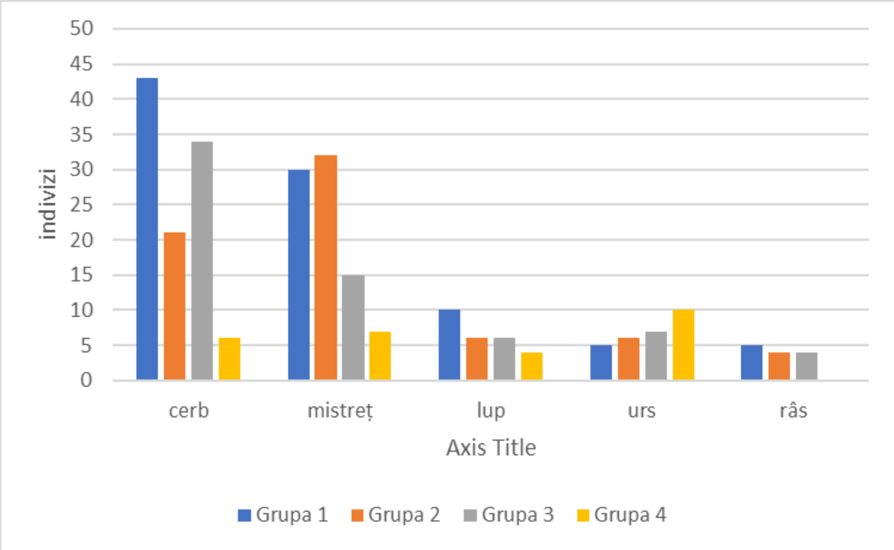

Figure 39 Species densities via the N-mixture method in the Crasna-Valea Mare area

Compared to the REM method, the N-mixture method gives a much larger difference in results between the analysis groups. In addition to the major difference from the results of Group 4, which was generated due to the absence of records, a large variation is also observed in the first three groups. For wild boar, the greatest difference is seen in Group 3, with 50% lower estimates than those using data from Group 1.

For the Rovina area, the abundance estimates using the N-mixture method were 37 individuals (2.07 ex./ km²) for wild boar and 57 individuals (1.32 ex./ km²) for roe deer. Compared to the reference method densities of 1.47 ex./ km² for wild boar and 2.1 ex./ km² for roe deer, the results for wild boar are lower, while those for roe deer are higher.

4.5.4 Determining the Number of Individuals Using the Reference Method

The estimation of the number of individuals in the study area was done by applying the procedures from the reference methodology used in other studies, such as the estimation of cervids in the O.S. Tinca area. The results from the species estimation based on the official reference method used nationally are shown in Table 5, and Figure 40 presents the graphical representation of the estimates.

Table 5. Estimation Summary by Reference Method – Crasna-Valea Mare Area

Valley, Ridge/Species	Red Deer	Wild Boar	Bear	Wolf	Lynx
C_INCAS-Nebuni	4	7	3	3	1
C_Nebuni-Moașa	2	1	2		
C_Plai-Moasa	8	2	4	5	
C-Băjenari-Bombe	7	4	3		1
V_Crasna- Crăsnuța		1	4		
V_Crasna-Nebuni	5	2	5		
V_Moașa-Radila	2	1	3		
V_Valea Mare		3	1		
Total	*28*	*21*	*25*	*8*	*2*

The data analysis obtained through the reference method reveals a balanced structure of species in the trophic pyramid, with a good representation of red deer and a lower one for wild boar due to the epizootic of swine fever. It can also be observed that the estimated number for bears, using the reference method, reflects the well-structured habitat conditions in the study area.

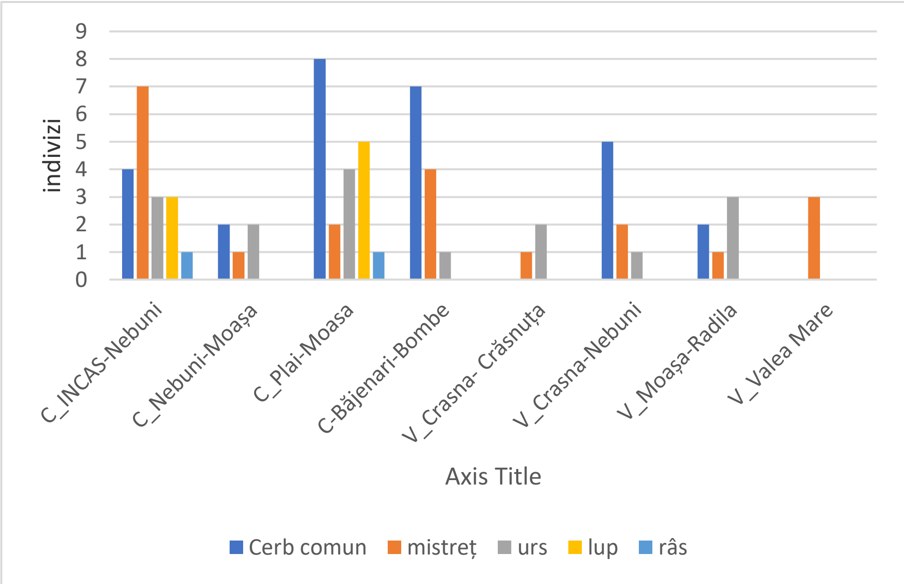

Figure 40 Estimation of the number of individuals for studied species in the Crasna-Valea Mare area

4.5.5 Integrated Analysis of Data Obtained Through the Three Methods

For the comparative analysis of the data, the results from the REM method for Group 3 in the Crasna_Valea Mare area were considered. The integrated analysis aimed to determine whether there is a correlation between the methods. The estimates for the studied species (Table 6) are graphically represented in Figure 41.

For the bear species, in the comparative analysis of methods, the reference method considered 5 specimens that frequented the feeding points for wild boar and deer during the monitoring period from January to February, with the other specimens in the reference estimate for the year being withdrawn to their dens in other areas.

Table 6. Summary of estimates from the three applied methods

Method/Species	**REM Method**	**N_mixture Method**	**Reference Method**
Red Deer	26	34	28
Wild Boar	24	15	21
Wolf	6	6	8
Bear	7	7	5
Lynx	1	4	2

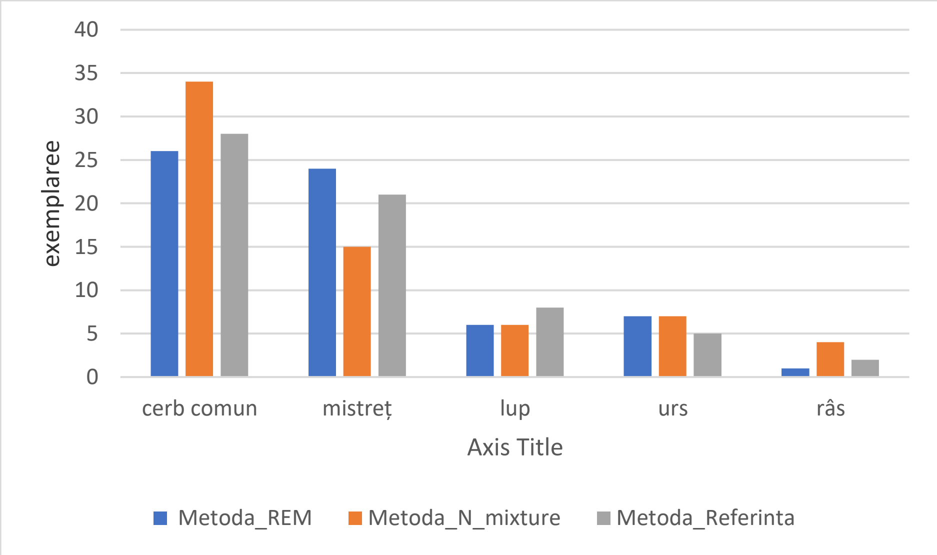

Figure 41. Estimation of the number of individuals by the three methods

The analysis matrix of the results from the three methods (Figure 42) indicates that there is a very strong correlation between the REM Method and the Reference Method (r = 0.98), and a strong correlation between the N_mixture Method and the Reference Method (r = 0.93), as well as between the REM Method and the N_mixture Method (r = 0.87). In conclusion, it can be said that there is a correlation between the three methods, but the results from the REM Method are more strongly correlated with those from the Reference Method.

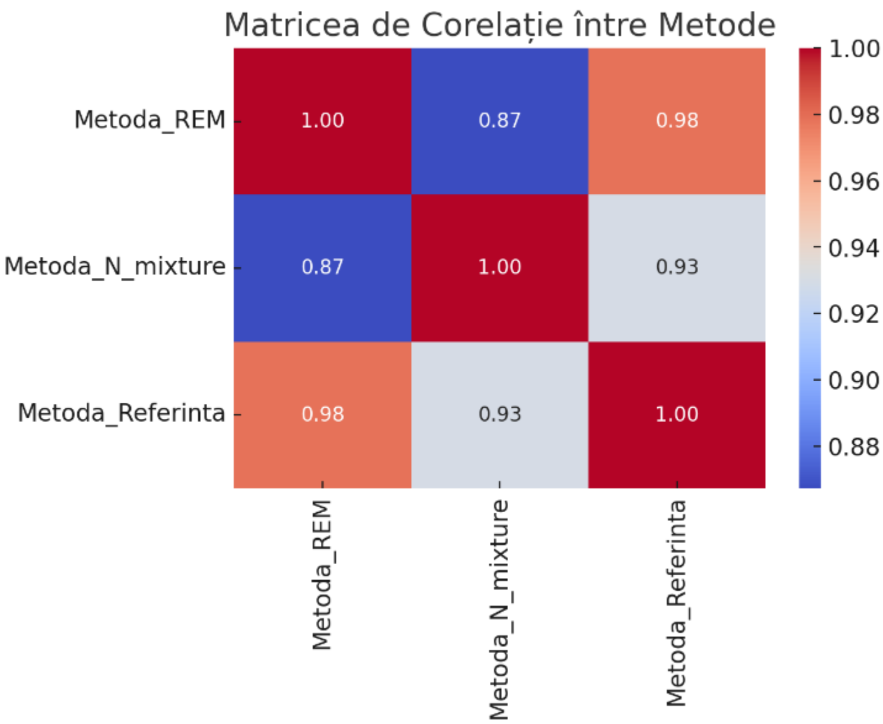

Figure 42. Correlation matrix of the three methods

CHAPTER 5

CONCLUSIONS. ORIGINAL CONTRIBUTIONS. DISSEMINATION OF RESULTS. FUTURE RESEARCH DIRECTIONS

5.1 Conclusions

As a result of the research work carried out, the processing of captured images and species presence signs, and the analysis of the results obtained in this doctoral thesis, several pertinent conclusions can be drawn, based on scientific foundations, contributing to the development of methods and software packages used for estimating large mammal populations using camera traps. Regarding the establishment of comparative estimation methods for large mammal populations in the study area, the research work was rigorously implemented using different sampling models for the two research areas. Field data were collected during the established periods, which were optimal for data collection, and various equipment and standardized procedures were used to achieve the proposed objectives.

For the efficient processing, analysis, and interpretation of the field data, the "cammtraps" and "unmarked" packages from the chosen R programming module provided solutions compatible with the objectives set in the doctoral thesis. Additionally, the "DigiKam" application allowed for the structuring of a reliable database with an operating environment, ensuring good management of the field data collected by camera traps.

The approaches regarding data analysis took into account the complexity and diversity of field-collected data on species presence signs. Multicriteria analysis and Principal Component Analysis constituted the solution for an integrated analysis of these data with habitat conditions. The KDE method also ensured the possibility of transforming point data into continuous density surfaces for the studied species.

The REM and N_mixture analysis methods, specific to processing data collected by camera traps, where individual identification is not possible, also proved to be useful given the results obtained. Regarding the determination of large mammal population parameters in the two research areas, these were the result of applying the analysis methods outlined in the methodology. Data processing and result interpretation were carried out using the statistical software mentioned in the thesis. The use of the DigiKam application proved to be a reliable solution for processing field data and creating metadata databases.

The efficiency of camera traps in estimating large mammal populations was evaluated separately by grouping the data collected according to the model of equipment used and then analyzing it comparatively. Similar results were recorded by ForestCam LS 870 and Bolly BG 310 cameras, while the Reolink Keen Ranger cameras performed poorly in the habitat conditions in which they operated. The reduced detection range and dependence on external temperature for proper functioning were the main causes of the limited video recordings from the Reolink cameras.

The results obtained through the application of analysis methods differed depending on the sampling model used and the number of recordings. The N_mixture method leads to better results by using a randomized sampling model with a higher number of recordings over a longer period, while the REM method provides results close to the reference ones when using a systematic sampling model, which allows for more precise values of the daily activity radius.

5.2 Original Contributions

The conclusions drawn from the results obtained through the research carried out during the preparation of the doctoral thesis highlighted personal contributions with an original character regarding the high potential of using camera traps combined with statistical analysis methods in estimating large mammal populations, as follows:

- Testing the Multicriteria Analysis and Principal Component Analysis methods for processing field data on species presence provides a new contribution to understanding species' ethology and deepening the knowledge of their ecological requirements.
- The development of continuous probability density maps for the studied species using the KDE method, based on point data sets, is a novelty in wildlife research.
- Highlighting the effectiveness of image capture equipment through different sampling and grouping models of data sets, with the results providing the basis for future research.
- Testing and comparing the results of two data analysis methods (REM and N_mixture) for the conditions of ecosystems in Romania.
- Developing a data collection, processing, and interpretation methodology that will allow the future standardization of mammal population estimation methods using camera traps.
- Developing a standardized database that could serve as support for the development of digital applications regarding the use of camera traps in estimating mammal populations.

5.3 Dissemination of Results

- List of publications related to the thesis topic:

1. Mirea, I., Cazacu, R., Fedorca, M., Fedorca, A., Toiu, L., & Ionescu, G. (2023). Evaluation of large mammals in the Bucharest area (Hunedoara, Romania). *Revista de Silvicultură şi Cinegetică, 27(52).*
2. Mirea, I., Fedorca, M., Baciu, I., Cazacu, R., Iordache, D., Ionescu, O. (2022) An Overview of the Photo Trap Camera as a Survey Tool for Wildlife. *Proceedings of the International Symposium "Forest and Sustainable Development" 10th Edition, 14th-15th of October 2022, Brașov, Romania.*
3. Ștefan, C., Fedorca, M., Fedorca, A., Mirea, I., Mariș, C., & Ionescu, O. (2023). Monitoring the golden jackal (Canis aureus) in the Smârdan area, Tulcea County (Romania). *Revista de Silvicultură şi Cinegetică, 27(52).*
4. Cazacu, R., Ionescu, O., & Mirea, I. (2021). CITES-importance, strategic vision, and implementation in Romania. *Revista de Silvicultură şi Cinegetică, 26(48).*
5. Hardalau, D., Fedorca, M., Popovici, D., Ionescu, G., Fedorca, A., Mirea, I., Iordache, D., Ionescu, O. Insights in Managing Ungulates Population and Forest Sustainability in Romania. *Diversity 2025, 17(3).*

- List of publications outside the thesis topic:

1. Cazacu, R., Baciu, I., Dutcă, I., Vodă, G., Mirea, I., & Fedorca, A. (2024). Reporting damages caused by species of game interest in Romania: current context, perceptions, and efficiency solutions. *Revista de Silvicultură şi Cinegetică, 29(54).*

- Conference participation with presentations:

1. Ion MIREA, Roxana CAZACU, Ovidiu IONESCU, Adrian LORENȚ, Georgeta IONESCU, The photo trap method, a tool in estimating the density of large mammalian populations. *International Symposium "Forest and Sustainable Development" 8th Edition, 25th-27th of October 2018, Brașov, Romania.*
2. Ion MIREA, Adrian LORENȚ, Ovidiu IONESCU, The estimation of mammal populations using photo trap cameras, 9th International Symposium Forest and Sustainable Development, Brașov, Romania, 16 October 2020.
3. Ion MIREA, Mihai FEDORCA, Iulia BACIU, Roxana CAZACU, Daniel IORDACHE, Ovidiu IONESCU, The history of the photo trap camera as a survey tool for wildlife. *10th International Symposium Forest and Sustainable Development 14-15 Oct 2022.*
4. Ion MIREA, Danie Ștefan ILIE, Mihai FEDORCA, Ancuța FEDORCA, Roxana CAZACU, Ramon JURJ, Alex GRIDAN, Daniel IORDACHE, First step in standardizing the collection of game statistics in Romania: a case study AJVPS Prahova. *11th International Symposium Forest and Sustainable Development, Brașov, Romania, 17-18 October 2024.*

5.4 Future Research Directions

The premises and results obtained from the research work in this doctoral thesis provide hope for the future widespread use of camera traps in estimating mammal populations.

- The main development direction of research in this field will certainly be technical, which will allow the development of more reliable equipment, increasing energy autonomy, achieving detection over greater distances, with wider angles and higher mobility, and enabling remote automatic data downloading.
- From the perspective of using data collected by camera traps, further research should delve into analysis methods by studying sampling models, densities, equipment installation methods, and the standardization of collection protocols.
- One area that should be explored is the development of software packages that allow game managers with a focus on wildlife conservation to upload field data from camera traps into a standardized database.
- Developing advanced species recognition algorithms based on deep learning (AI) for individual recognition.
- Creating digital applications that enable downloading, filtering, and storing captured images.

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Abbreviation List

(KDE) - Kernel Density Estimation

(PCA) - Principal Component Analysis

(REM) - Random Encounter Analyses

(Pz_fauna) - Fauna Presence

(ALT) - Altitude

(Cat_Pad) - Forest Category

(SUP) - Production Subunit

(EXPOZITIE) - Terrain Exposure

(INC) - Terrain Inclination

(CRT_PAD) - Current Forest Type Character

(LITIERA) - Litter

(STR) - Stand Structure

(DNS) - Stand Consistency

(VRT) - Stand Age

(LCR_EXT) - Works Executed

(SP_PRINC_ARB) - Main Species

(VOLUM) - Stand Volume

(PPA) - African Swine Fever

O.S. - Forestry District

Figure List

Table List