Development of a Spatial Database for Camera Trapping by Palombar

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Abstract: Camera trapping, used by Palombar in the Northeast of Portugal, is the basis of this study aimed at enhancing local biodiversity management and analysis. By integrating tools like QGIS, PostgreSQL, and PostGIS, a spatial database was developed. The primary focus is on identifying areas of high biological richness, the geographic distribution of various species, and their habitat preferences. This method provides detailed and valuable insights for wildlife conservation, optimizing data usage in environmental projects.

Keywords: Camera Trapping, Database, QGIS, PostgreSQL, PostGIS

1. Introduction

Camera trapping (CT) is a biodiversity monitoring technique that captures photos or videos using cameras installed in the field (Forrester et al., 2016). These cameras detect the infrared radiation emitted by animals' body heat, passively recording wildlife (Wearn & Glover-Kapfer, 2017). The increased use of this method has led to a growing volume of information that needs to be stored, managed, and analyzed (Forrester et al., 2016). In Portugal, it serves various purposes such as detecting species presence, monitoring their health status, or studying their behavior.

Palombar's mission is to conserve biodiversity, ecosystems, and rural heritage. They promote various projects using CT (Palombar, n.d.). This study aims to develop and implement a spatial database to manage CT data from Palombar's campaigns, using records from two projects: ENET WILD (monitoring wildlife populations and health in Europe) (Palombar, 2021) and UP4Rehab (ecological restoration in Vimioso) (Palombar, 2022).

Specific objectives:

1. Identify areas with higher species richness: Using geographic records of species and GIS software, perform geospatial analysis to identify and map areas of high biodiversity, facilitating conservation efforts.
2. Understand the geographic distribution of species: Develop maps illustrating species presence and absence within a distribution grid.
3. Conduct Habitat Preference Analysis: Measure species observation frequency for each land use class by overlaying database records with a land use map, indicating species habitat preferences or lack thereof.

The goal is to reduce data preprocessing time, currently stored in Excel spreadsheets, by contributing to Palombar's data management system.

2. Study Area

Palombar's intervention area is in the Northeast of Portugal, with expanding territory. The ENET WILD project began in collaboration with the Instituto de Investigación en Recursos Cinegéticos of the University of Castilla-La Mancha, Spain, in September 2021, aiming to improve wildlife population monitoring tools, focusing initially on wild boar (Sus scrofa) (Palombar, 2021). The project's intervention area is in the Santulhão Game Zone, Vimioso municipality, Bragança district (Figure 1). The goal is to collect comparable wildlife data across Europe to assess disease risks shared between wild animals (Palombar, 2021).

The UP4REHAB project, approved in 2022, responds to the COVID-19 pandemic's climate transition support component - resilience of territories to erosion risk. The study area is in the Northeast, specifically in the former parish of Algoso, Vimioso municipality, Bragança district, integrating the Iberian Meseta Transboundary Biosphere Reserve and Natura 2000 Rios Sabor and Maçãs Special Protection Zone (Palombar, 2021).

Based on ICNF information, the Biosphere Reserve and Special Protection Zone boundaries are identified (ICNF, 2022; 2023) (Figure 1).

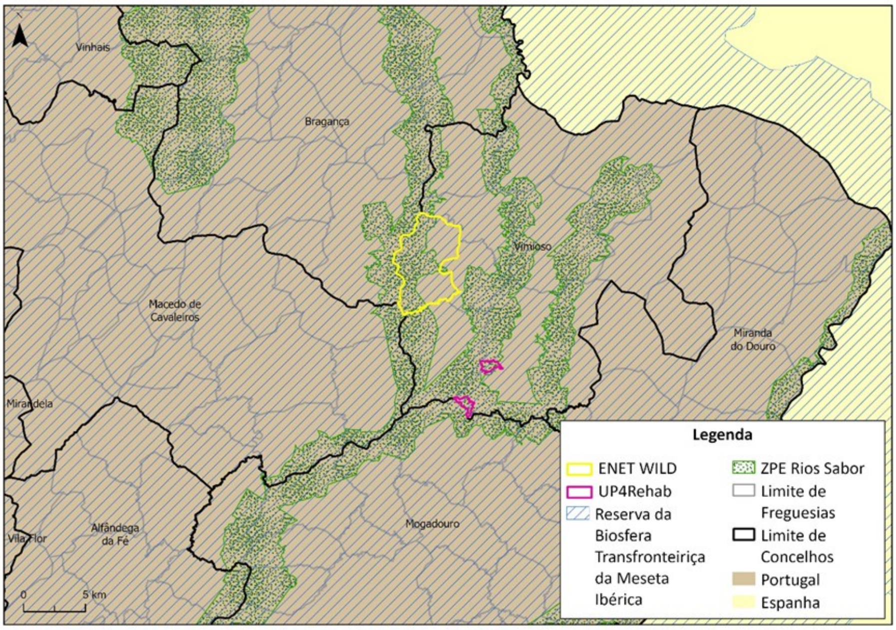

Figure 1. Geographical framework of the study areas.

3. Data and Methodology

Creating and implementing a spatial database ideally starts with Preliminary Analysis. This phase captures "business rules," guiding database design and data collection. This approach wasn't possible as we used pre-collected data. The geographic coordinate system was WGS 1984.

Additionally, we used the 2018 Land Use and Occupation Map (COS) from the Directorate-General for Territory (DGT, 2019) to address the third objective.

The first step in creating the relational database involved analyzing the spreadsheet provided by Palombar, following the taught workflow (Figure 2).

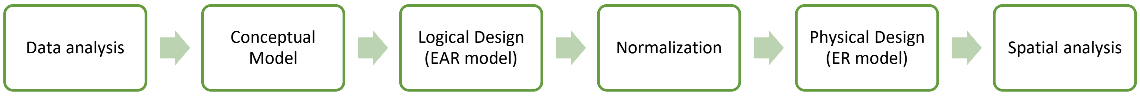

Figure 2. Workflow of creating a spatial relational database.

An integrated approach using PostgreSQL, with PostGIS extension, combined with QGIS spatial analysis capabilities, was adopted. PostgreSQL is an open-source object-relational database management system (ORDBMS) that allows defining custom data types, functions, and operators, particularly useful for complex data and domain-specific operations found in GIS. For PostgreSQL to support geographic data, the PostGIS extension is necessary (Obe & Hsu, 2021).

3.1. Relational Database

3.1.1. Conceptual Model

The conceptual model is the first model to be designed, aiming to capture the "business rules" and describing in an abstract and high-level manner how the data interrelates. The CT database starts with teams that develop conservation and research projects. Each project and team conduct CT campaigns, which involve installing CT cameras at various locations for variable periods. These locations overlay different land use types. Each campaign produces media, which in turn contain observations (Figure 3).

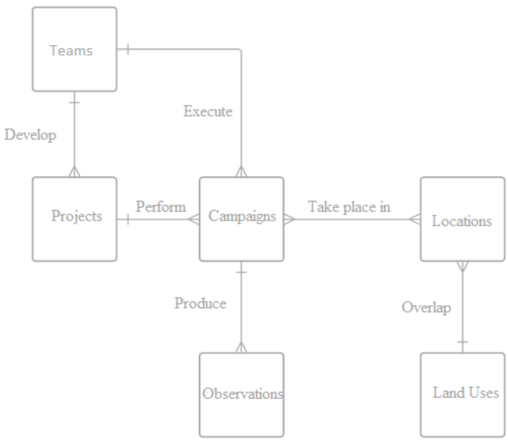

Figure 3. Conceptual model of the CT database.

3.1.2. Logical Design – Entity-Attribute-Relationship Modeling

Transforming the conceptual model to a logical model involves Entity-Attribute-Relationship (EAR) modeling:

- Identify Entities: Entities were defined in the conceptual model.
- Identification of the relationship between entities - it was found that the entities maintain a 1:M relationship with each other, with the exception of the relationship between LOCATIONS and CAMPAIGNS, which is M:N;
- Identify Attributes: Each entity's attributes were established, along with primary (PK) and foreign keys.
- Derive tables - does not always have to be fulfilled, as it is only necessary when there are M:N relationships, which cannot be modeled through the EAR process. In the case of the present work, it is necessary to derive a table, since each CT campaign takes place in many locations, but the same location can be occupied by several campaigns over time. To solve this problem, an intermediate table was introduced that allows 1:M relationships between the two entities. In this sense, a new table called LOCATION OF CAMPAIGNS was added.

The next phase is normalization. The first normal form ensures that primary keys are made of atomic (indivisible) non-null, unique values and eliminates repeated groups, which manifest as redundant data. Although the primary keys in the project are all made of unique alphanumeric sequences, it was found that there were repeated groups in the following entities:

- Teams: Contained repeated names of technicians and coordinators. To solve this problem, two tables were derived: one containing technician data and another containing coordinator data.
- Observations: Contained repeated scientific names as well as observation types. The problem was solved by creating two tables - Species and Observation Type, where each scientific name and observation type were assigned an alphanumeric code.

The second normal form requires that if there are composite primary keys, all attributes must depend on both. Since there were no composite primary keys in this work, the second normal form was guaranteed. The third normal form insists that attributes can only depend on the primary key and not on other attributes. As the data respected this condition, the third normal form was also guaranteed. The logical design after normalization consisted of 11 entities that have cardinalities of 1:1 and 1:M (Figure 4).

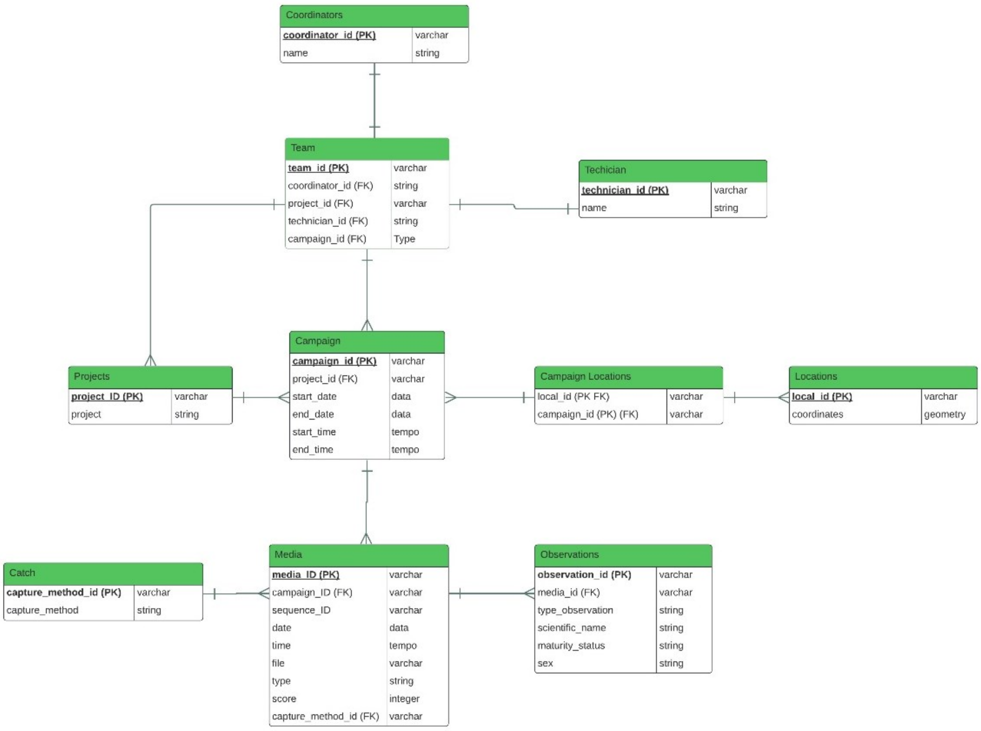

Figure 4. Logical Design for building the CT database, carried out using EAR modeling.

3.1.3. Physical Design

Data was initially processed and organized in Microsoft Excel, ensuring quality before importing into the PostgreSQL database using PgAdmin 4.

Non-spatial entities were imported from .csv files. For spatial data in the LOCATIONS table, the PostGIS extension was activated in PgAdmin 4, and shapefiles were imported using the PostGIS Shapefile Import/Export Manager.The COS 2018[1] land use classes were also imported after being processed in QGIS, where they were clipped to the study area and joined with CT location data, resulting in a table linking each location with land use classes. Queries and data analysis were conducted using the QGIS DB Manager.

[1] https://www.dgterritorio.gov.pt/Carta-de-Uso-e-Ocupacao-do-Solo-para-2018

3.2. Data Dictionary

To develop this project, a comprehensive data dictionary was created, serving as a detailed repository of collected information (Table 1).

Table 1. Dictionary of data used in the scope of the work.

Entity	Attribute	Definition	Type
Projects	**Project_ID**	Identification code for projects	varchar
	Project	Project names	string
Campaigns	**Campaign_ID**	Identification of the CT campaign, consisting of several cameras active for varying periods	varchar
	Start_Date	Campaign start date	data
	End_Date	Campaign end date	data
	Start_Time	Campaign start time	tempo
	End_Time	Campaign end time	tempo
Coordinators	**Coordinator_ID**	Identification code for project coordinators	varchar
	Name	Coordinator names	string
Technicians	**Technician_ID**	Identification code for technicians responsible for camera installations	varchar
	Name	Technician names	string
Locations	**Location_ID**	Identification of locations where CT campaigns took place	varchar
	Coordinates	Latitude and Longitude (WGS84) of each point	point
COS 2018	**COS_ID**	Identification code for each land use class at CT locations	integer
	Cos2018_lg	Land use classes	varchar
	geom	Spatial information of polygons for each land use class	geom
Observations	**Observation_ID**	Identification code for observations, each corresponding to a photo or video	varchar
	Timestamp	Observation timestamp	timestamp
	Sequence_ID	Identification of the sequence in which each photo or video was obtained	varchar
	Count	Number of individuals in each observation	integer
Tipo_Observação	**Observation_Type**	Identification code for each observation type	varchar
	Observation_Type	Observation type: blank data, animal, human, unknown, unclassified, vehicle	string
Espécies	**Scientific_Name_ID**	Identification code for species recorded in each observation	varchar
	Scientific_Name	Scientific name of the species recorded in each observation	string

4. Results

After implementing the database, the CT campaign results were explored. Using QGIS's DB Manager, various queries were conducted to address the study's objectives.

Given the high number of species, it was decided to present only the results of the ENET WILD project, and to select some demonstrative taxa, since repeating the analysis for each taxonomic group would be repetitive work, and would not bring added value to the objective of the discipline.

4.1. Identification of Areas with Higher Species Richness

To identify locations with the highest biodiversity, three queries were made:

- Total number of observations
- Number of observations per CT location
- Number of distinct species per CT station

4.1.1. Total Number of Observations

A query excluding all observation types except animals (AA) and excluding domestic animals (*Equus asinus, Capra hircus, Bos taurus, Canis lupus familiaris, Ovis aries, and ambiguous classes like Mammalia*) indicated a total of 2742 observations between 18-07-2022 and 15-05-2023 (Figure 15, Appendix 3).

4.1.2. Number of Distinct Species

A query counting distinct species (COUNT (DISTINCT observacoes.nome_cient_id)) while excluding the same categories as before revealed 59 distinct species (Figure 16, Appendix 3).

4.1.3. Number of Observations by Location

A query summing the counts of wild animals for each location (local_id) and grouping results by location_id and geometry maintained spatial data integrity (Figure 17**Figure *16***, Appendix 3). To obtain the number of distinct species per location, a similar query was conducted (Figure 18, Appendix 3).

Creating a map with these spatial tables generated new layers in the QGIS project. The results showed the distribution of observation numbers and distinct species for each CT location in the ENET WILD project (Figure 5).

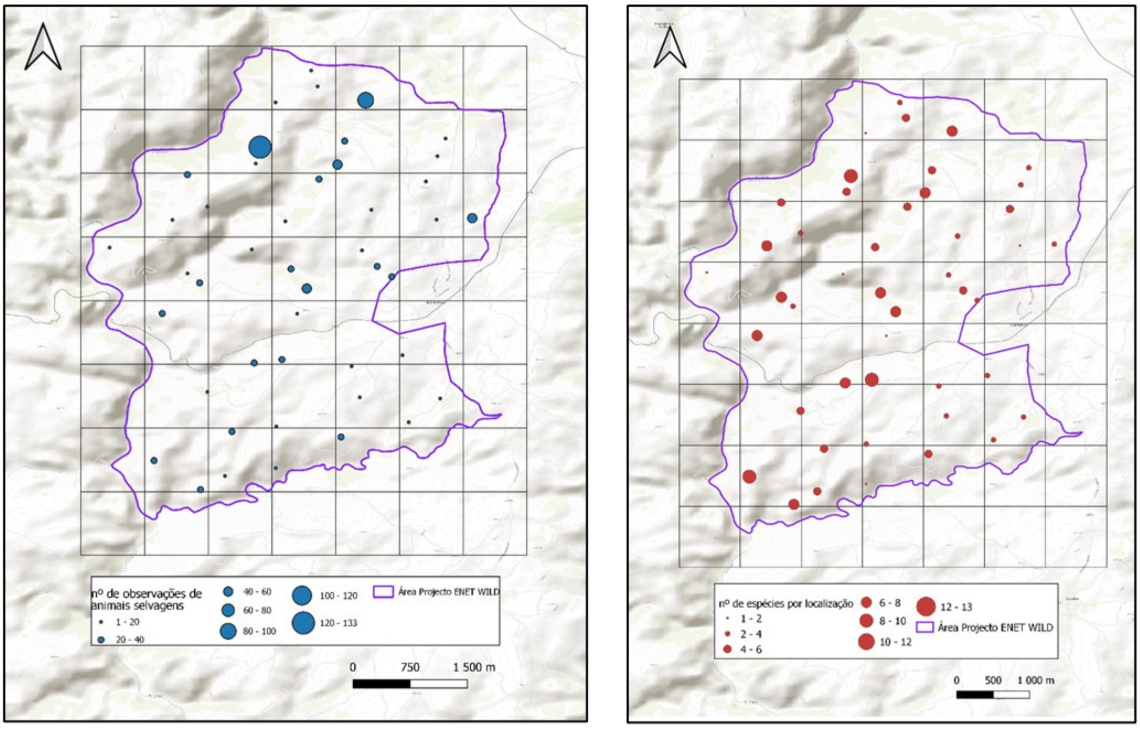

Figure 5. Spatial representation of queries made to the database. A: number of observations of wild animals in each location; B - number of different wild species captured in each location.

4.2. Geographic Distribution of Species

Species distribution was mapped using presence/absence maps, common in ecology. Only three species were selected for demonstration. Besides presence/absence, the number of individuals photographed per taxon was added. Queries returned observation numbers for selected species at each CT point. The first query was for roe deer (*Capreolus capreolus*) (Figure 19 Appendix 3).

Loading the new table as a new layer produced a presence/absence map for roe deer (Figure 6). Visual analysis showed the species well-distributed in the study area, with more records in the Northeast.

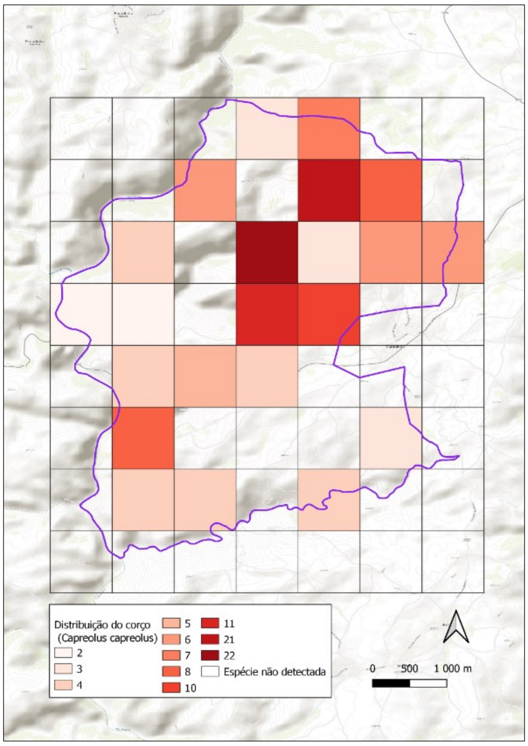

Figure 6. Map of presence/absence of roe deer (*Capreolus capreolus*) in the ENET WILD project area.

Queries for badger (*Meles meles*) and fox (*Vulpes vulpes*) highlighted significant differences in their distribution and observation numbers. The badger's distribution was limited, while the fox was nearly omnipresent across the grid (Figure 7 and Figure 8).

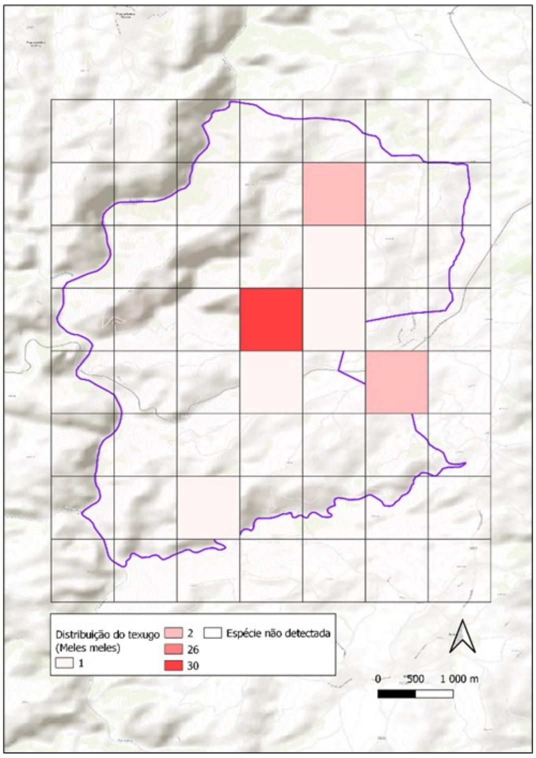

Figure 7. Map of presence/absence of badger (Meles meles) (A), in the ENET WILD project area.

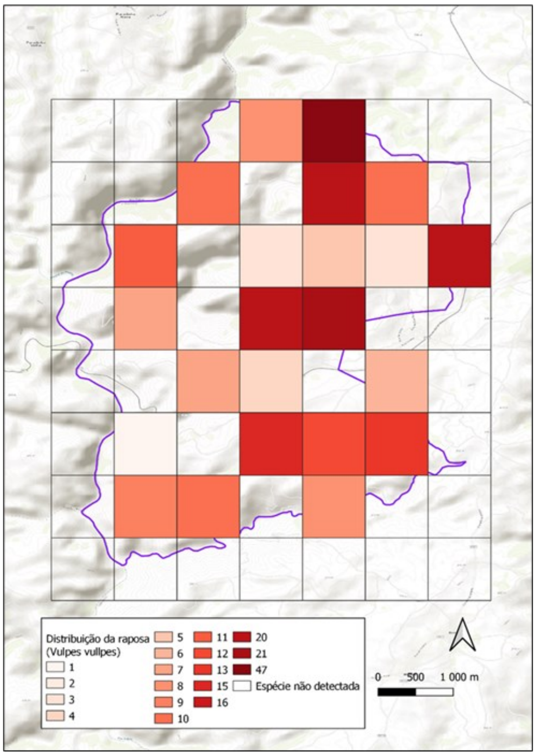

Figure 8. Map of presence/absence of foxes (Vulpes vulpes) (B), in the ENET WILD project area.

4.3. Land Use Analysis

Species preferences for land use classes were analyzed using a query that calculated total observations for five selected species (roe deer, fox, wild boar, genet, and badger) in each land use category present in the study area (Figure 20, Appendix 3).

A brief analysis of the obtained table reveals that globally, 52% of the observations of the five species overlap with the shrubland class (n=288), followed by other oak forests (n=155) (Figure 9). Dryland and irrigated crops (n=7) had the fewest records.

The overlap of the number of records of each species for each land use class is an indicator of their habitat preference. Therefore, individual maps for each species and a brief quantitative analysis of the data were prepared.

The analysis of Figure 10 reveals that although the fox occurs in a wide range of habitats, most observations were recorded in shrublands (58%) and other oak forests (16%), following the overall trend presented above. However, this analysis is redundant since the fox was the most photographed animal in the project, which significantly contributed to the overall trend values. The spatial analysis shows that a significant part of the observations is concentrated in the northern part of the project area.

For the roe deer, 158 observations were recorded in the project area. Similar to the fox and the general trend of the species as a whole, roe deer predominantly occur in shrublands and other oak forests (Figure 11). There is also a higher number of observations in the northern quadrant of the project area.

In the case of the wild boar (*Sus scrofa*), fewer observations were recorded, and these are more evenly distributed throughout the project area compared to the two previous species. Regarding land use, this species also shows a predominance in shrublands and other oak forests (17%) (Figure 12).

The badger (*Meles meles*) was captured by the CT technique 39 times, 28 of which were in a single location situated in the central area of the study and overlapping with other oak forests (72% of observations) (Figure 13).

Of the selected species, the genet (*Genetta genetta*) had the fewest observations with only 13 records. Of these, 6 correspond to other oak forests, comprising almost half of the observations. Shrublands follow with 31% of the observations (n=4) (Figure 14).

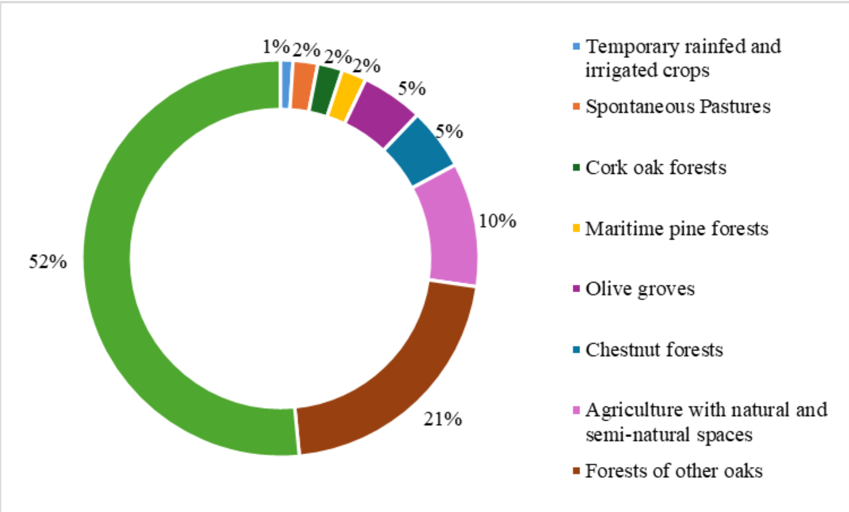

Figure 9. Number of observations of fox, roe deer, wild boar, genet and roe deer in land use classes in the ENET WILD project

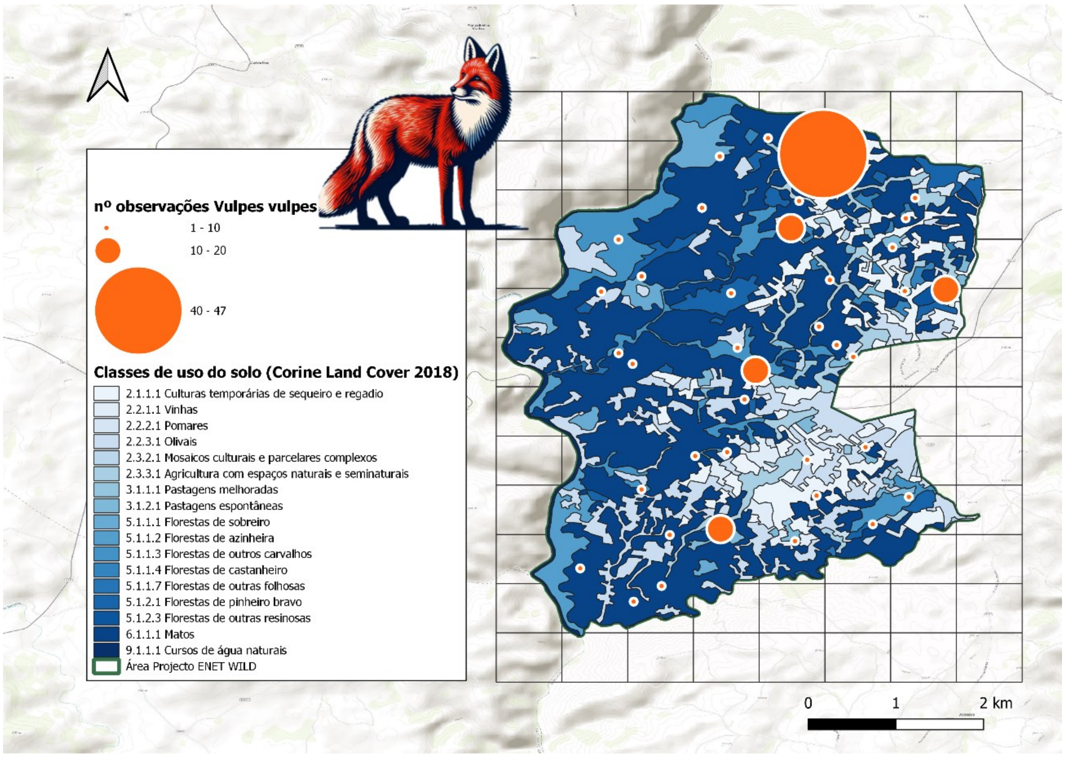

Figure 10. Number of fox observations, in the different land use classes in the ENET WILD project area.

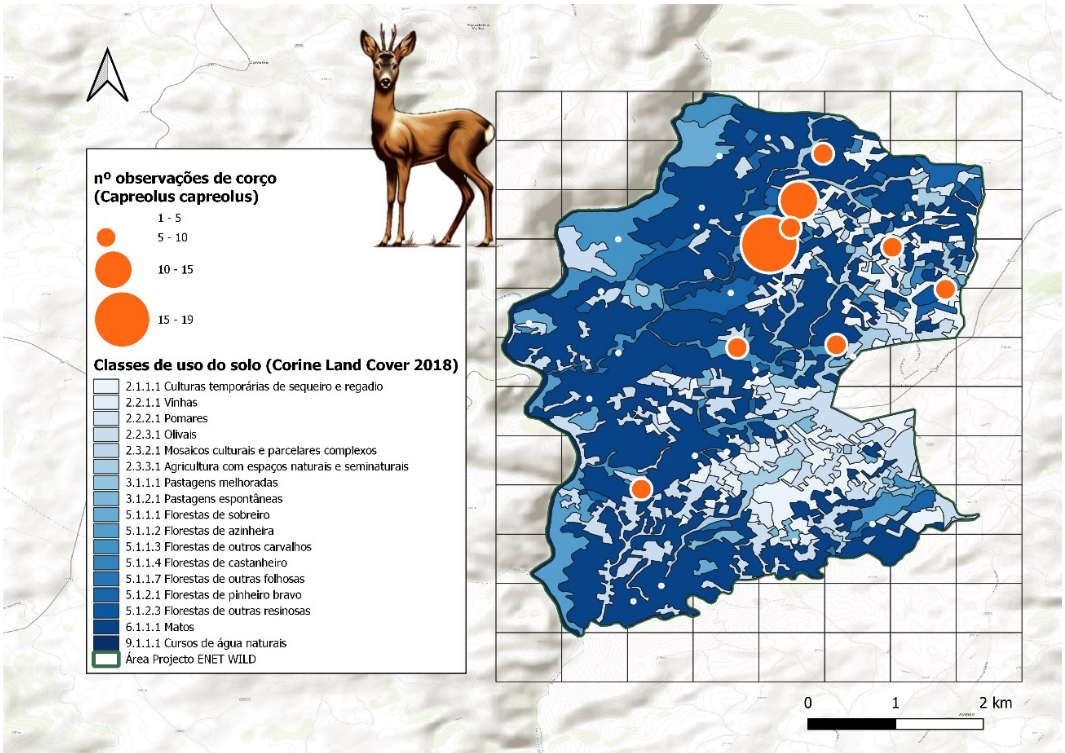

Figure 11. Number of roe deer observations, in the different land use classes in the ENET WILD project area.

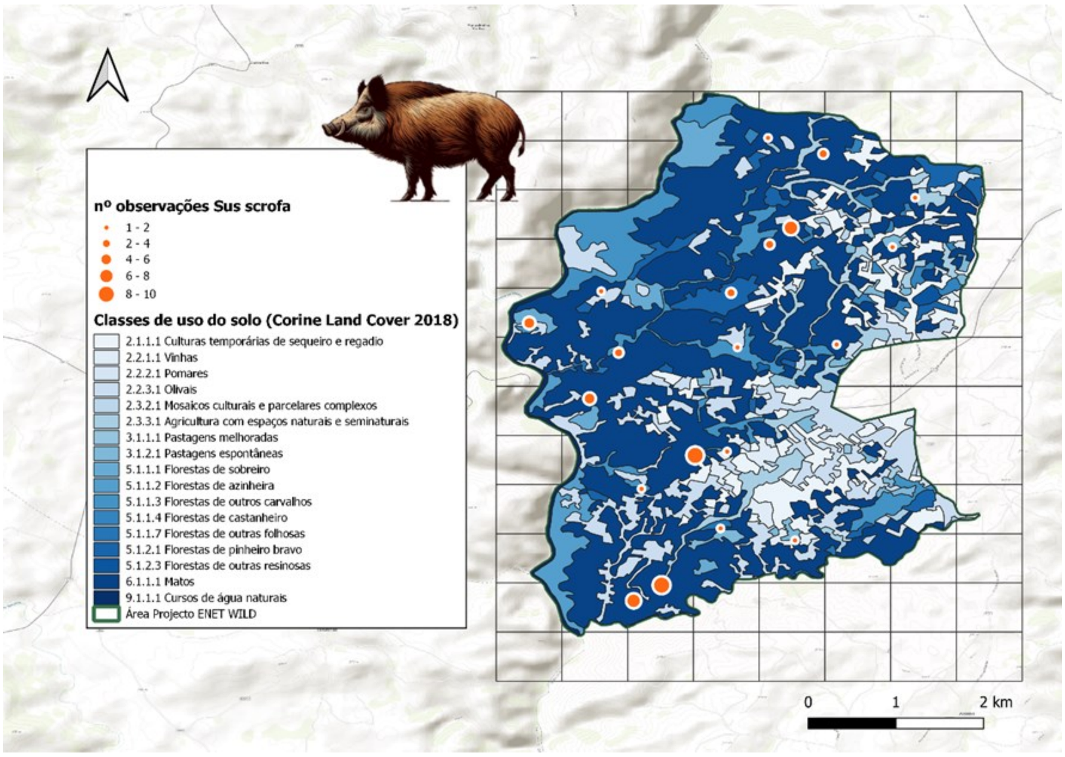

Figure 12. Number of wild boar observations, in the different land use classes in the ENET WILD project area.

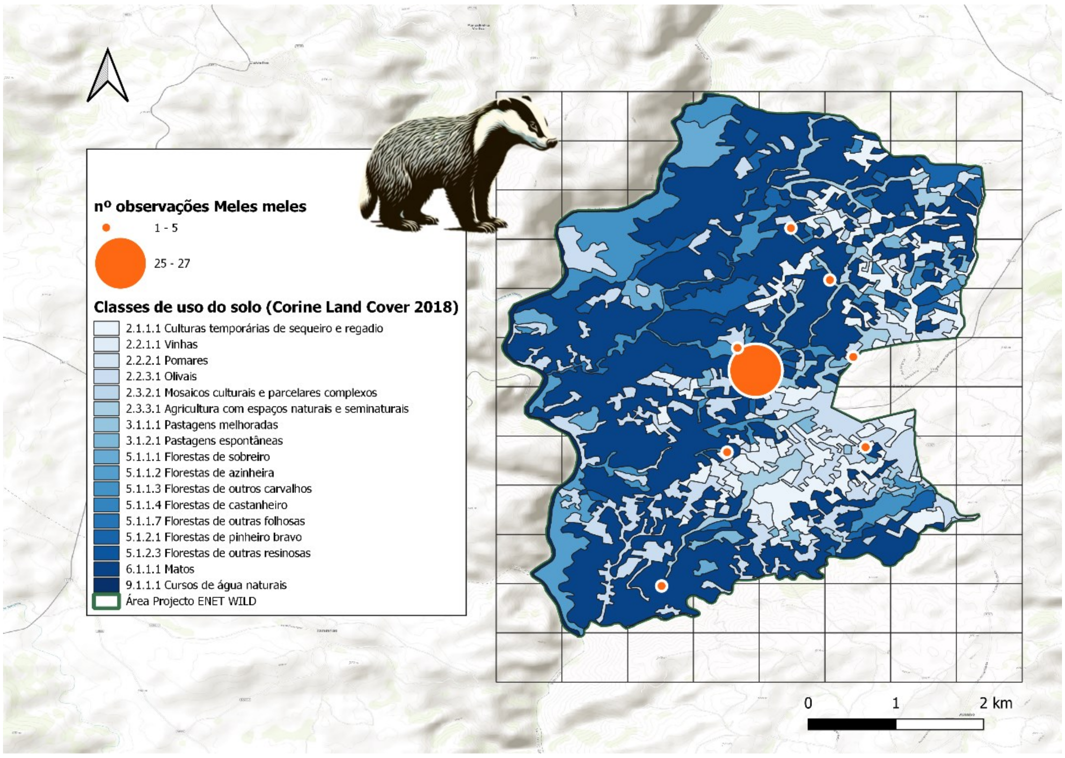

Figure 13. Number of badger observations, in the different land use classes in the ENET WILD project area.

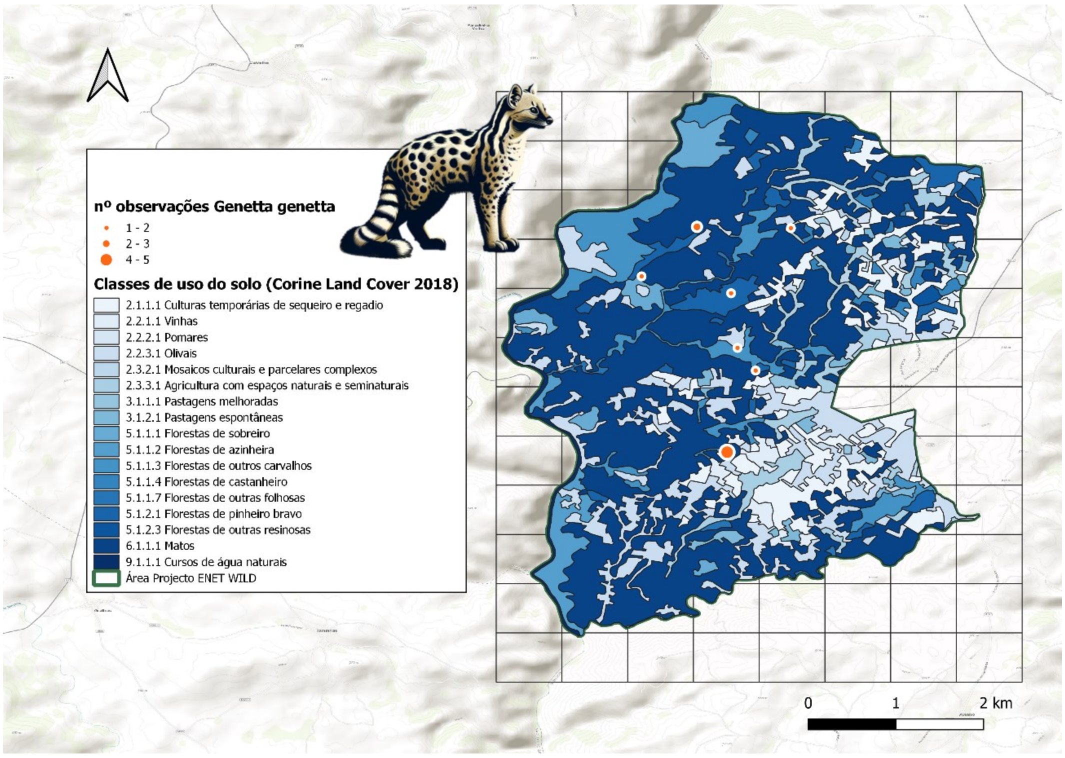

Figure 14. Number of genet observations, in the different land use classes in the ENET WILD project area.

5. Discussion

The results indicated that the number of animal observations and species counts do not spatially coincide. This discrepancy could stem from habitat characteristics. Areas with significant heterogeneous habitats may provide refuge and food for more species, even if the observation number is lower. Human disturbance levels could also influence this difference, as areas with higher human activity might have numerous observations from a limited number of species tolerant to human presence.

The first objective - identifying areas with higher species richness - was achieved through the species count. The study's western area showed higher biodiversity, likely due to proximity to the Sabor River and reduced human impact from Santulhão village activities.

The second objective - understanding species' geographic distribution - was met with three demonstrative presence/absence maps for roe deer, fox, and badger. These maps revealed distinct distributions, aligning with ecological knowledge. The fox was the most common and well-distributed species, while the badger had fewer observations in fewer grid cells. The roe deer showed a distribution pattern similar to the fox but with fewer captures.

The third objective - analyzing species habitat preferences - was addressed with five selected species. Overall, species were more frequently captured in shrub areas, though this land use type represents 60.7% of the study area, making the high observation number a contingency. The second most observed land use type - other oak forests - occupies only 4.28% of the area, suggesting a true habitat preference. The fox, wild boar, and roe deer were mostly recorded in shrub areas, while the badger and genet preferred other oak forests.

Despite the simple analysis, the study's goals were achieved: logical and physical database design, implementation, and results analysis. Future data could support more complex statistical analyses, like species occupancy models, representing the probability of species presence based on environmental variables associated with their ecological preferences.

Habitat preference analysis limitations included spatial resolution, as COS 2018 is developed at 1:25,000 scale (macro) while our study area is local. Access to habitat classification by botany experts using the National Classified Natural Values Register system would be ideal. Another limitation is data outdatedness, with COS 2018 being at least four years old and CT data from 2022-2023.

Such work, involving spatial database creation and analysis in biodiversity, is vital for nature conservation and wildlife study. Integrating software like QGIS, PostgreSQL, and PostGIS enables efficient management of large data volumes and complex spatial analyses, essential for understanding ecological dynamics and environmental interactions.

This approach identified high species richness areas, mapped species distribution, and understood habitat preferences, crucial for informed conservation and habitat management decisions. The ability to store and process geospatial data contributes to more effective, targeted strategies in wildlife protection and ecological balance preservation.

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Appendix 1 - Number of individuals photographed, by faunal group and species

Table 2. Number of individuals photographed, by faunal group and species

Faunistic Group	Species	number of observations
Amphibian	*Bufo bufo*	2
Bird	*Alectoris rufa*	103
	Anser sp.	1
	Anthus trivialis	1
	Ardea cinerea	1
	Buteo buteo	2
	Caprimulgus europaeus	1
	Carduelis carduelis	7
	Chloris chloris	1
	Columba livia	8
	Columba palumbus	27
	Corvus sp.	1
	Coturnix coturnix	1
	Curruca melanocephala	10
	Cyanistes caeruleus	1
	Cyanopica cooki	10
	Dendrocopos major	1
	Emberiza cia	9
	Erithacus rubecula	118
	Ficedula hypoleuca	6
	Fringilla coelebs	9
	Galerida cristata	1
	Galerida theklae	4
	Garrulus glandarius	8
	Linaria cannabina	4
	Oenanthe oenanthe	4
	Parus major	4
	Passeriformes	1
	Phoenicurus ochruros	12
	Phoenicurus phoenicurus	1
	Phylloscopus sp.	2
	Phylloscopus collybita	1
	Picus viridis	23
	Prunella modularis	4
	Saxicola rubicola	11
	Sitta europaea	1
	Streptopelia turtur	2
	Sylvia atricapilla	4
	Troglodytes troglodytes	1
	Turdus sp.	1
	Turdus merula	346
	Turdus philomelos	71
	Upupa epops	1
Mammal	*Apodemus sylvaticus*	10
	Capreolus capreolus	482
	Cervus elaphus	7
	Chiroptera	1
	Genetta genetta	29
	Leporidae	2
	Lepus granatensis	28
	Lutra lutra	1
	Martes sp.	26
	Martes foina	92
	Meles meles	44
	Neovison vison	1
	Oryctolagus cuniculus	201

Faunistic Group	Species	number of observations
	Rodentia	87
	Sus scrofa	173
	Vulpes vulpes	732

Appendix 2 - COS 2018 classes, by some species and number of individuals photographed

Table 3. COS 2018 classes, by species and number of individuals photographed

Species	COS 2018 Class	No. of individuals
Alectoris rufa	Agriculture with natural and semi-natural spaces	21
	Forests of other oaks	2
	Matos	20
Apodemus sylvaticus	Matos	7
Capreolus capreolus	Agriculture with natural and semi-natural spaces	17
	Chestnut forests	7
	Forests of other oaks	27
	maritime pine forests	5
	Cork oak forests	2
	Matos	85
	olive groves	9
	Spontaneous pastures	6
Columba palumbus	maritime pine forests	1
	Matos	8
Curruca melanocephala	Forests of other oaks	2
	Matos	3
Cyanopica cooki	Agriculture with natural and semi-natural spaces	6
	Matos	4
Emberiza cia	Matos	4
Erithacus rubecula	Chestnut forests	4
	Forests of other oaks	9
	Matos	12
	Spontaneous pastures	1
Fringilla coelebs	Forests of other oaks	1
	Matos	5
Genetta genetta	Agriculture with natural and semi-natural spaces	1
	Forests of other oaks	6
	Maritime pine forests	1
	Matos	4
	olive groves	1
Lepus granatensis	Temporary rainfed and irrigated crops	2
	Matos	5
Martes foina	Agriculture with natural and semi-natural spaces	2
	Forests of other oaks	2
	maritime pine forests	2
	Matos	25
	olive groves	4
Meles meles	Agriculture with natural and semi-natural spaces	4
	Forests of other oaks	28
	Matos	3
	olive groves	4
Picus viridis	Forests of other oaks	1
	Matos	12
Saxicola rubicola	Matos	9
Sus scrofa	Agriculture with natural and semi-natural spaces	10
	Forests of other oaks	12
	maritime pine forests	3
	Matos	38
	olive groves	7

Species	COS 2018 Class	No. of individuals
	Spontaneous pastures	1
Turdus merula	Agriculture with natural and semi-natural spaces	15
	Temporary rainfed and irrigated crops	2
	Chestnut forests	11
	Forests of other oaks	34
	Matos	77
	olive groves	2
Vulpes vulpes	Agriculture with natural and semi-natural spaces	26
	Temporary rainfed and irrigated crops	7
	Chestnut forests	20
	Forests of other oaks	42
	Maritime pine forests	3
	Cork oak forests	7
	Matos	158
	olive groves	4
	Spontaneous pastures	3

Appendix 3 - Database queries

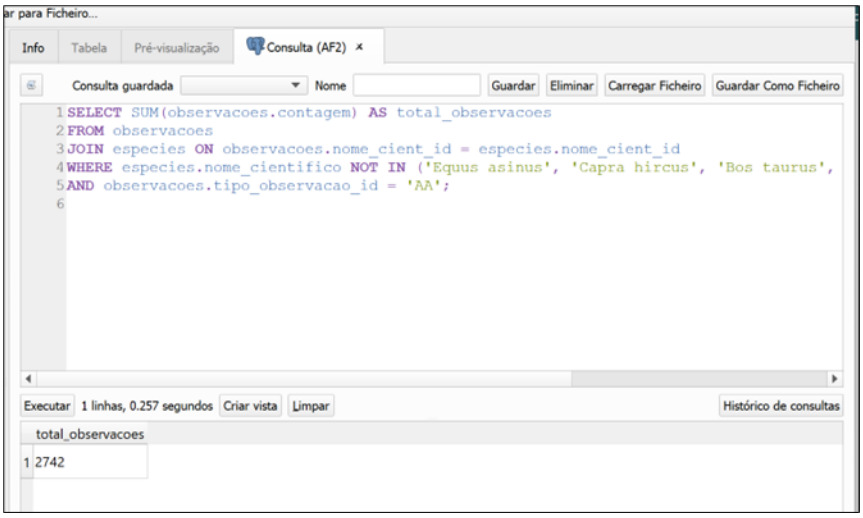

Figure 15. Consult the database to find out the total number of wild animals, excluding people, domestic animals and *Mammalia*.

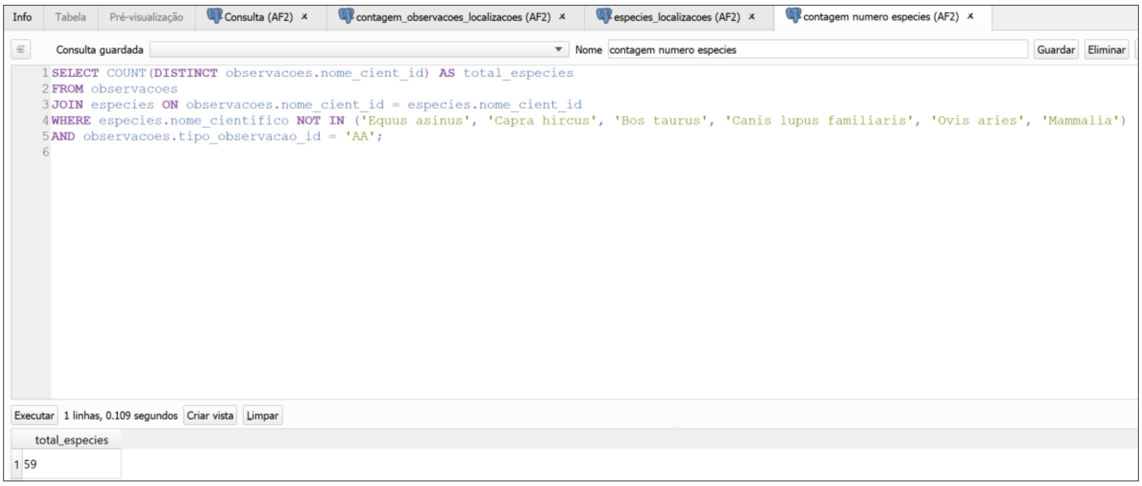

Figure 16. Consult the database to find out the total number of wild animal species, excluding people, domestic animals and *Mammalia*.

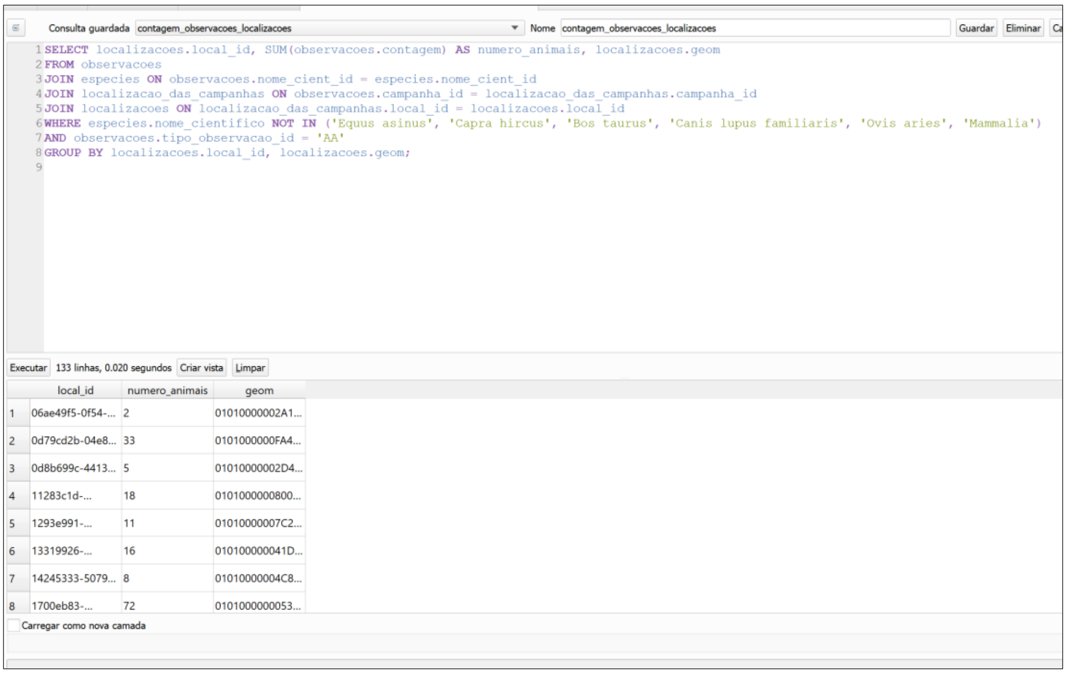

Figure 17. Query the database to obtain the total number of wildlife observations, excluding people, domestic animals and *Mammalia*, for each CT location.

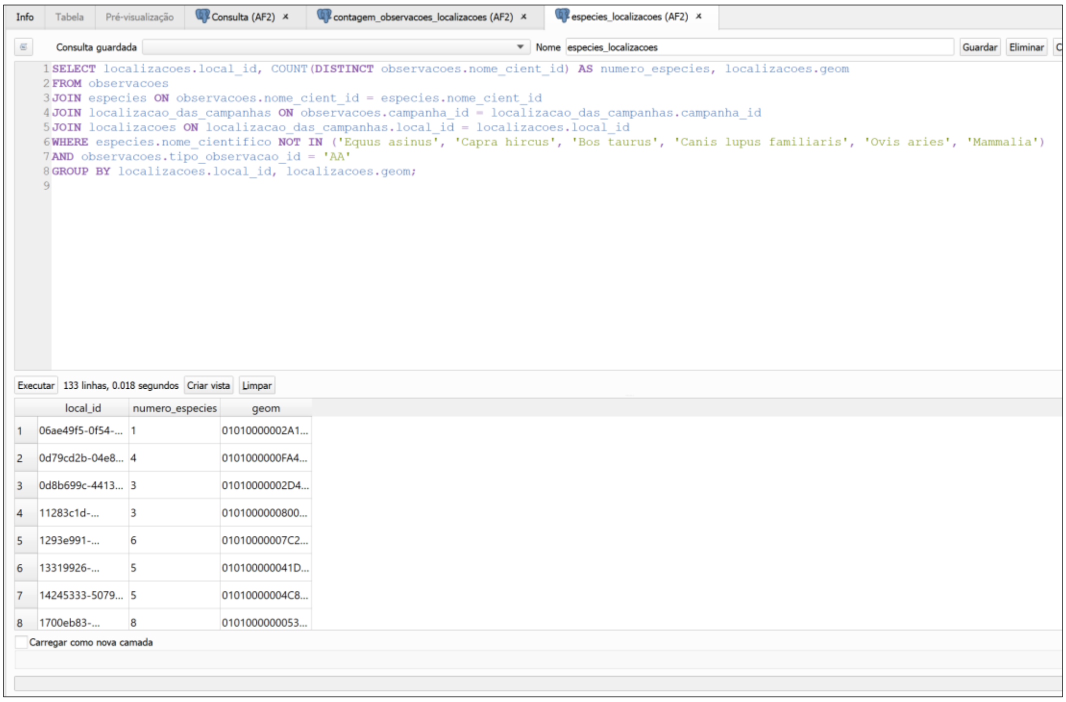

Figure 18. Query the database to obtain the total number of wild animal species, excluding people, domestic animals and *Mammalia*, for each CT location.

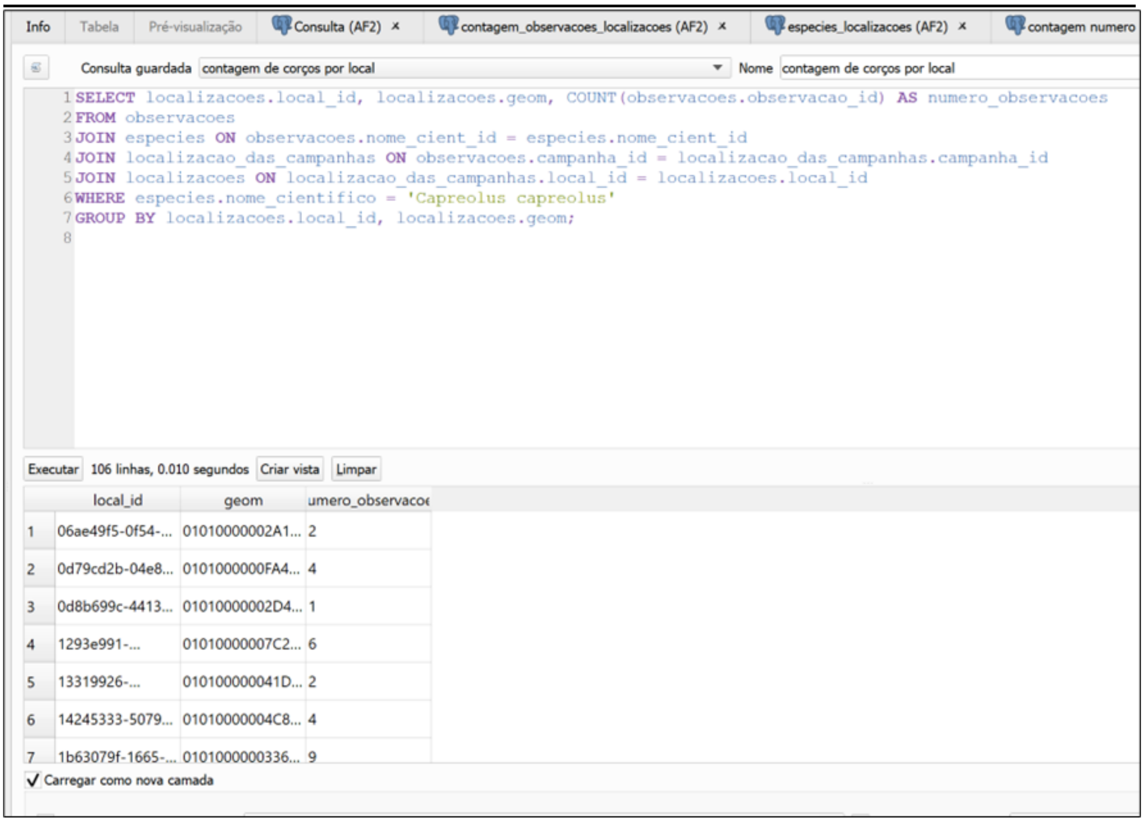

Figure 19. Query on the number of roe deer (*Capreolus capreolus*) observations at each CT location.

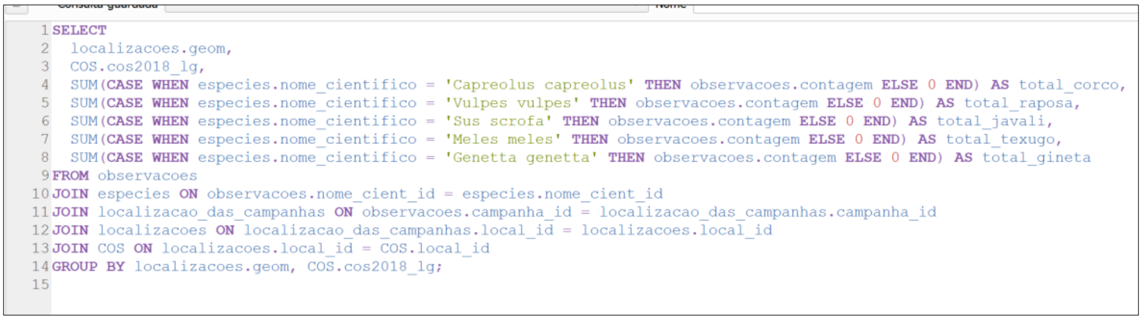

Figure 20. Query carried out to obtain the number of observations of 5 species in the land use classes of the COS table