


## ARTICLE

## Methods, Tools, and Technologies

# Emergency-line calls as an indicator to assess human–wildlife interaction in urban areas

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**Funding information**

Unitatea Executiva pentru Finantarea Invatamantului Superior, a Cercetarii, Dezvoltarii si Inovarii, Grant/Award Number: PN-III-P1-1.1-PD-2019-1207

**Handling Editor:** Rebecca J. Rowe

**Abstract**

Human–wildlife interactions (HWIs) are increasingly common human disturbances as development continues to remove wildlife habitats. Documenting HWI is critical for environmental protection agencies to develop strategies and management decisions that meet the needs of both people and wildlife. However, evaluation of the frequency and types of HWI at broad spatial scales (e.g., national or regional level) can be costly and difficult to implement by managers. In this study, we apply a novel method for the evaluation of patterns of HWI in urban areas by using publicly available data from emergency calls (ECs) placed by inhabitants of Romania’s urban areas. We used information from 4601 ECs placed at the Romanian National Emergency Call System 112, which consisted of (1) wildlife species, (2) spatial location, (3) date and time, and (4) a short description of the emergency. Of the 318 analyzed cities, 300 cities documented ECs on HWI between 2015 and 2020, with roe deer and brown bear being the most frequently mentioned species. We recorded an increasing trend in HWI-related ECs in 73% of the urban areas over the five-year period. We mapped the large-scale distribution of HWI by species and type of interactions in order to capture variations at the national level. Further, we analyzed the social and the biophysical factors potentially influencing the occurrence and frequency of HWI. The results showed that social factors have the same effect on all species, while the effect of the biophysical factors varied between species. Particularly, the presence of large natural habitats, represented by forests, influenced the number of calls only for brown bears. Seminatural landscapes with agricultural land have a different influence in terms of effect and significance for the considered species. Our results suggest that publicly available data from ECs can be used for the rapid assessment of HWI and for evaluating trends and predictors of HWI at broad spatial scales.

Mihai I. Pop and Simona R. Gradinaru contributed equally to the work reported here.

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**KEYWORDS**

emergency call, human–wildlife conflicts, human–wildlife interactions, urban systems, *Ursus arctos*

**INTRODUCTION**

People sharing the same landscape with wildlife create the ecological context for human–wildlife interactions (HWIs). The occurrence and patterns of HWIs are highly influenced by the local landscape and the social–economic context (Soga & Gaston, 2020), and they evolve in synchrony with environmental changes (Fischer et al., 2015). Further, the context is shaped by different cultural and governance systems (Johansson et al., 2016), which build individual or group attitudes toward wildlife (Schell et al., 2021; Teel & Manfredro, 2010). HWIs are frequently assessed through the lens of an anthropocentric paradigm (Treves & Santiago-Ávila, 2020). Consequently, based on the direction of outcomes for humans (Soga & Gaston, 2020), interactions can vary from positive (e.g., educational, well-being benefits) to negative (e.g., injury, property damage, zoonoses). A high interest was shown by scholars and policy makers to the negative interactions, usually defined as human–wildlife conflicts (HWCs) (Schell et al., 2021; Soulsbury & White, 2015). Dealing with positive and negative perspectives is a complex process, which usually generates social conflict around wildlife or landscape management (Teel & Manfredro, 2010). Thus, human response in the form of strategies and management decisions must find a balance between ecological and social needs (Johansson et al., 2016). This approach is particularly suitable for urban systems because urban space is a heterogeneous and dynamic socio-ecosystem. Urban systems are also inhabited by nonhumans that benefit from ecological processes and ecosystem services (Cadenasso & Pickett, 2008). There is still a need to look deeper into the relationship between wildlife and humans (Perry et al., 2020) as urban wildlife management and conservation is a young field of research (Collins et al., 2021).

Urban areas are a heterogeneous matrix of buildings, transportation infrastructures, green spaces, agricultural fields, private gardens, and remnant natural areas (Kowarik, 2018). Besides providing important benefits to humans, urban areas also play an ecological role (Magle et al., 2012). Therefore, there is no doubt that wildlife species, which typically live independently of people in natural ecosystems (often referred to as wilderness), are increasingly referred to as urban wildlife (Egerer & Buchholz, 2021; Soulsbury & White, 2015). These species use, occasionally or permanently, remnant or restored natural areas and human-built structures within the

urban and peri-urban areas (Iojă et al., 2020). Studies have categorized wildlife species based on the usage of urban and peri-urban areas into (1) exploiters/utilizers, (2) adapters/dwellers, and (3) avoiders (Fischer et al., 2015; McKinney, 2006). Behind these categories lies the reality of urban areas offering food or shelter to different wildlife by following the rules of any other natural ecosystem (Cadenasso & Pickett, 2008).

Collecting real and valid information and quantifying and describing HWI in urban areas (typically with large areas and human populations) are challenging for administrators and wildlife managers mainly because interactions happen routinely at a personal level (Morzillo et al., 2014). Many of the methods currently applied to describe HWI involve collecting data occasionally or periodically, with information being recorded long after the interaction has occurred. HWI reports frequently contain information about the costs, in terms of people affected or amounts spent, the size of wildlife populations, or their distribution. Over the past two decades, studies on urban wildlife focused on wildlife behavior, conservation, and management (Collins et al., 2021), while those on HWC assessed mainly cases of aggression, injury and/or death, nuisance, property damage (including car accidents), disease, and economic costs (Peterson et al., 2010; Soulsbury & White, 2015). It makes sense, therefore, for most of the research studies to focus on describing the context of HWC from the ecological (e.g., landscape, suitable habitats) and social (e.g., values, emotions, attitudes, acceptance) perspectives, by using indicators that describe mainly the context of conflicts and their impacts on people (Merkle et al., 2011; Morzillo et al., 2014).

By looking beyond the wildlife component, Soga and Gaston (2020) classified the forms of human–nature interactions along five key dimensions: immediateness, consciousness, intentionality, degree of human mediation, and directions of outcomes. However, in most cases, it is difficult to collect data that integrate all five dimensions. Generally, studies address a small number of species at a local level, missing, therefore, the relevance of spatial variation on multiple landscapes, species, and human reactions (Teixeira et al., 2021). This might be because it is more practical to analyze the context of the interaction through the lenses of the relationship between the event and human reaction, and this type of research is usually pursued at small scales (Morzillo et al., 2014).

In Romania, there is increased interest in wildlife conservation and the consequences of the presence of protected species near urban areas. Considering that the country hosts one of the richest biodiversities in the European Union, including high numbers of large carnivores, there is a need to develop management approaches for HWI. Moreover, as urban inhabitants plead for more green spaces and natural areas in cities and peri-urban areas (Gavriliidis et al., 2020), an increase in HWI is expected in the long term. However, currently, Romania does not have a coherent set of data about the ecological and social drivers of the HWI in urban spaces. No national system to centralize and analyze the HWI is in place. The present approach, which involves collecting data opportunistically or by following different methodologies, makes it difficult to understand the real picture of HWI. Information is collected mainly from areas with a high interest in wildlife (e.g., touristic areas, hunting grounds, etc.) (Salvatori et al., 2020), the news, social media, or the experts. This approach allows authorities to evaluate only the effect of the HWC and thus fail to register neutral or positive HWI. Moreover, the present indicators and reporting system do not record situations in which wildlife finds itself in a dangerous situation. In consequence, this approach has a low potential for working toward prevention measures. Furthermore, it makes it difficult for policy makers to set policies and approach the HWI issue from a legal and administrative perspective (Pătru-Stupariu et al., 2020).

Nevertheless, in urban spaces, one context allows for data collection, namely the event in which a person, materially or emotionally affected by an interaction with a wild animal (Wieczorek Hudenko, 2012), might ask for authority's support by calling the Emergency Call System. The use of Emergency Call System data is a common approach to improve authorities' capacity to plan intervention strategies, to allocate resources to respond to emergencies, or to prevent accidents (Bărnănescu et al., 2021; Chohlas-Wood et al., 2015; Vasilca et al., 2019). Therefore, we considered an emergency call (EC) related to a wild animal to be an official confirmation of an event in which a person interacts, directly or indirectly, with a specific wildlife species, ensuing the effect, negative or not, is registered. To be considered viable, information sources on HWI must allow for the quick and efficient collection and interpretation of data, while at the same time allowing the scaling of HWI in some of the dimensions proposed by Soga and Gaston (2020; e.g., immediateness, the direction of outcomes). We believe that centralized and automatized systems, such as the Emergency Call System, fulfill these criteria and allow the registration of individual interactions and their storage at a large geographical scale (e.g., national, regional),

for a high number of inhabitants of an urban space, or multiple communities.

The main goal of our study is to assess the potential of ECs to be used as an indicator for monitoring (i.e., number, spatial and temporal distribution, etc.) and assessment (i.e., factors influencing the number of calls, local patterns, etc.) of HWI in urban space. We set three objectives based on EC data, along with other urban datasets, to provide new insight to different stakeholders involved in managing HWI:

1. reveal dynamics and patterns (caller motivation and main species involved) in local ECs to inform the emergency system to improve reactions to HWI;
2. provide insights into the differences and similarities between cities in terms of issues raised by the emergency callers and species involved in HWI;
3. assess which are the most important biophysical and socioeconomic factors influencing the number of calls for the main species of wildlife identified as generating the action to call.

## METHODS

### Study area

Romanian urban areas cover 4.456 km<sup>2</sup> and represent 1.8% of the country's surface. The urban system includes 227 small cities (less than 20,000 inhabitants), 72 medium-size cities (between 20,000 and 100,000 inhabitants), 19 large cities (between 100,000 and 400,000 inhabitants), and a very large city (Bucharest, with 2.1 million inhabitants) (Mitrică et al., 2014). The total population of Romania is estimated at 19.5 million inhabitants (medium density of 84 inhabitants/km<sup>2</sup>), of which 53.7% (10.5 million) are living in urban areas (TEMPO Online (insse.ro)). The urban and peri-urban areas of cities in Romania are distributed in three main geographical regions: mountains (28% of the territory), hills and plateau (42%), and plains, including the Danube Delta (30%).

As an Eastern European ex-communist country, Romania's past 30 years of developments were related to land use changes, with arable land and pasture being replaced by new industrial sites and housing (Grădinaru et al., 2020). The time lag between the abandonment of agricultural land and expansion of built-up (Grădinaru et al., 2015) allowed several wildlife species to intensively use the areas in the proximity of the cities (Mustățea & Pătru-Stupariu, 2021). Moreover, the expansion of urban areas often took place close to forests and rivers (Ioja et al., 2021). These changes created the context for city inhabitants to live and work closer to natural (i.e., forests,

lakes, rivers) or seminatural areas (i.e., pastures, grasslands, agro-forest systems), therefore sharing more space with wildlife species.

In Romania, the 112 National Emergency Call System has been running since 2005 (Bărbănescu et al., 2021). In 2014, a new Informational Node was added to the 112 Call Index, namely the incidents involving wildlife. The main objective was the establishment of institutional responsibilities and improvement of official response in risk situations in which a person is (1) attacked by a wild animal, (2) bitten/stung by an insect, or (3) an animal becomes captive or accidentally trapped. Therefore, the introduction of a wildlife-related incident system, in addition to the reality of people reporting to authorities a critical situation, indicates the need to reduce risks in a fast and effective manner. In 2019, the list of emergency situations was expanded by the Romanian Government to include the “attacks of large carnivores on people,” and authorities encouraged people to call the emergency number in case such interactions with wildlife occur. Furthermore, in 2021, the Romanian Government established an emergency protocol for mitigating the risk of brown bear presence in human settlements, which gave the responsibilities to deal with HWI to city administrations. This created a new context, namely the need to start thinking about and planning a management system for urban wildlife at the local level.

## Data collection

Data on the ECs related to human interactions with mammals (i.e., badger, roe deer, beaver, red deer, ferret, marten, wolf, wild boar, brown bear, otter, fox) and reptile species (i.e., turtles and snakes) were provided by the Romanian Special Telecommunications Service, which is the administrator of the National Emergency Call System.

The original database contained information on 22,450 nationwide calls related to wildlife interactions that took place between 2015 and 2020. The 112 answer protocol consists of determination of caller identity, location of the claim, and the type of claim, and then a specific interview is conducted by the intervention forces with the caller (Vasilca et al., 2019). First, we filtered the original database and selected only the calls registered in urban areas. For our study, we considered the calls registered in all urban municipalities in Romania, except Bucharest ( $N = 318$  urban areas); with its over 2 million inhabitants and sprawling development (412 km<sup>2</sup>), Bucharest was an outlier that would have introduced bias in the statistical analysis. This preliminary filtering resulted in 4950 calls. The database was then curated to exclude information not relevant to our study, such as double calls for the same case, potential fake calls, and calls without spatial

information. Furthermore, birds were excluded from our study because negative interactions with birds (e.g., crows) are usually reported by people directly to city administrations or to nongovernmental organizations in the form of complaints instead of calling 112. For similar reasons, we did not consider other wildlife species such as mice, invertebrates, amphibians, fishes, and reptiles (except snakes) taxonomic groups. The remaining 4601 ECs, representing 93% of all calls that occurred in urban areas, formed our final database and were used in the analysis. Information attributed to each call in our sample consisted of (1) spatial localization of the caller in terms of city name and county of origin, location on the road, highway, or railroad (using both the spatial localization registered by the operator and/or the information offered by the caller when describing the problem), (2) date (i.e., day, month, year) and time (i.e., hour, minute), and (3) a short description of the caller’s motivation to contact the Emergency Call System.

## Dynamics and patterns of ECs related to human–wildlife interactions

We were able to identify six main groups of wildlife with a high frequency of ECs, namely roe deer (*Capreolus capreolus*), brown bear (*Ursus arctos*), wild boar (*Sus scrofa*), red fox (*Vulpes vulpes*), red deer (*Cervus elaphus*), and snake species (Table 1). These calls sum to 98.4% (4531) of the 4601 selected calls. We filtered the description of the event using keywords (i.e., accident, attacked, bite, injured, street, yard, etc.), and we further classified the ECs into four main classes comprising 17 detailed categories: (1) wildlife in danger (WD), which included calls related to wild animals in difficulty in urban space, wild animals in difficulty in natural areas, wild animals dead in urban space, wild animal dead in natural space, train accident, poaching with dogs, snares, poaching with

**TABLE 1** Species frequently reported and their classification (based on Fischer et al., 2015).

Species	Classification	Reason for the usage of urban and peri-urban areas
Roe deer	Dweller	Feeding and shelter from predators
Brown bear	Avoider	Feeding
Wild boar	Avoider	Feeding
Snake	Utilizer	Feeding, breeding, and shelter
Fox	Dweller	Feeding, occasionally breeding, and shelter
Red deer	Avoider	Feeding and shelter from predators

weapons, dogs attacking wild animals, and wild animal presence on roads ( $N = 320$ ); (2) roadkill or accident (RA;  $N = 1610$ ); (3) human in danger (HD), which included calls related to humans meeting an animal in natural areas, human attacked/threatened, human injured/mauled by a wild animal, wild animal presence in urban space, damage produced by wildlife ( $N = 2012$ ); and (4) other (O), which included other complaints that could not be classified as above or the motivation for the call was not clear ( $N = 589$ ) (for details, see Appendix S1). Furthermore, we assessed the number of calls per month and hour for each of the main six species. We analyzed the dynamics of the ECs during the studied period by assessing the annual trend for each city and the evolution of calls for the main categories.

### Evaluating cities' profiles in terms of human–wildlife interactions

Similarities and differences between cities with respect to HWI were assessed using hierarchical clustering on principal components (HCPC) analysis. The goal of this method is to identify groups of similar objects (i.e., cities) in a dataset (Husson & Josse, 2014). Within the HCPC, we employed a principal components analysis to reveal the underlying structure of the data and simplify the complexity of the dataset. This step is particularly useful as it is suitable for data in which variables are correlated with one another. Next, we applied a hierarchical clustering on the principal components to choose the clusters based on the hierarchical tree. Ward's criterion was used to calculate the distance between clusters. HCPC has been used before to identify city differences, for example, in determining Covid-19 epidemic patterns in Italian cities (Maugeri et al., 2021). The analysis was conducted using the FactoMineR (Husson et al., 2020) and Factoshiny (Vaissie et al., 2021) R packages.

Two HCPC analyses were conducted. First, clusters of cities depending on the issues raised by 112 callers were identified based on the number of calls following the four situations defined in the previous section, respectively, WD, RA, HD, and O categories. Second, to identify patterns concerning the species involved in the interaction, we used six variables representing the number of calls recorded in each city for each of the six species: roe deer, red deer, wild boar, snake, bear, and fox. Following the two HCPC analyses, we obtained two cluster maps that show individual cities on the principal component map and according to the cluster to which they belong. The higher the distance between the clusters, the higher the dissimilarities among cities. Moreover, we spatially represented the cities as well as the cluster to which they belonged to facilitate the interpretation of the structure of the data.

### Predictors for ECs related to human–wildlife interactions

We analyzed the landscape and inner urban context (i.e., infrastructure and social aspects) to determine the factors influencing the number of human–wildlife interactions described by the number of calls to 112 (Table 2). To describe the landscape setting of individual urban areas, we quantified the proportion of major habitat categories from CORINE Land Cover 2018 (CLC) European database (level-three CLC nomenclature; European Environmental Agency, Copenhagen, Denmark) at two spatial scales: 2-km buffers around the urban perimeter (because daily average movement of the brown bear in Romania was estimated at 1.8 km by Pop et al., 2018) and at a 10-km<sup>2</sup> scale moving-window approach (this is the scale frequently used in environmental reporting in Europe). We reclassified the level-three CLC classes into three main categories: artificial surfaces, agriculture, and forests (see Appendix S2). To describe inner urban space, we used the following variables: (1) population as a reflection of the city size, (2) street density as a reflection of the urban infrastructure development facilitating both human and wildlife movements, (3) percentage of green space, and (4) percentage of urban parks as potential wildlife habitat (e.g., for refuge, feeding), (5) the rate of growth of built areas during 2006–2015 period, and (6) human population changes between years 2010 and 2019 (Table 2). As socioeconomic factors of interest, we considered it relevant to describe the influence of the following aspects on the number of calls: (1) the level of education of city inhabitants as an indicator of social understanding of ecological processes or mutualism orientation toward wildlife (Manfredo et al., 2020); (2) the orientation of the city toward agriculture because agricultural land is prone to high human–wildlife interaction (Table 2) (König et al., 2020).

### Statistical analysis

We evaluated the impact of biophysical and socioeconomic factors (Table 2) on the frequency of 112 ECs separately for each of the six species. For brown bear and red deer, whose geographic ranges are limited across our study area, we used a hurdle model (using function “hurdle” in R package *pscl*; Zeileis et al., 2008), by creating a subset of the number of calls for cities included in the brown bear or red deer range. Hurdle models are a hierarchical class of models that first use a binomial model to determine predictors for a binary outcome (in our case, predictors of HWI inside or outside the species geographic distribution), then use a model for count data to determine predictors for a frequency outcome (in our case, using a negative

**TABLE 2** Variables considered in the triggering factors analysis.

Proposed variable	Units	Source	Description
Surface	ha	TEMPO online (insse.ro)	The surface of an administrative urban area, which influences the available areas for wildlife.
Landscape	Mountain, hill, plain	Geomorphological map of Romania	The cities located in the mountain landscape impose on many wildlife species habitats. In hills, plateaus, and plains, the landscape is more human-transformed, resulting in lower suitability for wildlife.
Population	Inhabitants	TEMPO online (insse.ro)	The no. inhabitants influences the no. calls.
Population changes between 2010 and 2019	%	TEMPO online (insse.ro)	The increase or decrease of the population shows the potential of land use change and abandonment, which influence the attractiveness of the city for wildlife.
Percentage of population with a university degree	%	Citadini.ro	Tertiary education attainment is expected to influence individual behavior in terms of trust in the institution and involvement.
Percentage of the population working in agriculture	%	Citadini.ro	The percentage of employment in agriculture is related to the availability of habitats and food for wildlife inside or close to cities.
Built area change rate	%	Citadini.ro	Built area change rate indicates the intensity of urban expansion, which disfavors adequate habitats for wildlife.
Street density	km/km <sup>2</sup>	Citadini.ro	A higher street density is an indicator of the level of urbanization of the cities and of the fragmentation and mortality risk for wildlife.
Green space	%	TEMPO online (insse.ro)	The proportion of urban green spaces influences the availability of habitats for wildlife in terms of food resources and temporary cover.
Urban parks	%	Citadini.ro	The proportion of urban parks in the city or its proximity influences species presence and dynamics in urban space and proximity because they can offer shelter and food.
Forest (buffer 2 km)	% of forest within a 2-km buffer	Extracted from CLC2018	The proportion of forests within a 2-km buffer around the built area emphasizes how close the wildlife is to cities. Forest proximity to cities increases the potential for interactions to be more frequent either in the city or in the forest.

(Continues)

TABLE 2 (Continued)

Proposed variable	Units	Source	Description
Agriculture land (buffer 2 km)	% within a 2-km buffer	Extracted from CLC2018	Agricultural land within a 2-km buffer around the built area offers food resources for wildlife in the proximity of the cities.
Forest_10km	% at a 10-km <sup>2</sup> scale, moving-window approach	Extracted from CLC2018	The proportion of forests at a 10-km <sup>2</sup> scale using a moving-window approach indicates the presence of wildlife-suitable habitats within the landscape. A large proportion of forest indicates a natural landscape in which the city is located.
Agriculture_10km	% at a 10-km <sup>2</sup> scale, moving-window approach	Extracted from CLC2018	The proportion of agricultural land at a 10-km <sup>2</sup> scale using a moving-window approach. A large proportion of agricultural land indicates a seminatural landscape on which the city is located.
Urban_10km	% at a 10-km <sup>2</sup> scale, moving-window approach	Extracted from CLC2018	The proportion of artificial areas at a 10-km <sup>2</sup> scale using a moving-window approach is used to determine the level of urbanization of the landscape. A large proportion of urbanization indicates a human-modified landscape on which the city is located.
Connectivity	%	Citadini.ro	Percentage of natural habitats located at a distance less than 100 m from one another, being therefore considered to be ecologically and landscape-connected contributes to the movement of wildlife between suitable (cover and feeding) habitat patches.

binomial distribution to predict the number of HWI). For roe deer, wild boar, fox, and snakes, we ran a negative binomial generalized linear model (GLM) for count data in program R version 4.4.1 (R Core Team, 2019) using the function “glm.nb” in R package MASS (Venables & Ripley, 2002). We omitted variables that were highly correlated (Spearman’s  $r > |0.7|$ ) (Zuur et al., 2010).

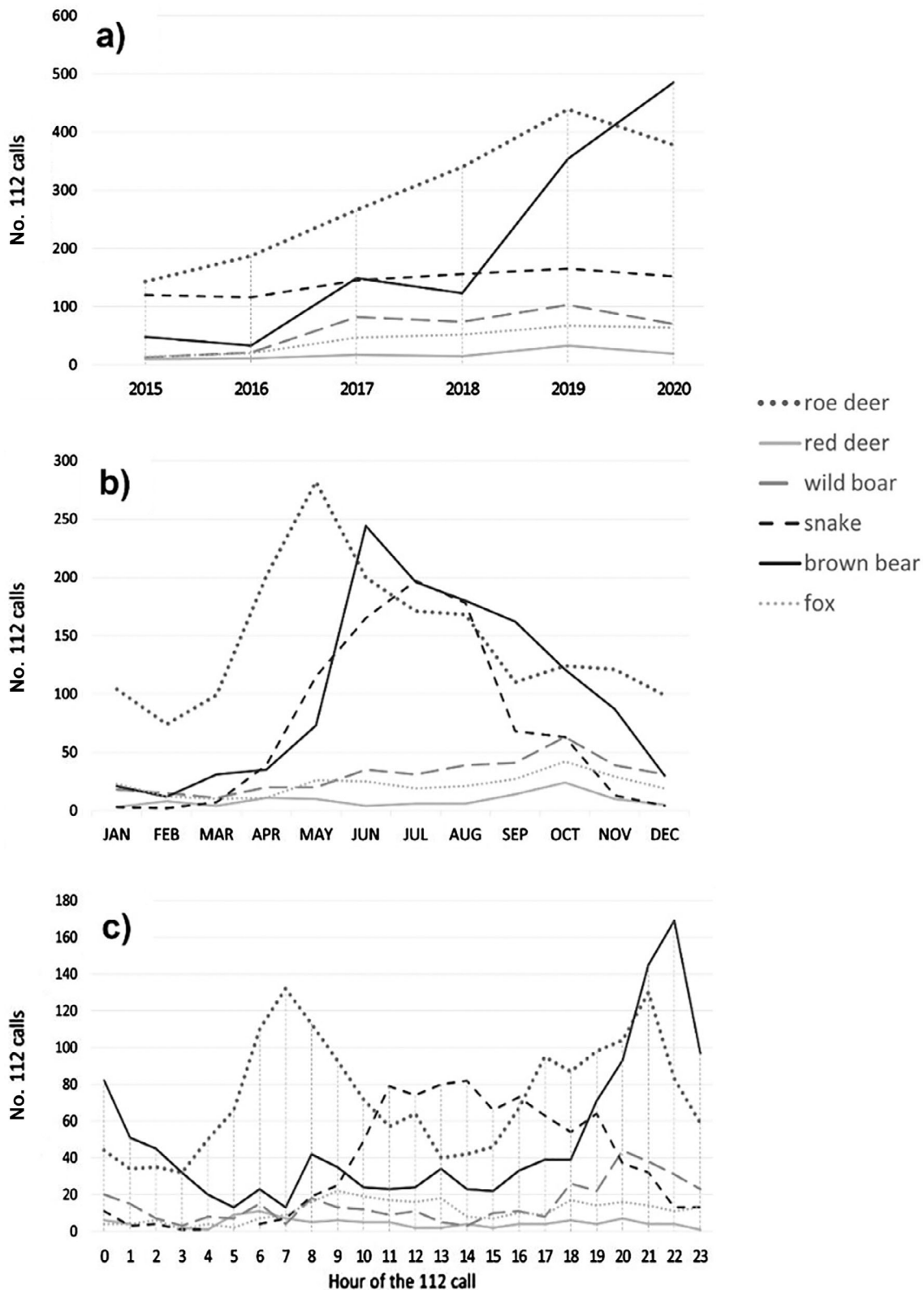
For each species, we developed a set of 33 models that tested hypotheses regarding the influences of different factors on the number of calls for each wildlife species (Appendix S2). We compared these models to null and global models using an information-theoretic approach based on the corrected Akaike information criterion adjusted for a small sample size (AIC<sub>c</sub>; Burnham & Anderson, 2002) using R package MuMIn (Barton, 2020).

If no clear top model emerged (i.e., one or more models within 2 AIC<sub>c</sub> units of the top model), we conducted model averaging using models with an AIC<sub>c</sub> cumulative weight of 0.95 for model predictions.

## RESULTS

### Dynamics and patterns of ECs related to human–wildlife interactions

The main species that were the object of the ECs were: roe deer (*C. capreolus*;  $N = 1753$  calls; 38.7% of total calls) and brown bears (*U. arctos*;  $N = 1192$ ; 26.3%) (Figure 1). Other species were the wild boar (*S. scrofa*;  $N = 363$ ; 8%),



**FIGURE 1** Emergency calls placed at the Romanian National Emergency Call System 112 from 2015 to 2020 representing (a) yearly evolution; (b) monthly number of 112 calls; and (c) number of 112 calls at different times of the day.

red fox (*V. vulpes*;  $N = 264$ ; 5.8%), and red deer (*C. elaphus*;  $N = 105$ ; 2.3%), and undetermined snake species ( $N = 854$ ; 18.9%).

The overall results showed an increase of approximately 230% of the total number of ECs during the 2015–2020 period, with a high increase starting with the



year 2018 (Figure 1a). The highest increase (annual minimum value and maximum value) in the number of calls was recorded for calls related to bears (~900%) and wild boar (~700%). For roe deer, red deer, and fox, the increase was smaller, at ~200%, ~230%, and ~380%, respectively, while for snake species the increase was ~40% (Figure 1a). This increase took place in the context of a decreasing number of ECs at the national level, from 15.5 million in 2015 to 10.3 million in 2021 (Statisticii 112 (sts.ro)).

Of 318 analyzed cities, 300 cities recorded ECs on HWI. Of the 300 cities, for 220 cities (73%) we observed an increasing trend in the number of ECs, with the top five cities with the highest increase being important mountain tourism towns and cities (i.e., Predeal, Braşov, Bălan, Sinaia, and Buşteni). For 66 cities (22%), we observed a decreasing trend in ECs. The top five cities with the highest decrease in ECs (i.e., Piatra Neamţ, Sănnicolau Mare, Băile Govora, Mărăşeşti, Buziaş) have different sizes in terms of area and population, are located in different geographic regions, and have very few common landscape characteristics. For 14 cities (5%), the trend was stable. The average number of calls per city during the six-year study period was 14 (0–305; SD = 28.72). Most cities (73.6%) recorded many calls below the average, while a few of the (5.7%) recorded no calls at all. The average call index (number of calls  $\times$  1000/population) for the period 2015–2020 was 1.5 calls/1000 inhabitants (0–79.45, SD = 6.12 s).

Most of the calls were recorded during the April–September period (Figure 1b). While for roe deer and snake species, most of the ECs were made during the day (from 6 a.m. to 9 p.m.) (Figure 1c) the calls

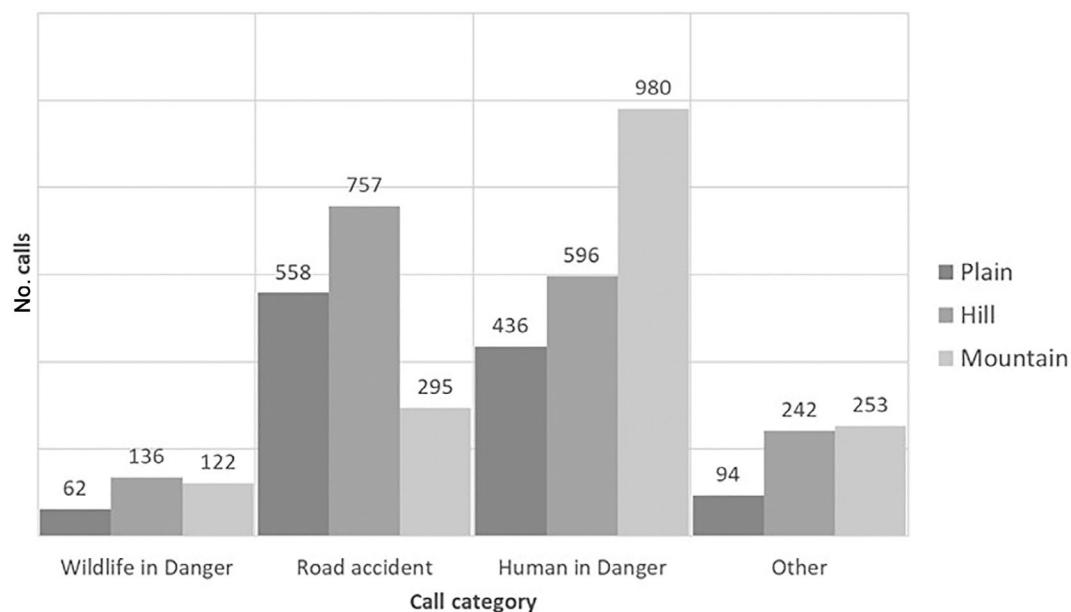
regarding brown bear HWI were made during the night (from 8 p.m. to 1 a.m.). For red deer, wild boar, and fox, the ECs were distributed almost evenly during the 24 h (Figure 1c).

The calls were distributed almost equally between the mountain (36.1%) and the hill regions (38.4%). For the plain region, the number of calls was lower (25.5%) (Figure 2). The cities located in the mountain region have a higher number of calls related to bears than to other spaces, but there are also cities where brown bear-related calls were dominant (i.e., Predeal, Sinaia, Azuga, Băile Tuşnad; Figure 4). In the cities located in hill and plain regions, ECs were mainly related to roe deer roadkill accidents and the presence of snake species in houses and cars (Figures 2 and 3).

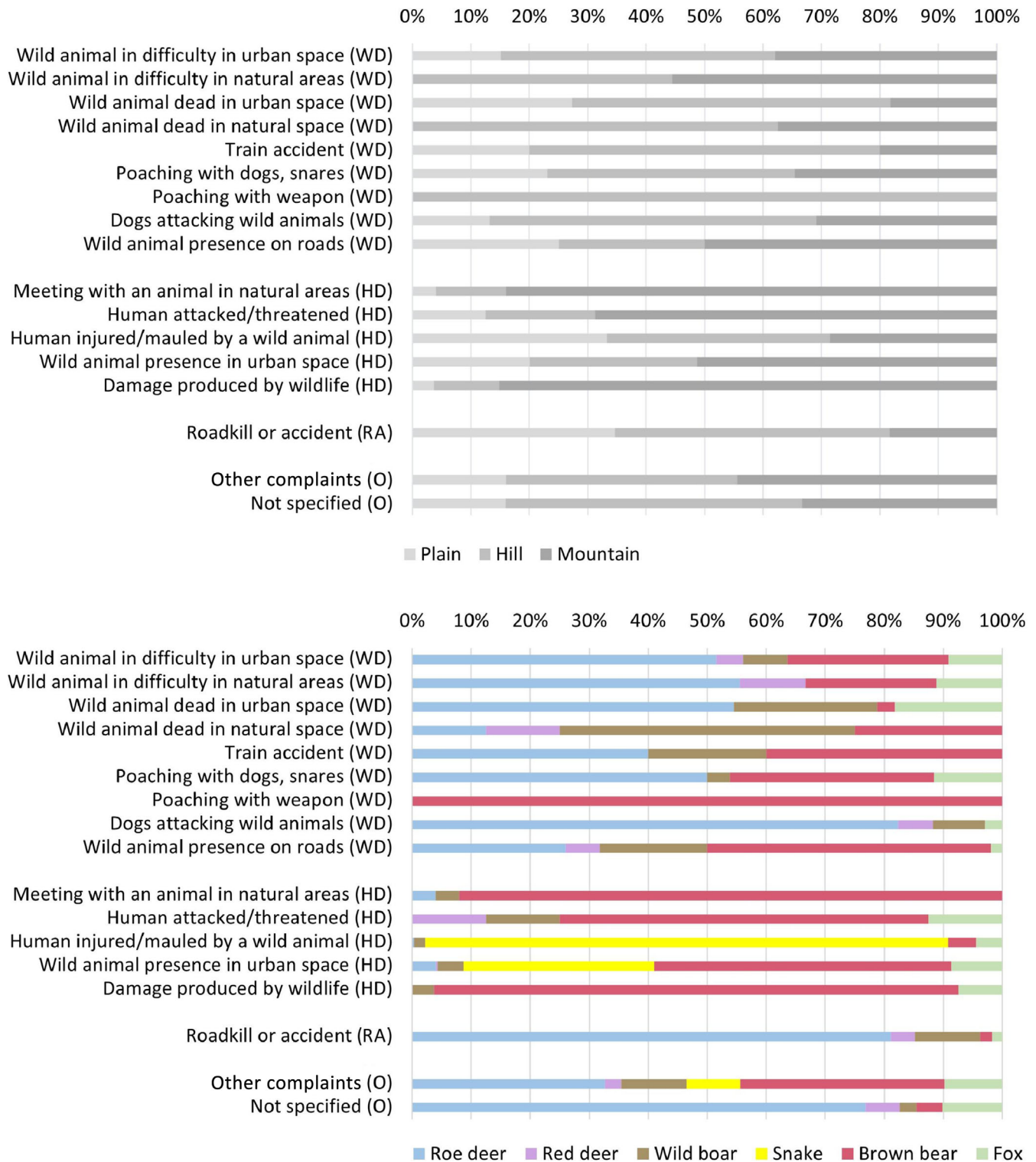
The highest number of ECs was included in the HD category ( $N = 2012$  calls), followed by the RA ( $N = 1610$  calls) category. The EC included in the category WD registered the lowest number ( $N = 320$  calls), but this category included the highest diversity of calls (Figure 3). The main types of calls were related to the presence of wildlife in urban space ( $N = 1629$  calls) and road accidents ( $N = 1610$  calls) (Figure 1; Appendix S1).

### Similarities and differences in ECs between cities

Of the 318 cities included in our study, 94.3% recorded at least one EC during the 2015–2020 period. Some cities were more sensitive from the perspective of HWI than others, as 10 cities cumulated 77.5% of the calls. The



**FIGURE 2** Number of emergency calls in four main categories and their distribution by landscape type.

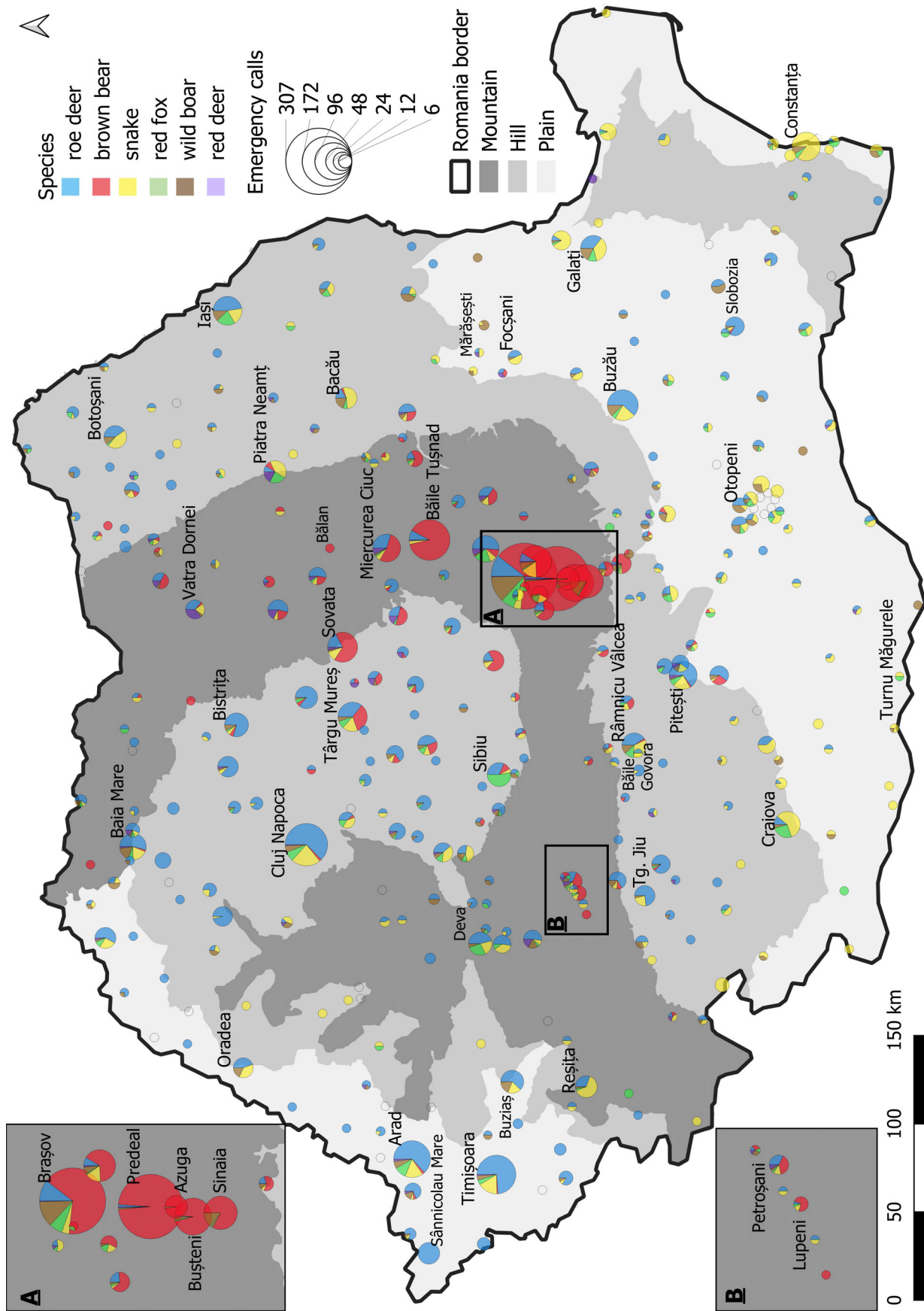


**FIGURE 3** Emergency call categories by landscape type and species. Main class abbreviations are: HD, human in danger; O, other; RA, roadkill or accident; WD, wildlife in danger.

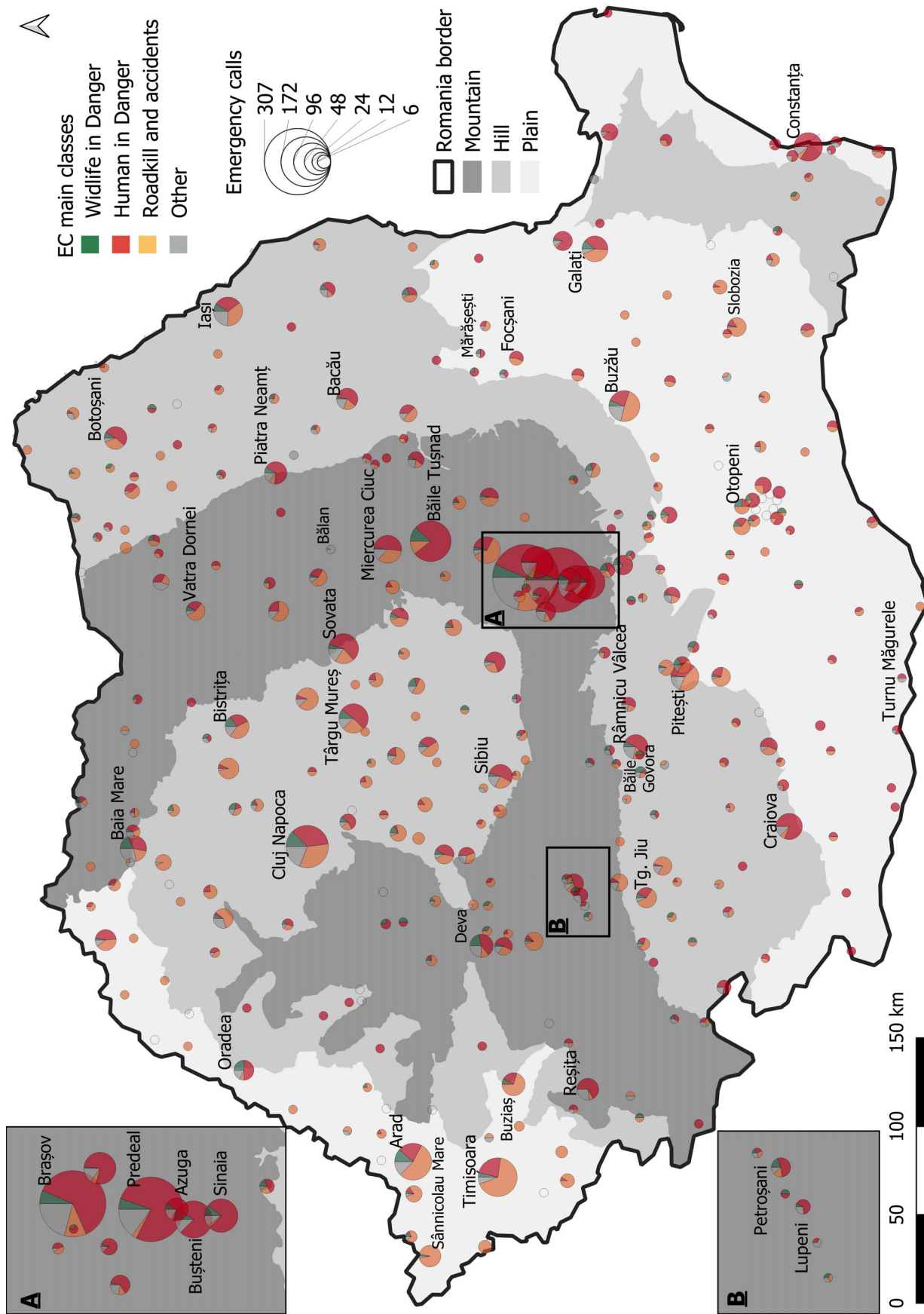
results of the two HCPC analyses showed a more nuanced picture of the patterns, highlighting the cities prone to interactions with certain species (Figure 4) and to certain types of interactions (Figure 5). For example, 10 out of the 319 cities in Romania cumulated 77% of the

brown bear-related calls; the same 10 cities also cumulated 25% of the roe/deer related calls.

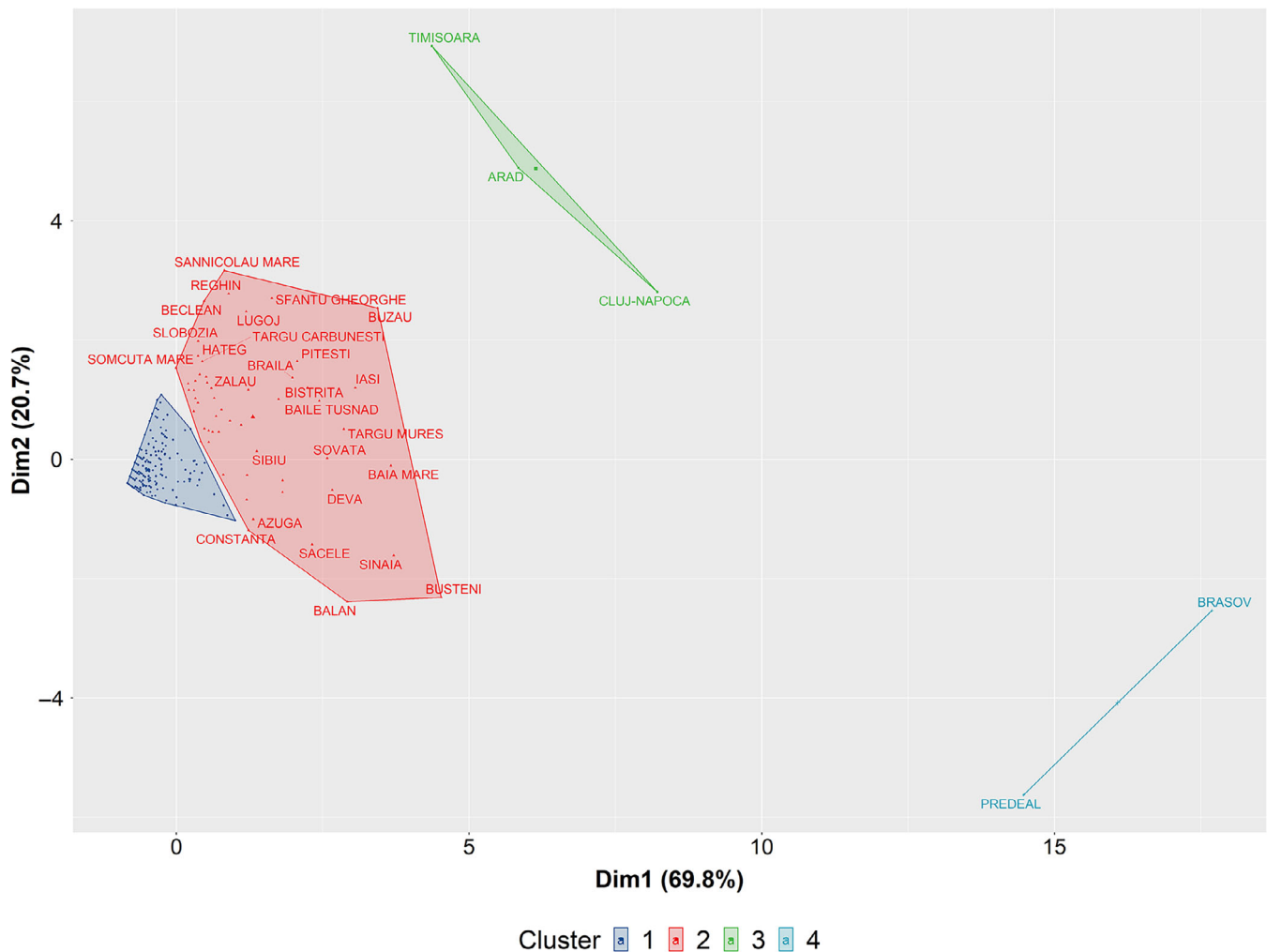
We identified four differentiated clusters of cities based on the issues raised by callers (Figure 6). Five cities separated themselves from all the other cities, while the



**FIGURE 4** Number and distribution of emergency calls/species/city by landscape type. The number of species registered varied between cities as follows: one species in 69 cities, two species in 75 cities, three species in 66 cities, four species in 54 cities, five species in 54 cities, and six species in 12 cities.



**FIGURE 5** Number and distribution of emergency calls (ECs) associated with the four main classes: wildlife in danger, roadkill or accident, human in danger, and other.



**FIGURE 6** Grouping of the city clusters based on problems reported in emergency calls (Cluster 1, none or very few interactions; Cluster 2, fewer interactions, mainly for reporting roadkill or accident and human in danger; Cluster 3, highest number of calls for reporting roadkill or accident and human in danger; Cluster 4, highest number of calls for reporting humans in danger and wildlife in danger). Dim1 and Dim2 represent the two dimensions retained after dimensionality reduction using HCPC.

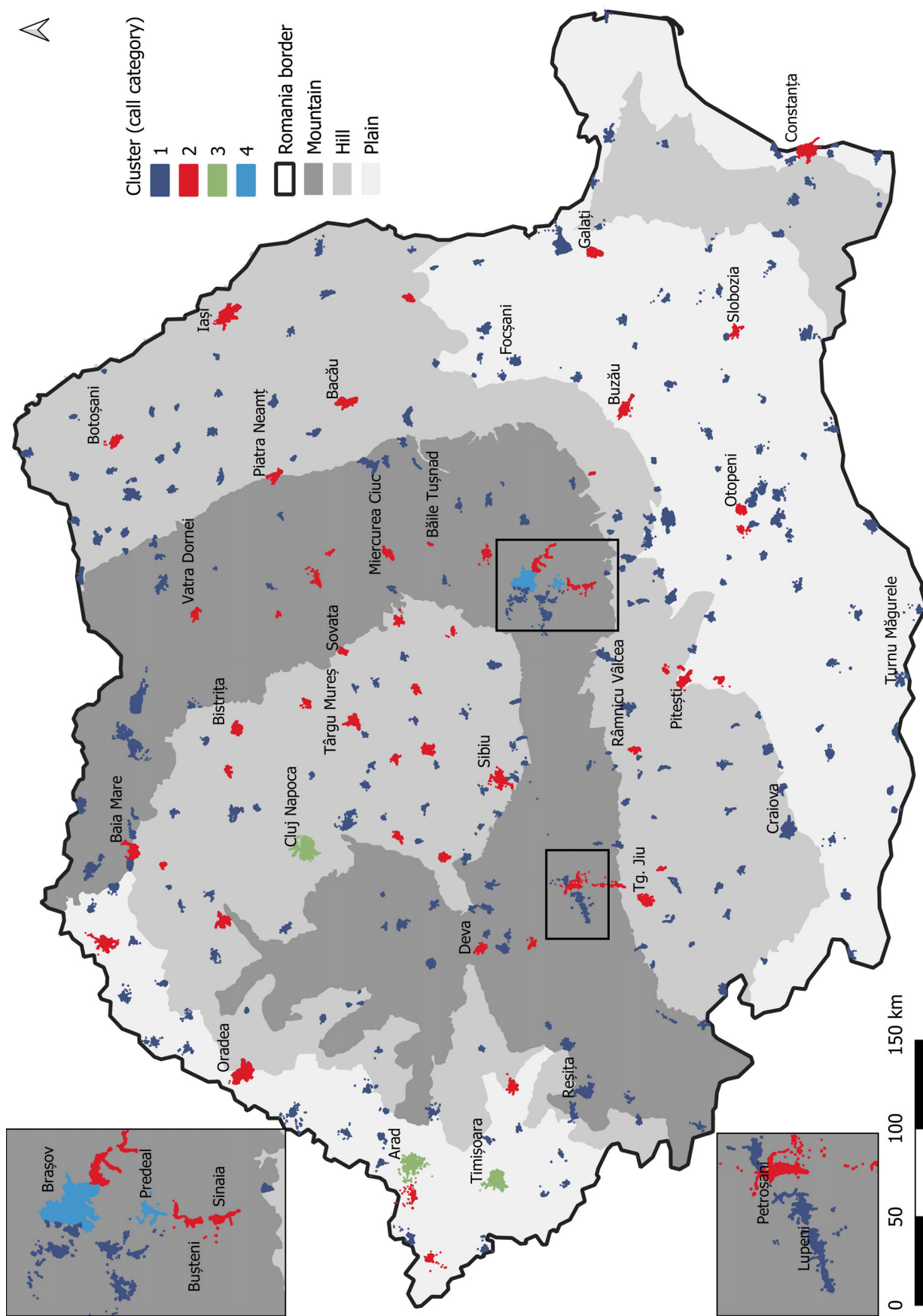
rest of the data tended to be grouped into two clusters. Cluster 4 grouped the two cities in Romania (Braşov and Predeal; Figure 7) with the highest number of calls for reporting HD, WD, and other types of calls, while Cluster 3 comprised three cities (i.e., Cluj-Napoca, Timisoara, and Arad; Figure 7), which reported the highest number of calls for reporting RA, and a high number of calls for reporting HD. Cluster 2 included cities with fewer interactions, mainly for reporting RA and HD, while Cluster 1 was comprised of cities with none or very few interactions.

Findings regarding the species involved in the interactions were, overall, less clearly separated (Figure 8). A separate cluster was, again, formed by cities Braşov and Predeal (Figure 9), which recorded the highest number of calls for reporting interactions with bears and a relatively high number of calls for reporting interactions with wild

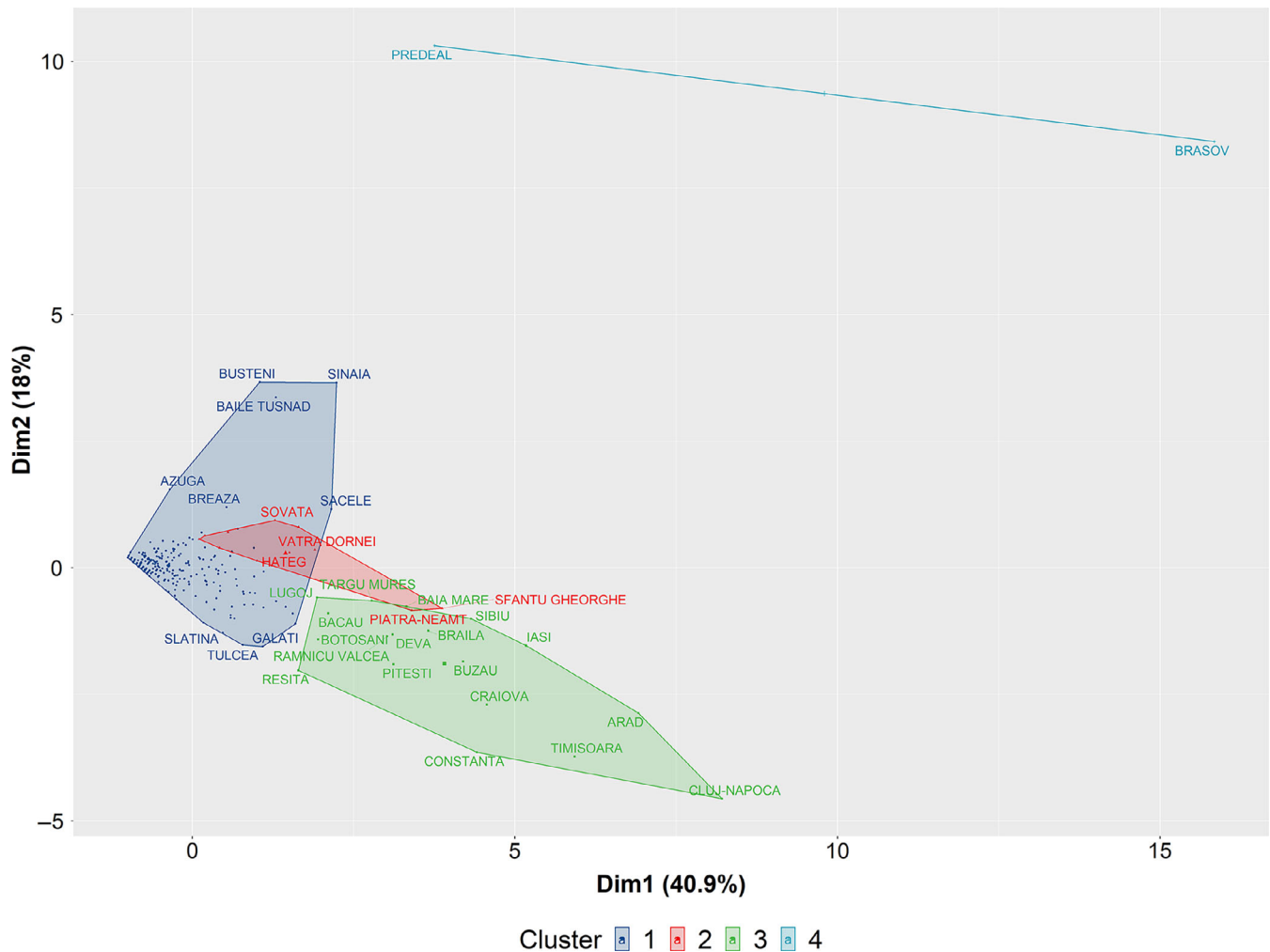
boars and foxes. Cluster 3 comprised cities with the highest number of interactions with snakes and roe deer, as well as a high number of calls for reporting interactions with foxes and wild boars. Cluster 2 was formed by cities that only registered calls for reporting interactions with red deer, while Cluster 1 included cities that registered low interactions with all the six species in our analysis.

### Factors influencing the number of ECs

As expected, there were different landscape and social factors influencing the number of EC for each species, with human population size positively influencing the number of EC for all species (Table 3). The city area (used in the models without the population size) was also a variable significantly influencing the number of calls,



**FIGURE 7** The spatial distribution of the cities depending on their membership in a certain cluster based on problems reported in emergency calls (Cluster 1, none or very few interactions; Cluster 2, fewer interactions, mainly for reporting roadkill or accident and human in danger; Cluster 3, highest number of calls for reporting roadkill or accident and human in danger; Cluster 4, highest number of calls for reporting humans in danger and wildlife in danger).



**FIGURE 8** Grouping of the clusters based on species involved in the interaction (Cluster 1, low interactions with all six species; Cluster 2, interactions with red deer; Cluster 3, highest interactions with snakes, red deer, wild boars, and foxes; Cluster 4, highest interactions with brown bears). Dim1 and Dim2 represent the two dimensions retained after dimensionality reduction using HCPC.

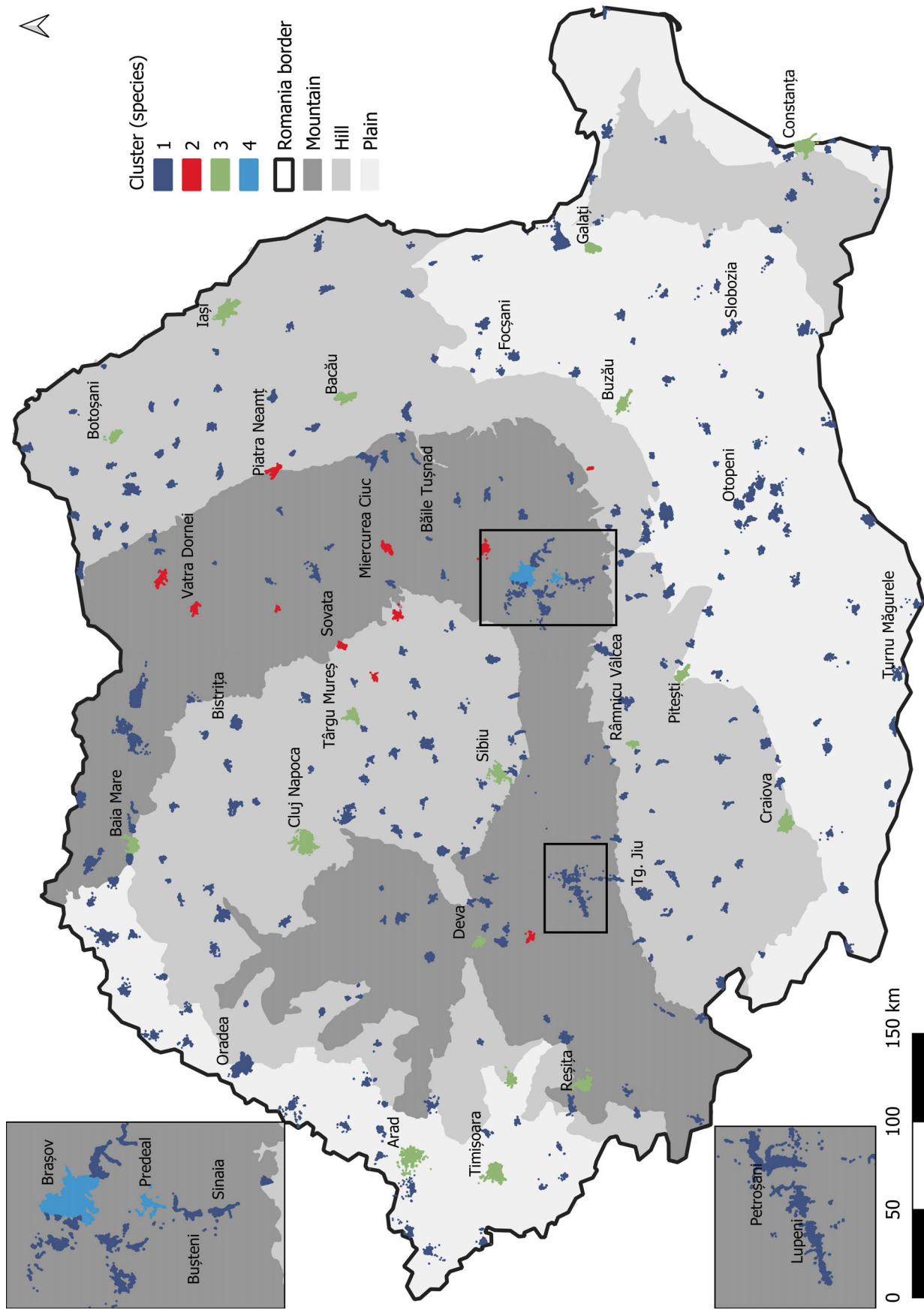
except for wild boar and snake species. The percentage of the population having a university degree was a significant positive predictor for the number of EC for roe deer, wild boar, fox, and snakes.

The proportion of forest habitat (within a 10-km<sup>2</sup> moving window and within a 2-km buffer around the cities) registered a positive association with the number of calls for brown bears and a negative effect on calls regarding roe deer. The percentage of agricultural land registered a significant positive effect on roe deer and a negative effect on wild boar- and snakes-related calls. The natural space within the proximity of cities associated with the connectivity of natural areas had no significant influence on mammal species (Table 3). The variable associated with the socioeconomic factors had the same positive or negative effect (even if not significant) for all species, while the effect of the biophysical factors varied, as expected, because there are significant

ecological and behavioral differences between the species. We did not consider the red deer for our analysis because the null model was within two  $\Delta AIC_c$  of the top model with  $AIC_c = 270.58$  and a weight of 0.99, suggesting that for this species the number of calls was lower and highly distributed between cities.

## DISCUSSION

Our study confirmed the potential of EC data to be used for monitoring and assessment of human–wildlife interactions in urban areas. Interactions records showed that HD and road accidents were the most frequent reasons for wildlife-related ECs. We were able to map, at a large scale, the distribution of HWI by species (Figure 4) and the type of interactions (Figure 5). Moreover, we identified patterns and dynamics over time and space and



**FIGURE 9** The spatial distribution of the cities depending on their membership in a certain cluster based on species involved in the interaction (Cluster 1, low interactions with all six species; Cluster 2, interactions with red deer; Cluster 3, highest interactions with snakes, red deer, wild boars, and foxes; Cluster 4, highest interactions with brown bears).



**TABLE 3** Influence of biophysical and socioeconomic factors on the number of emergency calls (effects, with significance in parentheses).

Metric	Brown bear <sup>2</sup>	Roe deer <sup>2</sup>	Wild boar <sup>1</sup>	Fox <sup>2</sup>	Snake <sup>2</sup>
Population	+(**)	+(***)	+(*)	+(**)	+(***)
Population change 2010–2019	<i>n</i>	–	<i>n</i>	–	+
Percentage of population with a university degree	–	+(***)	+(*)	+(***)	+(***)
Percentage of the population working in agriculture	–	–(*)	<i>n</i>	–	–
City area	+(*)	+(**)	<i>n</i>	+(*)	<i>n</i>
Build area increasing rate	<i>n</i>	+	<i>n</i>	+	<i>n</i>
Street density	–	–	<i>n</i>	–	–
Percent green space	–	–	–	–	+
Percent urban parks	+	+	–	+	+
Percent forest (buffer 2 km)	+(*)	–	<i>n</i>	<i>n</i>	+
Percent agriculture land (buffer 2 km)	<i>n</i>	+(*)	–(**)	–	–(*)
ForMN (10 km)	+(**)	–	<i>n</i>	<i>n</i>	<i>n</i>
AgMN (10 km)	–(*)	<i>n</i>	<i>n</i>	<i>n</i>	<i>n</i>
UrbnMN (10 km)	<i>n</i>	–(**)	+	+	+
Percent natural space (max. 100 m between natural land)—connectivity	+	–	<i>n</i>	+	–(ns)
Models	M22, M23, M30	M8, M21, M25, M26, M30, M28	M26	M1, M6, M8, M101, M21, M26, M10	M21, M10, M101, M30, M1, M26
AIC value for the first model	565.33	1624.70	830.89	603.17	1143.83

Note: Analysis used: hurdle models (brown bear) and generalized linear model (roe deer, wild boar, fox, and snake). Model (M) description available in Appendix S2. Models (M), indicated by numbers in superscript: 1, best model; 2, model averaging (Appendix S2). Variable effect: +, positive; –, negative; *n*, variable not included in the model.

Abbreviations: AIC, Akaike information criterion; max., maximum.

\* $p \leq 0.05$ ; \*\* $p \leq 0.01$ ; \*\*\* $p \leq 0.001$ ; ns,  $p \leq 0.10$ .

showed that HWI varied between regions and species involved. The intensity of interactions differs among cities, thus exposing the existence of hotspots of HWI.

### Dynamics and patterns of ECs related to human–wildlife interactions

The results showed that the number of wildlife-related ECs increased during the 2015–2020 period. This increase could be interpreted as (1) an increase in the number of HWI and (2) an increase in people's interest in reporting wildlife presence. We believe both interpretations are valid because the increase in HWI, mainly those related to brown bears, was also reported by the local communities (Pătru-Stupariu et al., 2020), while the public authorities (local and national) expressed repeatedly since 2018 their willingness to become actively involved in

solving wildlife-related problems. However, in 2018, the Romanian Government initiated an emergency system dedicated only to brown bear interactions. This suggests an existing interest only in risk avoidance and not toward a holistic strategy for all HWI. The slight decrease of calls recorded in 2020 for all interactions except those with brown bears could be related to reduced activity during Covid-19 restrictions.

Most ECs were related to HD, showing that the main context of people calling the emergency number is signaling a potentially dangerous situation for their safety. Nevertheless, the high increase in calls was related to brown bears and roe deer (Figure 1a), and because roe deer do not normally pose a risk to human safety, we can speculate that the interest in animals in difficulty also increased. A significant proportion of calls (35%) were related to roadkill or accidents (Figure 2), a context in which, using only the information registered by the

operator, it is impossible to establish whether people are signaling risk to their safety, reporting a car crash for insurance purposes, or they are concerned about animal safety. A low number of EC were related to the damages made by wildlife to farms or other goods. Linked to brown bears, this is unusual since other studies suggest a high level of damage also into urban spaces (Pop, Dyck, et al., 2023; Salvatori et al., 2021). We can speculate that once the damage is noticed, people are (1) using the procedure in place for claiming compensation by informing the local administrations or (2) the damage is of low value and it does not justify the effort of claiming compensation. Over 12% of the calls included in the “Other” category had no clear information on the interaction, suggesting that (1) the system might incorporate some kind of abusive calls as suggested by Bărnănescu et al. (2021) or (2) the available time to register relevant data was too short.

### Similarities and differences in ECs between cities

A large proportion of urban areas in Romania experienced HWI; however, the intensity of the interaction differed among cities (Figure 4). A small number of cities experienced a high number of interactions, suggesting the existence of hotspots of HWI. In these cities, city administration could improve the planning of interventions and resource allocation in order to reduce the severity and frequency of encounters between wildlife and humans (Treves et al., 2009). Relevant in this regard could be information regarding periods when most interactions occur, for example, in the case of roe deer and brown bears that prevail during the April–October period (Figure 1b).

Our results regarding interactions with brown bear are consistent with the findings of Pătru-Stupariu et al. (2020). Most of the ECs to signal interactions with this species were made from 7 p.m. to 2 a.m. (Figure 1c), which is not unusual since brown bears are urban avoiders. Some of the cities in Romania have already started to implement measures for the management of HWI, a good example being Băile Tușnad, where interactions with brown bears have been frequent (Erős et al., 2021). Also, awareness measures are particularly important as wildlife is a vector for zoonotic pathogens (Borșan et al., 2021).

The HCPC analysis highlights the existence of several cities where specific interventions are needed to prevent roadkill or accidents. These cities are located in parts of the country where major infrastructure projects have been developed over the past years, suggesting possible issues related to habitat fragmentation and the

effectiveness of the measures put in place to mitigate it. Corroborated with data on traffic volume (Basak et al., 2022; Fedorca et al., 2021), information on EC related to HWI could be used to design more efficient measures to prevent wildlife–vehicle collisions.

### Combinations of factors that influence the number of ECs

The analysis of biophysical and social factors shows that specific combinations of factors influence the number of ECs. Overall, we noticed a higher influence of socioeconomic factors compared with the influence exerted by biophysical ones. Soga and Gaston (2020) suggested that interactions are more a reflection of socioeconomic diversity, and from the perspective of using EC as an indicator of HWI, our results support this idea. We also observed some similar influences of the factors between roe deer and red fox classified as dwellers, wild boar classified as an avoider, and snakes classified as utilizers, reinforcing the assumption that social factors might be more relevant for these species. The effects of the biophysical factors varied between species. Particularly, the presence of large natural habitats represented by forests in the proximity of the city influenced the number of calls for brown bears, and seminatural landscapes dominated by agriculture in the proximity of the cities had a different influence in terms of effect and significance for the considered species. Nevertheless, future studies could use models in which socioeconomic and environmental factors are considered together to provide a comprehensive understanding of the characteristics of HWI (Morzillo et al., 2014).

Our results showed that cities with high shares of green spaces recorded low numbers of calls, while cities with high shares of urban parks had a high number of calls (Table 3). However, the presence of large natural habitats represented by forests in the proximity of the city influenced the number of calls only for brown bears. This suggests that, for the species considered in our study, urban green spaces represent a less attractive habitat than urban parks and forests because they generally have a small surface and are disconnected from large habitats outside the city. Moreover, our results confirmed the results of Merkle et al. (2011) that small patches of forest (urban or peri-urban) have no or small impact on interaction with bears unless they are connected to the large forest patches.

We expected that a more developed city transport infrastructure, expressed as street density, to lead to higher ECs being made, because fragmentation and disturbance are higher. However, street density influence on

models was not significant (Table 3). This might be because Romanian cities are rather compact compared with other cities in Europe that exhibit more sprawling patterns. The high number of calls related to the presence of animals on roads and the high number of road accidents confirmed that transport infrastructure plays an important role in the movement of animals within the urban space and proximity. Further studies are required to better understand the cumulative impact of road density and forest/urban parks on wildlife presence and interactions. As expected, the number of ECs was related to the size of the city, with large cities experiencing the highest number of calls. Nevertheless, some small cities (e.g., Predeal, Sovata, Băile Tușnad; Figure 5) had a high call index also, showing that local context is important and extrapolation of local context to the national level is a misleading approach.

Agricultural activities practiced within seminatural landscapes increase the chances of recording a high number of calls only for roe deer, despite its potential to be a factor for HWI with omnivorous species (König et al., 2020). We would have expected that agricultural activities provide opportunities to HWI due to human presence and diversity of food sources for wildlife. However, our results suggested that the presence of agricultural land in the proximity of the cities has a negative influence on the number of EC for species such as wild boar and red foxes. This observation can be highly relevant in terms of understanding how agricultural land abandonment can influence the presence of urban adapters and dwellers. Furthermore, if reliable information on abundance or density of species is available for the areas in close proximity to cities, we recommend using it to improve the potential models. The fact that our data and model showed species-specific patterns indicates that the information obtained from the ECs can be used to better identify and describe the biophysical factors' influence at the local level.

Finally, we observed that a high proportion of tertiary educational attainment in a community leads to high numbers of calls, except for calls related to brown bears. As we assumed that high levels of education lead to an increased interest in wildlife, our observation is consistent with the findings by Manfredo et al. (2020), which showed that higher interest in wildlife leads to a higher demand for institutional involvement. This result supports the need to look deeper into the community characteristics to better understand the perception and the behavior of humans during an interaction with wildlife (Perry et al., 2020; Wieczorek Hudenko, 2012). In this regard, it might be relevant to also investigate the history of conservation, management, or coexistence initiatives as they might change locals' perceptions of wildlife.

## Implications of the study

Because urban systems, presently growing worldwide, are socio-ecological systems containing old, remnant, and natural areas with rich biodiversity, it is unequivocal that we have to consider them valuable ecosystems and use the opportunities offered for biodiversity conservation (Collins et al., 2021; Egerer & Buchholz, 2021; Kowarik et al., 2020; McKinney, 2002; Perry et al., 2020). Furthermore, the elimination of all the risks to human safety and property may prove to be expensive (Soulsbury & White, 2015), and thus urban planners need to rethink coexistence with wildlife within an ethical representation of both humans and nonhumans within urban space (Treves & Santiago-Ávila, 2020). In this regard, as proposed by Morzillo et al. (2014), scientists need to diversify and improve the tools used to look deeper into the human–wildlife interactions.

Our study has shown that ECs can be used as an indicator for HWI in urban areas and this quality is accompanied by several advantages. The freely available information is stored in real time, and it can be redirected immediately to professional groups (e.g., planners, protected areas managers) and researchers for supplementary assessment. Moreover, data collected through an emergency line are reliable and can be used as a monitoring instrument at a large scale in terms of landscapes or a human population, and when analyzing HWI, both socioeconomic and ecological factors can be considered. Describing the factors that influence the number of ECs can inform local administration to better predict the potential of their community to become a hotspot for human–wildlife interaction. We suggest local city administrations with high or average number of ECs and high number of species involved to consider including in their local strategies specific objectives related to wildlife management and human–wildlife interactions. Based on our assessment, asking for more details from the caller could make the data obtained from EC more relevant and reliable for studying social–ecological interactions.

However, ECs fail to capture most positive interactions, except those interactions in which humans act to rescue wildlife individuals. For recording other positive interactions, interested parties could use, also with precaution, social media platforms as a source of information (Bergman et al., 2022; Kretser et al., 2009). We caution against using the simple reporting of the number of HWI-related ECs as indicators of conflict in a given area as such information can be easily politicized, particularly when involving large predators (Darimont et al., 2018). For example, the presence of brown bears in urban areas has been used to fuel conflicts between hunters and conservationists or between people from rural areas affected

negatively by large predators and public authorities (Hossu et al., 2018; Salvatori et al., 2020).

## CONCLUSIONS

The approach to evaluate HWI developed in our study is highly relevant for supporting decision-making by management agencies. First, the data are public and fully available free of charge. Second, the data provide an overview of HWI dynamics throughout the day and seasons and for many species simultaneously. Third, the large volume of information that is continuously being collected via ECs is useful for evaluating trends and monitoring the outcomes of implementing HWI mitigation measures. Lastly, information on human–nature interactions, immediateness, intentionality, and direction of outcomes (Soga & Gaston, 2020), can be gained from EC data. Therefore, the characteristics of an indicator, such as spatial and temporal continuity, embeddedness in cause-and-effect chains, validity, and legitimacy as defined by Heink and Kowarik (2010) are thus fulfilled.

## AUTHOR CONTRIBUTIONS

Hereby we acknowledge the involvement of the authors' individual contributions to the paper as follows: **Mihai I. Pop**: Conceptualization; data curation; investigation; formal analysis; writing—original draft; project administration. **Simona R. Grădinaru**: Formal analysis; writing—original draft. **Viorel D. Popescu**: Formal analysis; writing—review and editing. **Dagmar Haase**: Writing—review and editing. **Cristian I. Iojă**: Conceptualization; writing—review and editing; supervision.

## ACKNOWLEDGMENTS

The work of Mihai I. Pop and Cristian I. Iojă was supported by a grant from the Romanian Ministry of Education and Research, CNCS-UEFISCDI, project number PN-III-P1-1.1-PD-2019-1207, within PNCDI III. The authors would like to thank the editors and the anonymous reviewers for their helpful comments.

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could appear to have influenced the work reported in this paper.

## DATA AVAILABILITY STATEMENT

Data (Pop, Grădinaru, et al., 2023) are available from Dryad: <https://doi.org/10.5061/dryad.sqv9s4n6j>.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Pop, Mihai I., Simona R. Gradinaru, Viorel D. Popescu, Dagmar Haase, and Cristian I. Ioja. 2023. "Emergency-Line Calls as an Indicator to Assess Human–Wildlife Interaction in Urban Areas." *Ecosphere* 14(2): e4418. <https://doi.org/10.1002/ecs2.4418>