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A Rich Person's Problem? Socio-Ecological Analysis of Human-Wild Boar Conflict Distribution in an Urban Setting

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Abstract

Our study presents a comprehensive method for measuring the distribution of urban wildlife and human-wildlife conflicts based on citizen reports. We investigate the ecological and social factors affecting the distribution of synurbic wild boars (*Sus scrofa*) and related human-wildlife conflicts within Haifa, northern Israel. Using Maximum Entropy (Maxent) species distribution modeling, we analyzed 2,921 citizen reports of wild boar sightings collected between January 2014 and May 2016. We modeled two distribution maps predicting: (1) wild boar presence, and (2) human-wild boar conflict within the city. Our models incorporated both ecological variables (e.g., normalized difference vegetation index, built area density, distance to nature reserves) and social variables (e.g., human population and density, socioeconomic status). The results of the wild boar habitat suitability model confirm previous studies, associating boar presence with the availability and fragmentation of green areas. In contrast, the conflict model suggests that human-boar conflicts are primarily linked to human population size, density, and socioeconomic status. Notably, areas with higher socioeconomic status exhibited a greater likelihood of reported conflicts, even after controlling for ecological factors. This study highlights the importance of integrating both ecological and social factors in understanding and managing urban human-wildlife conflicts. Our findings suggest that effective management strategies should consider the ecological needs of urban wildlife along with the social and economic contexts of urban neighborhoods.

Keywords Human-Wildlife Conflict · Urban Wildlife Management · Synurbization · Socio-ecology

Introduction

Around the world, wildlife populations are adapting to living alongside humans in urban environments. The term "Synurbization" is used to describe the overall phenomenon of wildlife adapting to human-dominated areas (Luniak, 2004). Although synurbization has been occurring since ancient human settlements (Soulsbury & White, 2016), systematic research on it has only started since the 1970 s (Magle et al., 2012). Wildlife responses to urban conditions can vary greatly over time and location, as well as due to differences in urban areas, public perceptions, and human behavior (Collins et al., 2000, Luniak, 2004, Parker & Nilon, 2012, Soulsbury & White, 2016, Stillfried et al., 2017). Therefore, a synurbic population in a specific area may be different not only from other populations of the same species but also from other synurbic populations in the same city (Parker & Nilon, 2012).

Although some researchers described synurbization as "taking up a free ecological niche" (Luniak, 2004), urban areas are not accurately considered "free." Instead, they are

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inhabited by a keystone species – *Homo sapiens* (Adams, 2016). Besides their ecological role as niche constructors, humans and their social dynamics—including demographics, socioeconomics, politics, and technology—are all factors that influence and define urban ecosystems (Alberti, 2005). Furthermore, humans often engage directly with synurbic species in various positive and negative human-wildlife interactions (Nyhus, 2016; Soulsbury & White, 2016).

Interactions between humans and wildlife in urban areas often lead to conflicts, but they can also produce positive results. The term "human-wildlife conflict" is frequently used to describe negative encounters, although some researchers argue that this terminology might unintentionally suggest wildlife is deliberately causing problems (Redpath et al., 2013). Other frameworks, such as "human-wildlife coexistence" or "human-wildlife interactions," have been proposed to offer a more balanced view (König et al., 2020).

According to the IUCN (2020), human-wildlife conflicts include a variety of negative interactions between people and wildlife. These range from disputes among humans over wildlife management to confrontations with potentially dangerous or economically impactful wild animals. The IUCN notes that conflict usually occurs when "people react negatively to this real or perceived damage and especially if the situation becomes a recurring event" (IUCN, 2020). Unlike other conflicts, human-wildlife conflicts are mostly unilateral, with wildlife interests represented only by human agents (Peterson et al., 2010). Redpath et al. (2015) provocatively suggest that nearly all (98%) human-wildlife conflicts are human-human conflicts involving wildlife. While this claim is controversial, it underscores the crucial role of socio-cultural perspectives in addressing these issues (IUCN, 2020, Peterson et al., 2010, Dickman, 2010).

Socio-cultural factors such as religious affiliation, cultural beliefs, and public perceptions play key roles in shaping human-animal interactions (Manfredo, 2008; Dickman, 2010). These perceptions influence whether certain wildlife encounters are seen as conflicts and, if so, how they should be managed (IUCN, 2020, Peterson et al., 2010). As synurbization varies between cities and is highly localized, so do human-wildlife conflicts (IUCN, 2020). Human-wildlife conflicts in urban areas are therefore complex, embedded within the local ecosystem, socio-cultural context, and political system, and correctly identified as part of coupled human and natural systems (Liu et al., 2007).

Despite emerging insights into the vital role of social factors in nature conservation (Alberti et al., 2003; Liu et al., 2007; Manfredo, 2008; Mascia et al., 2003; Miller & Hobbs, 2002), they are still often ignored in urban human-wildlife conflict studies (Magle et al., 2012). Acknowledging the dominant social component in these conflicts, social sciences can provide valuable theoretical frameworks and methodological tools to better understand their development and find solutions (Madden, 2004; Baruch-Mordo et al., 2009, Inskip & Zimmermann, 2009, Dickman, 2010, Peterson et al., 2013, Madden & McQuinn, 2014).

Regarding the ecological aspect of such conflicts, recent research on wildlife distribution in urban areas has mainly focused on the impacts of biophysical landscape features, such as green spaces, building density, and water bodies (e.g., Bradsworth et al., 2021, Gras et al., 2018, Jaman et al., 2021, Nelli et al., 2022). However, few studies have included social factors like socio-economic status, ethnicity, demographics, or education in their analyses (Baruch-Mordo et al., 2011; Ben-Moshe & Iwamura, 2020; Davis et al., 2012; Gilleland, 2010; Marley et al., 2017). The links between social factors, human-wildlife conflict, and the presence of synurbic species are still understudied, highlighting an important gap in our understanding of urban ecology.

This research gap raises questions about the potential impact of less-studied factors on wildlife distribution in urban settings. When examining wildlife presence in urban neighborhoods, it is important to consider not only biophysical factors like water sources and green spaces but also the characteristics of human residents. Our study aims to fill this gap by conducting a spatial socio-ecological analysis of urban human-wildlife conflicts, specifically focusing on the human-wild boar conflict in Haifa, Israel.

The wild boar (*Sus scrofa*) is a large (20–200 kg) omnivorous mammal (Davidson, 2021; Mendelson & Yom-Tov, 1987). It is one of the most widely distributed land mammals, with its range greatly expanded by human activities due to its adaptable habitat needs. The species currently exists (wild or feral) on all continents except Antarctica (Keuling & Leus, 2019). Boars are generalists, highly adaptable, and reproduce rapidly (Giménez-Anaya et al., 2008). They have the highest reproductive rate among ungulates, with annual population growth that can exceed 100% (Bieber & Ruf, 2005). The social structure of boars usually includes solitary adult males and herds consisting of females with young boars and groups of male juveniles. However, local conditions may cause deviations in this pattern (Davidson, 2021, Maselli et al., 2014, Mendelson & Yom-Tov, 1987).

These traits have transformed the human-boar conflict into one of the most difficult human-wildlife conflicts worldwide (Davison, 2021); in fact, the annual cost of boar damage in Europe was estimated at 80 million euros in 2010 (Apollonio et al., 2010). Mainly identified as a threat to agricultural crops (Davison, 2021, Keuling & Leus, 2019, Licoppe et al., 2013, Linnel et al., 2020, Massei et al., 2015), here we focus on urban human-boar conflict.

Boar dispersion into periurban and urban areas is facilitated by easy access to food and water, the absence or limitation of hunting and predation, and the expansion of urbanization into areas previously occupied by boars (Licoppe et al., 2013). Although some studies claim that boars are merely visiting urban sites, depending on natural rather than anthropogenic resources (Stillfried et al., 2017), it is well documented that urban boar populations are undergoing a synurbization process that includes increasing body mass and size, dietary shifts, biometric and physiological changes (Castillo-Contreras et al., 2021), as well as changes in fertility and group structure (Davidson, 2021).

Human perceptions of urban boars are complex and often conflicted. A survey in Berlin found that 36% of participants held conflicting views about boars in the city (Kotulski & König, 2008). In Haifa, Israel, the focus of our study, the increasing presence of boars is highly controversial. Perceived as a threat by many residents, opinions vary on management strategies, ranging from eradicating them as pests, protecting them as a natural resource, or even nurturing and feeding them (Beeri et al., 2025).

Haifa (Fig. 1), the third-largest city in Israel, with approximately 285,000 residents and a metropolitan area of over one million, is situated on the slopes of Mount Carmel, overlooking the Mediterranean Sea. It sits at an average height of 97 m above sea level, with a wide range between 0 and 546 m due to its mountainous terrain. Haifa's socio-economic cluster is rated 6 out of 10 (CBS, 2021a).

Fig. 1 Haifa. The area bounded by a black line is the area where the model was conducted, as detailed in the Methods section. The total area within the black line is 33.23 km^2

The mountainous terrain of the city features ravines ("wadis") that cut into the urban area (Toger et al., 2016). These long, finger-like wadis make Haifa accessible to wildlife entering the city, including jackals (*Canis aureus*), mongooses (*Herpestes ichneumon*), porcupines (*Hystrix indica*), badgers (*Meles meles*), rock hyrax (*Procavia capensis*), red foxes (*Vulpes vulpes*), and many other species (Broitman et al., 2017). Toger et al. (2018) modeled boar movement within Haifa and found that the wadis and the city's permeability allow boars to move into the city in search of food.

Broitman et al. (2017, 2019) suggest that although proximity to open and green spaces is positively linked to housing prices, wildlife presence has a negative impact. For many years, Haifa's boar management strategy involved culling (Beeri et al., 2025). Studies conducted since the implementation of this policy have shown that it has altered the boars' social structure and hormone levels. This may explain the observed increase in reproduction rates and the growth of the boar population (Davidson et al., 2021; Davidson, 2021). Although the culling policy was recently stopped and then reinstated (Beeri et al., 2025), it was continuously in use during our data collection period (2014–2016).

In similar research to the one presented here, Castillo-Contreras et al. (2018) demonstrated how biophysical factors create ecological corridors that facilitate boar movement in Barcelona. However, this study's social aspect was clearly overlooked. No social factors—such as the socioeconomic status of neighborhoods or human population density—were included in the model. Additionally, the data used to determine the distribution of wild boars was not the actual distribution of the animals but rather sightings reported by citizens via phone calls to the local emergency number (Ibid.). These reports are not randomly distributed; they reflect the distribution of human reporters, not the boars themselves. This represents a distinctly social and biased data source. Therefore, they should be regarded as a proxy for the distribution of human-boar conflicts.

We provide a detailed analysis that includes both ecological and social perspectives on boar presence in Haifa. We examine how socio-ecological factors influence the species distribution (i.e., where boars are likely to be found) and conflict distribution (i.e., locations where humans report negative encounters with boars). Specifically, we address the following research questions:

1. What are the ecological factors affecting boar distribution within Haifa?
2. What social and ecological factors influence the spatial distribution of human-boar conflicts?
3. How do the spatial patterns of boar distribution and human-boar conflicts differ, and what could explain these differences?

To answer these questions, we developed two distribution prediction maps using Maximum Entropy (Maxent) species distribution modeling: one showing the predicted distribution of boars, and another illustrating the distribution of human-boar conflicts within the city. By comparing the results of these models, we aim to clarify the complex interaction between ecological and social factors in shaping urban human-wildlife interactions.

Methods

Data Collection

To measure boar presence and distribution, we used data collected by the Haifa municipality, which recorded 3,000 citizen reports to the municipal call center between January 2014 and May 2016 (unpublished data, Haifa municipality). The call center serves as a hotline for residents to report local issues, including roaming boars. These reports were not collected systematically and included the date, address, and a free-text description of the complaint. We geocoded the data into 8-digit XY coordinates (WGS84 grid) using the Google Maps platform. As described above, these reports do not directly confirm the presence of boars but rather serve as a proxy for the occurrence of the human-boar conflict, as these calls reflect citizen complaints.

To analyze the potential impact of urban landscape characteristics on conflict and estimate its socio-ecological predictors, we characterized three aspects of the urban environment: structural, biophysical, and social (Table 1). We used data from various sources, including the Israel Central Bureau of Statistics (CBS), OpenStreetMap, Israel Nature and Parks Authority (INPA), Society for the Protection of Nature in Israel (SPNI), and HaMaarag – Israel's National Nature Assessment Program (Table 1). Each data layer was converted into a raster with a 10×10 m cell size, clipped to the study areas' boundaries, using ArcGIS Pro software version 2.7.0 (ESRI, 2019), and R programming language version 4.2.1 (R Core Team, 2022).

Built area density layers were generated from OpenStreetMap's Israel and Palestine building layer (OpenStreetMap, 2022). The building polygons were converted into a binary raster using the Polygon to Raster function in ArcGIS Pro. Using the Focal Statistics function, we summed the radii of 25 neighboring cells for each cell, creating a representative raster of built area density within a 250 m radius, following the distances specified by Castillo-Contreras et al. (2018).

The distance to a nature reserve or an urban nature site layer was generated using INPA's nature reserves and parks layer, along with SPNI's urban nature sites layer. The layers were created with the Euclidean distance function in

Table 1 Explanatory variables to be considered in the models

Urban context	Predictor [layer name]	Description	Source
Environment structure	Elevation [Elevation]	Elevation above sea level (m)	HaMaarag, unpublished
	Slope [Slope]	Slope steepness (degrees)	
	Built area density in 250 m search radius [Built25]	Proportion of built-up area within 250 m radius	OpenStreetMap (2022), Israel and Palestine, available at: https://download.geofabrik.de/asia/israel-and-palestine-latest-free.shp.zip
Biophysical environment	Distance to nature reserve/urban nature [Distance]	Euclidean distance to nearest nature reserve or urban nature site (m)	INPA, available at: https://www.parks.org.il/govmap/ SPNI, available at: https://mapateva.org.il/Apps/StoryTelling/PlayList_UrbanNatureIndex/
	NDVI average in 250 m search radius [NDVI25]	Average Normalized Difference Vegetation Index within 250 m radius	HaMaarag, unpublished
Social environment	Human population [Population]	Total population in statistical area	CBS 2019
	Human density [Density]	Population density (people/km^2) in statistical area	
	Socioeconomic Cluster [SE cluster]	CBS socioeconomic index (0–10 scale) for statistical area	

ArcGIS Pro. Based on the cell size, distances are measured on a 10 m scale. This layer primarily shows the distance from Mount Carmel Park and from the wadis that penetrate the city, creating corridors for boar movement (Toger et al., 2018, Castillo-Contreras et al., 2018).

The normalized difference vegetation index (NDVI) layers were obtained from HaMaarag. They were created using Sentinel-2 data and NDVI code in Google Earth Engine. These layers represent the average NDVI for August-September 2016 (Israel's dry season), serving as a valid proxy for evergreen green areas that are not seasonal, making them useful as reliable urban resources for food, canopy, and shelter throughout the year. Using the Focal Statistics function in ArcGIS Pro, they were transformed—similar to the built area layers—to reflect the average NDVI within a 250 m radius.

The topographic layers (elevation and slope) were also obtained from HaMaarag, who created them using Google Earth Engine. We included elevation and slope because of the landscape features of mountainous Haifa, which could influence boar movement (Toger et al., 2018).

Demographic layers (population, density, socio-economic cluster) were created using CBS's statistical areas layer (CBS, 2021b) and the socioeconomic clustering database from 2015 (CBS, 2019). These databases were integrated into three layers in ArcGIS Pro. CBS's socio-economic clustering is a 1–10 index, calculated based on 14 parameters (CBS, 2019). To include unclassified (non-residential) areas in the model, we assigned them a rank of 0. It is important to note that, unlike the layers described above, these layers are not processed at the cell level. The smallest spatial units of demographic data in Israel are "statistical area" polygons, which we converted into pixels. Although CBS (2021b) states that separation between areas requires geographical or statistical justification, these layers may create artificial boundaries between neighboring cells, based on different statistical areas they correspond to.

The pixel size we used (10 × 10 m) was selected based on the highest resolution NDVI layer available. Although we did not apply this scale to all layers, using statistical areas and focal statistics of 250 m, small cells still provide more precise information about the environment of each report's location and enable us to conduct meaningful analysis at higher resolutions (Hengl, 2006).

We chose not to include waterways and water bodies in the model despite their importance in several studies (e.g., Castillo-Contreras et al., 2018, Licoppe et al., 2013). In Haifa, waterways and water bodies are found within the wadis, which are already part of the model as nature reserves and urban nature sites, serving as a proxy layer. As Castillo-Contreras et al. (2018) reported, waterways and streams act as corridors for boar movement in the city, a role that the wadis in Haifa also fulfill (Toger et al., 2018).

Modelling

We generated the predicted distribution maps using the maximum entropy species distribution modeling approach with Maxent, version 3.4.4 (Phillips et al., 2022). Maxent is a machine-learning model that analyzes the relationship between spatial variables and the probability distribution of a species (Phillips et al., 2004, 2006, 2017). Maxent's output provides both a distribution map of the occurrence probability and an analysis of each environmental layer's contribution to the final distribution map (Elith et al., 2011; Merow et al., 2013).

According to the protocol provided by Merow et al. (2013), the layers were analyzed in R using Pearson's

Table 2 Pearson's correlation coefficient of haifa's environmental layers (rounded). Strongly related variables (≥0.8) appear in bold. Notably, the strong correlation between elevation and socio-economic cluster reflects the tendency of haifa's more affluent neighborhoods to be on top of the mountains

	Built25	NDVI25	Distance	Slope	Elevation	Population	SE cluster	Density
Built25	1							
NDVI25	0.313	1						
Distance	−0.172	−0.433	1					
Slope	0.051	0.226	−0.148	1				
Elevation	0.302	0.668	−0.525	0.451	1			
Population	0.269	0.333	−0.294	0.348	0.581	1		
SE cluster	0.206	0.401	−0.355	0.403	**0.834**	0.756	1	
Density	0.542	0.192	−0.131	0.394	0.322	0.594	0.418	1

Table 3 Summary of the models produced and their components

Model	No. of records	Background layers	Excess data removed	Proxy for
Socio-ecological model	2,921	NDVI25, Built25, Distance, Slope, Population, SE cluster, Density	No	Human-boar conflict
Ecological model	1,545	NDVI25, Built25, Distance, Slope	Duplicate presence records removed	Boar distri-bution

correlation coefficient (Table 2). Although machine-learning-based models are less impacted by covariates (Elith et al., 2011; Feng et al., 2019), we chose to exclude some predictors if they were strongly correlated with others that would be included in the model (≥0.8, as a compromise between Elith et al., 2006 and Dormann et al., 2013, as in Yang et al., 2013) for more accurate results (as suggested by Merow et al., 2013). Based on these results, we excluded several layers from the model—specifically, we omitted the elevation layer since, from a social perspective, it appears less relevant than the socio-economic cluster, and biologically, elevation layers are less significant for mammal distribution (Hof et al., 2012).

The regularization values, convergence threshold, and maximum number of iterations were all set to recommended default values in all the models (Elith et al., 2011; Phillips et al., 2017). All variables were assigned as continuous. To enable the reproduction of results, we used a random seed. Output maps were configured to Complementary log-log regression (cloglog, which is the default option), which visualizes the probability of distribution (Phillips et al., 2017). We set the model to run 10-fold cross-validation. With this feature, the model uses different train and test records each run and produces more generalized and robust predictions, as an average of the models generated in each run (Merow et al., 2013; Phillips et al., 2006).

Addressing Biases

Maxent, along with other machine-learning models, can be easily influenced by biased data (Elith et al., 2011; Merow et al., 2013, Phillips et al., 2017). Therefore, it is recommended to maximize the accuracy of the background data to align closely with the research's objectives (Merow et al., 2013).

To improve the accuracy of the background data, we clipped the background layers to only include the urbanized areas of each city. As Hysen et al. (2022) showed, Maxent is less sensitive to the number of background points. Therefore, refining the background data by clipping it does not appear to reduce the model's accuracy. Haifa's municipal area contains many wadis and parts of the Carmel Forest, which may bias the model to suggest that green areas and NDVI negatively affect the distribution of boar sightings, since there are almost no citizen reports from those regions. Since presence records outside urban areas were also excluded, the model used fewer records when background data was clipped. The exact number of records used in each model is detailed below (Table 3).

Although we rely on citizen reports as our main data source for boar presence, we recognize that they are a highly biased source. The biases in citizen reports include several major issues: the profile of reporters, which is often influenced by various social factors (e.g., Jefford et al., 2005); pseudo-replications caused by multiple reports of a single boar seen by different neighbors (Castillo-Contreras et al., 2018; Toger et al., 2018); and serial complainants that skew sampling towards their specific addresses. To address these biases, we aimed to create a heatmap of all reports submitted to the call center, regardless of their topic, to generate a bias background layer for weighting in the model (Merow et al., 2013; Elith et al., 2011). Unfortunately, Haifa's municipality refused our data requests.

Several researchers relying on similar data sets (citizen reports) have proposed strategies to address these inherent biases. Toger et al. (2018) used a human density layer to reduce these biases. We argue that human density alone cannot serve as a proxy for biases, as it does not mitigate pseudo-replications or the serial complainer's effect. Castillo-Contreras et al. (2018) employed a buffer in space and time (i.e., reports occurring within 500 m and two hours of each other) to omit pseudo-replications. While this method reduces pseudo-replication, it does not address the serial complainer's effect. Furthermore, this approach cannot be applied in Haifa, as a 500 m buffer could merge sightings from different wadis due to the fingered pattern of Haifa's built-up areas (Toger et al., 2016). Broitman et al. (2017, 2019) normalized boar observations using the Kernel density function in ArcGIS Pro, likely reducing the non-repetitive reports rather than the serial complainer's repetitive ones, while also amplifying the effect of the wadis. All three methods fail to consider the factors shaping the social profile of those reporting to the call center.

Configurations of Models

Due to those biases, we created separate models: one representing the conflict distribution and the other representing the boar distribution within the city. The model representing human-wildlife conflict simply includes all biases – since an unreported boar is a boar that conflicts with no one, while the reports indicate conflict. Once we apply this understanding to the study, these biases are no longer biases – they become features of the conflict that we are interested in. Pseudo-replications are no longer considered pseudo-replications, and the focus of the model shifts from the synurbic species to the citizens who express complaints. This is the socio-ecological model.

In the ecological model, which represents the species distribution within the city, we corrected for biases. The Maxent model was configured to remove duplicate presence records (Phillips et al., 2017; Merow et al., 2013). This feature makes random reports equivalent to serial complaint reports and consolidates pseudo-replication into the single pixels where they are located, significantly reducing biases. Addressing the bias related to the social profile of those reporting sightings (as described by Jefford et al., 2005), we did not include social background layers in the ecological model. Including such factors could cause the machine-learning algorithm to weigh them as predictors of boar distribution. Therefore, the ecological model was built and trained using cleaned presence data, including only structural and ecological background layers (Table 3). The socio-ecological model was built and trained using all reports and all background layers, embracing the biases, and thus predicting the socio-ecological niche of the conflict rather than the species itself.

Comparing Outputs

Converted output probability maps into a binary distribution map using the ArcGIS Pro Reclassifying raster tool, based on the Maximum training sensitivity plus specificity threshold values provided by Maxent output for each model (Liu et al., 2005). We used the Raster calculator function to subtract one raster from another, creating a map that visualizes the spatial differences between the socio-ecological and ecological models.

Results and Interpretation

Since Maxent outputs are generated by machine learning, they differ from traditional statistical model outputs and require additional interpretation (Zurell et al., 2020). Each of the model's results is analyzed and interpreted in this section alongside the presentation of the results, rather than in a separate discussion section.

Here we focus on four main Maxent outputs: Prediction map, Response curves, Variable contributions table, and Jackknife test of variable importance (training gain only). The prediction map is the ultimate output of Maxent – it is a map of the model's predictions, indicating the suitability of each cell for the species' occurrence being modeled. Response curves are graphs that display how each layer affects the model. Variable contribution tables show the percentage contribution of each layer to the model. The jackknife test assesses the importance of each variable to the model by testing its effect when omitted and when used alone.

Ecological Model

The ecological model, as mentioned above, aims to depict the distribution of Haifa's boars. The average test AUC (discrimination ability) across 10 replicate runs was 0.779, with a standard deviation of 0.013. Figure 2 shows the prediction map based on the model (Phillips et al., 2017), and Fig. 3 displays a binary distribution map derived from it using the Maximum training sensitivity plus specificity threshold value supplied by Maxent output, specifically for this model (0.3875).

The following curves (Fig. 4) illustrate how each environmental variable influences the Maxent prediction. They show how the predicted probability of presence varies as each environmental variable changes while keeping all other variables at their average sample values. The model may depend on covariates in ways that are not apparent in the curves. The curves display the mean response from 10

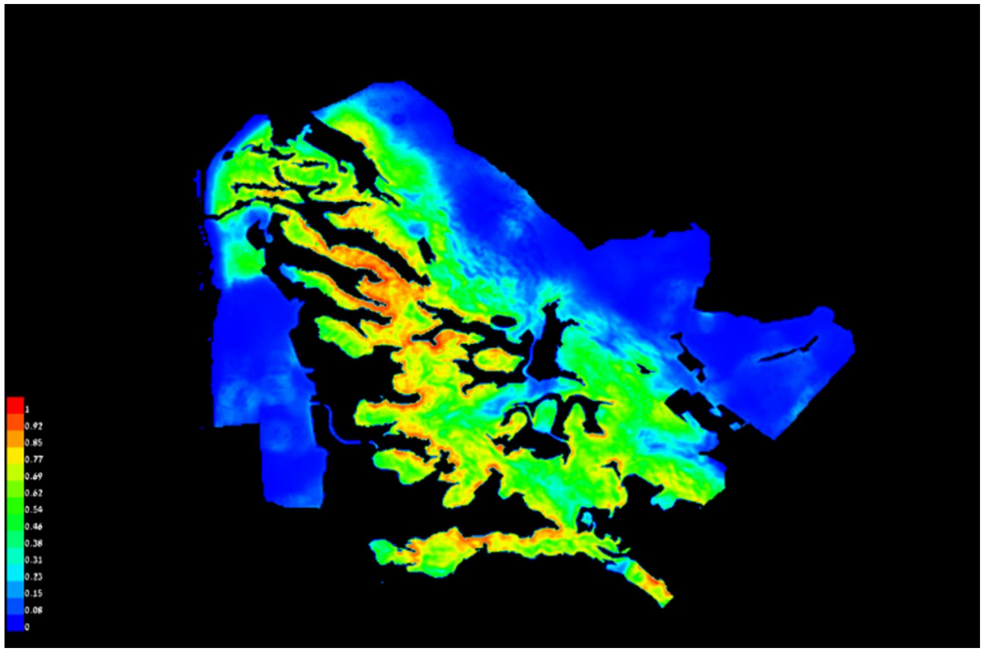


Fig. 2 Haifa's Ecological model prediction map, presenting the probability of occurrence estimated between 0 and 1. This map is made of the point-wise mean of the 10 output grids

replicate Maxent runs (red) and the mean plus or minus one standard deviation (blue).

These curves illustrate a simplified representation of the impact of individual variables while controlling for the others. However, they do not capture the effect of covariates. Unlike the marginal response curves described above, each of the following curves (Fig. 5) represents a different Maxent model built using only the corresponding variable. These plots illustrate how the predicted suitability depends both on the selected variable and on dependencies caused by correlations between that variable and others.

The differences in results between the representations are likely due to varying field conditions. While distance from nature reserves or urban green spaces appears beneficial after approximately 890 m in one analysis (Fig. 4), the effect remains negative at all distances when analyzed alone (Fig. 5). The spike in boar presence at short distances probably results from excluding non-urban areas where boars may go unreported. Similarly, building area density exhibits a bell curve effect, while high vegetation (NDVI) has a negative impact (Fig. 5), possibly because boars in very green areas near reserves or urban spaces go unreported. However, when controlling for other variables (Fig. 4), vegetation consistently exhibits a positive effect on boar presence. Essentially, boar presence seems linked to moderate urbanization and high vegetation levels, but very dense vegetation may hide reports, as boars use these areas too, but may not be reported there.

Table 4 shows the estimates of the relative contributions of environmental variables to the Maxent model, expressed as percentages. The model is re-evaluated using permuted data, and the resulting decrease in AUC is listed in the table. Permutation importance is a method used to determine the relative importance of different variables in a Maxent model. In this test, each environmental variable's values are randomly permuted in turn. The decrease in training AUC caused by permuting a variable indicates its permutation importance. The greater the drop, the more important that variable is to the model. This provides a reliable measure of variable importance because it considers both the independent explanatory power of a variable and its combined effects and interactions with other variables in the model.

As we observe, the NDVI layer has the greatest contribution, showing a large gap above the other layers. The importance of these variables remained consistent throughout the permutation trial. NDVI is the most significant factor for boar presence, exerting a positive influence while accounting for other factors. This finding is supported by the jackknife test of variable importance (Fig. 6). When examined alone, NDVI provides the highest gain, indicating it has the most useful information on its own. Additionally, NDVI causes the greatest decrease in gain when omitted, suggesting it contains the most unique information not found in the other variables.

Results from this model support previous studies. As Castillo-Contreras et al. (2018) demonstrated, streams and green areas are key variables in predicting boar distribution. Along with the effect of building density, which may indicate that fragmented areas—both built and green—are more attractive to boars, since high and low building densities have an adverse effect, while areas with moderate density have a positive effect (Figs. 4 and 5). The weaker effect of what can be described as ecological corridors (i.e., distance from nature reserves, which may serve as a proxy

Fig. 3 Haifa's wild boar distribution according to the model's Maximum training sensitivity plus specificity threshold value

for the wadis) can be explained by Toger et al. (2018), who observed that Haifa is porous, with many wadis penetrating the urban area. This may reduce the impact of this factor, since most of Haifa is close to a wadi or a nature reserve. However, this factor still has a positive effect on boar distribution, as noted in previous studies (Castillo-Contreras et al., 2018, Licoppe et al., 2013, Toger et al., 2018). Additionally, our results show that slope has a minor negative impact on distribution, but this effect appears very weak, as reflected in the jackknife test and the contribution table.

Socio-ecological Model

The socio-ecological model aims to depict the distribution of Haifa's human-boar conflict. The average test AUC across 10 replicate runs is 0.778, with a standard deviation of 0.010. Figure 7 shows the prediction map based on the

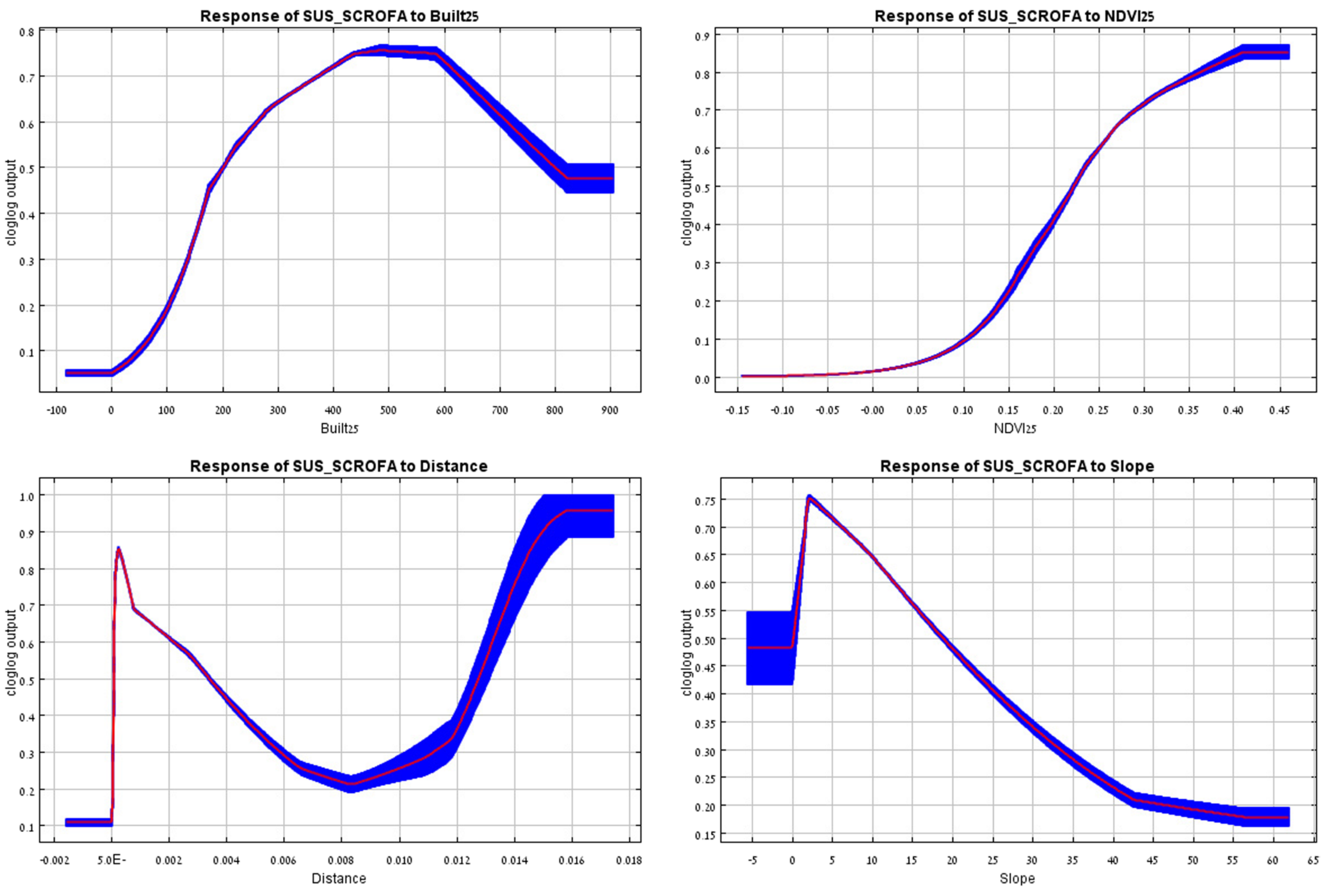


Fig. 4 Marginal response curves of Haifa's ecological model. These curves illustrate the effect of changing exactly one variable at a time, while the model may consider sets of variables changing together. The X axis shows the values of the variables. The Y axis displays the cloglog (complementary log-log regression) output—the probability of presence, ranging from 0 to 1

model (Phillips et al., 2017), and Fig. 8 presents a binary distribution map derived from the prediction map, using the maximum training sensitivity plus specificity threshold value provided by Maxent output for this model (0.461).

Compared to the ecological model maps, it is evident that the conflict does not cover the entire distribution area of boars. The following curves (Fig. 9) are the marginal response curves. The explanation for these is the same as in the previous section, but this time they relate to the variables in the socio-ecological model.

The following curves (Fig. 10) represent different Maxent models created using only the corresponding variable. An explanation can be found in the previous section.

The response curves of ecological factors (Figs. 9 and 10) changed little from the previous model (Fig. 5). However, their marginal response curves and relative importance changed significantly (Table 5, below). The negative effect of slope was reduced, while the positive effect of distance > ~ 890 m, as described above, was eliminated. The most notable change is the positive constant effect of built area density, which likely indicates more human-wildlife encounters, leading to higher conflict levels.

The social factors need to be interpreted carefully since the response curves are highly affected by their aggregation into statistical areas, which may explain their sharp-overfitting turns. In the marginal response curves, they were transformed into more continuous and theoretical representations, which are less influenced by field conditions and the effects of the statistical areas, resulting a smoother curves.

A larger human population and more affluent socio-economic groups are positively linked to human-wildlife conflict. These factors are highly correlated ($r = 0.756$), and the population's response curve differs from its marginal response curve: it begins to decline at populations exceeding approximately 3,500, but then sharply increases from about 5,400 to 5,600. This significant rise is influenced by Carmelia, a densely populated (~ 5,600) neighborhood, rank by the CBS in the 9th (second-highest) socio-economic cluster. Therefore, we suggest that density and population size may both exert similar effects—higher and lower values tend to decrease conflict, while moderate values increase it. We propose that in areas with fewer people and lower density, conflict is less frequent due to reduced human presence, whereas in areas with more people living

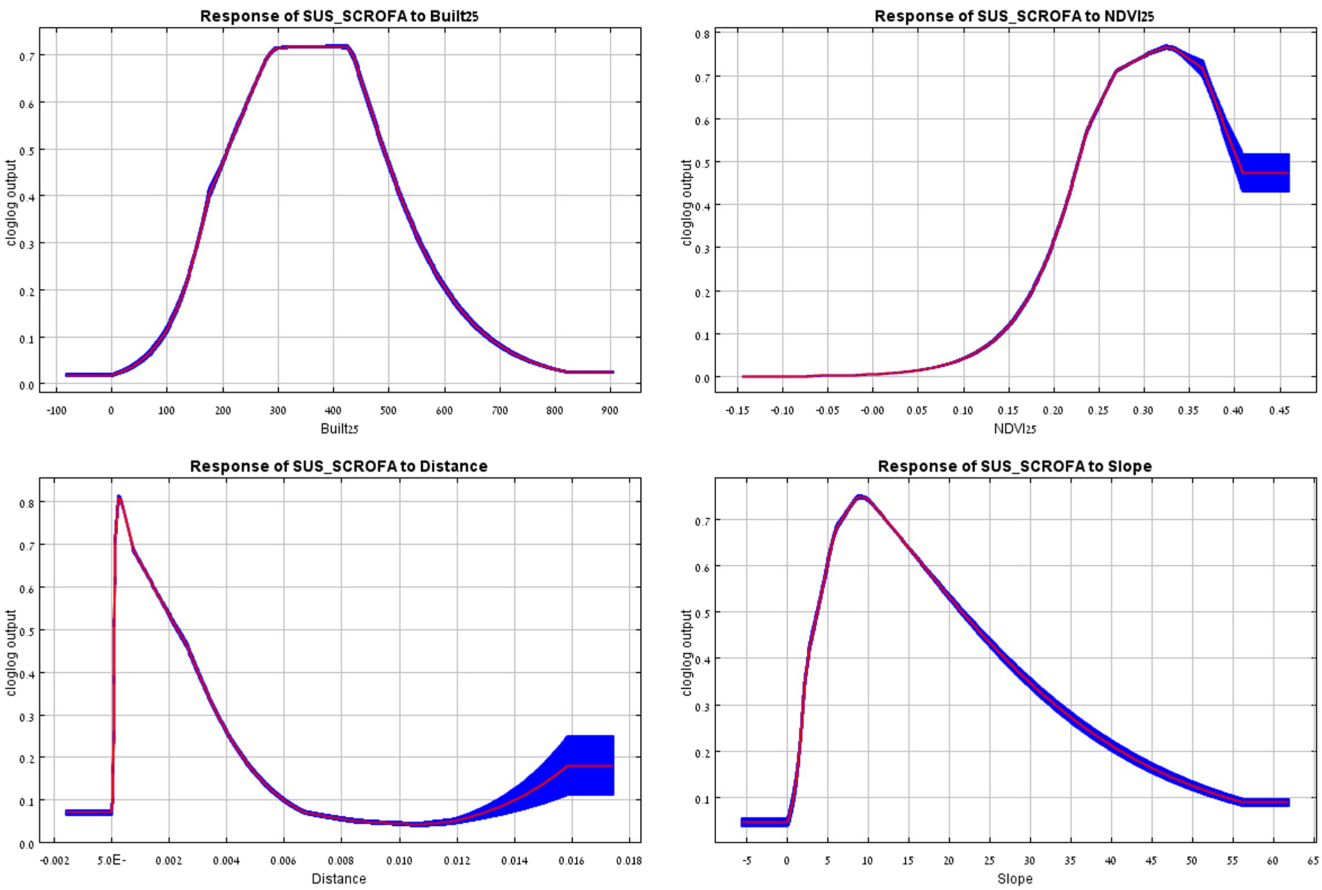


Fig. 5 Response curves of Haifa's ecological model. These curves illustrate how each variable affects the prediction when considered individually. Therefore, the graph of one variable may include correlations with other variables, which can alter the results of the Marginal response curves. The X-axis displays the values of the variables, while the Y-axis shows the cloglog output—the probability of presence, ranging from 0 to 1

Table 4 Ecological model's environmental variables contributions table. Values are the averages over 10 replicate runs

Variable	Percent contribution	Permutation importance
NDVI25	56.9	51.3
Built25	22.2	23.8
Distance	18.1	19.7
Slope	2.9	5.2

at higher densities—often accompanied by dense building patterns—conflict is also lower, likely due to reduced boar presence. Carmelia's exception arises from its unique characteristics—a low-density, highly populated, and highly socio-economically ranked neighborhood near a wadi. The population effect diminishes in this neighborhood because all other factors are positive influences.

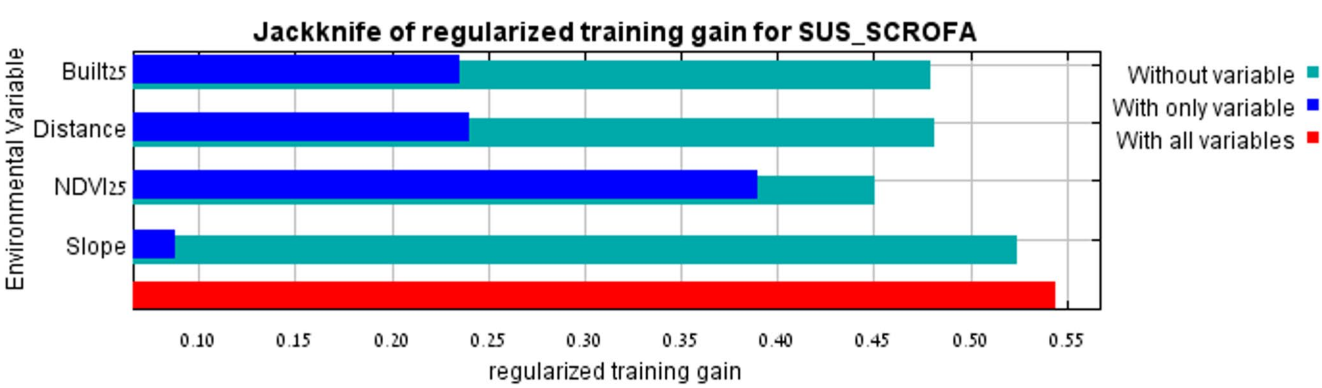


Fig. 6 Haifa's ecological model jackknife test for variable importance. Values represent averages over 10 replicate runs

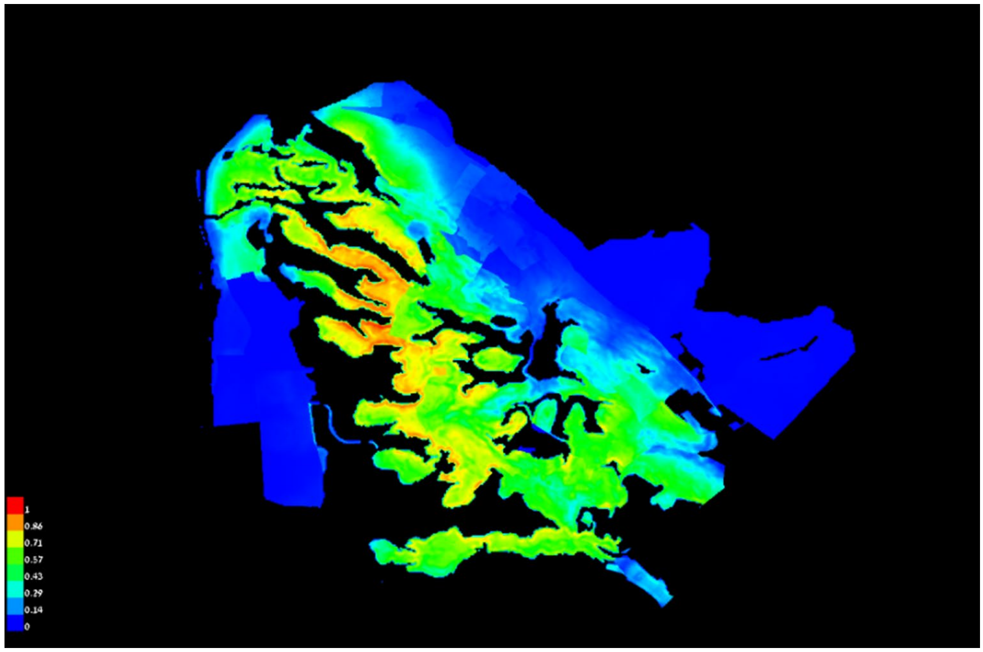


Fig. 7 Haifa's socio-ecological model prediction map, showing the probability of occurrence estimated between 0 and 1. This map is created by averaging the 10 output grids point-wise

The positive influence of the socio-economic cluster is significant in both curves. It is evident in the variable contribution table (Table 5), where this variable has the highest contribution, with a substantial gap above the contribution of the other layers. Although its major contribution decreases in the permutation trial, it remains the most important variable for predicting the distribution of human-boar conflict in Haifa.

Although the socio-economic cluster is identified by the model as the most significant variable for predicting conflict, it is challenging to determine whether conflicts in higher socio-economic clusters increase due to physical neighborhood characteristics or if they are mainly a social phenomenon. As seen in the marginal response curve, even when controlling for all other variables, the high socio-economic cluster continues to significantly contribute to the likelihood of conflict. One might argue that this effect results from wealthier neighborhoods where residents are more likely to use the municipal hotline than those in less affluent areas, or that their gardens and trash cans are more attractive to boars. We cannot verify either claim, and it is likely that both factors have an influence. It is also worth noting that some anecdotal evidence, such as the activism of neighborhood organizers encouraging residents to complain about the boars, supports this observation (personal experience).

Nevertheless, the jackknife test of variable importance results (Fig. 11) may weaken this claim. The variable with the highest gain when used alone is the socio-economic cluster, indicating it holds the most useful information by itself. However, the variable that reduces the gain the most when omitted is the distance from nature reserves and urban nature sites, suggesting it contains the most information not captured by the other variables. It seems that removing the socio-economic cluster hardly affects the gain.

On the other hand, when comparing the decrease across other variables, it appears that no variable actually causes a significant reduction when omitted (standard deviation of 0.00725). Therefore, we cautiously conclude that a high socio-economic cluster has a major impact on the human-boar conflict distribution, along with human population size and density.

Comparing Models

We used the ArcGIS Pro Raster Calculator function to subtract the ecological model's binary distribution map from the socio-ecological model's map. The resulting map shows two categories: areas where the model suggests boars are likely present but are not reported, so there is no conflict with the local population, and areas where conflicts could occur despite the low number of boars predicted by the model. Clearly, the second category is nearly nonexistent. Unlike the absence of areas in the conflict distribution but not in the boar distribution, the many areas in the boar distribution but not in the conflict distribution tell a different story. To highlight the main differences, we focus only on large patches covering significant areas rather than scattered cells or neighborhood margins.

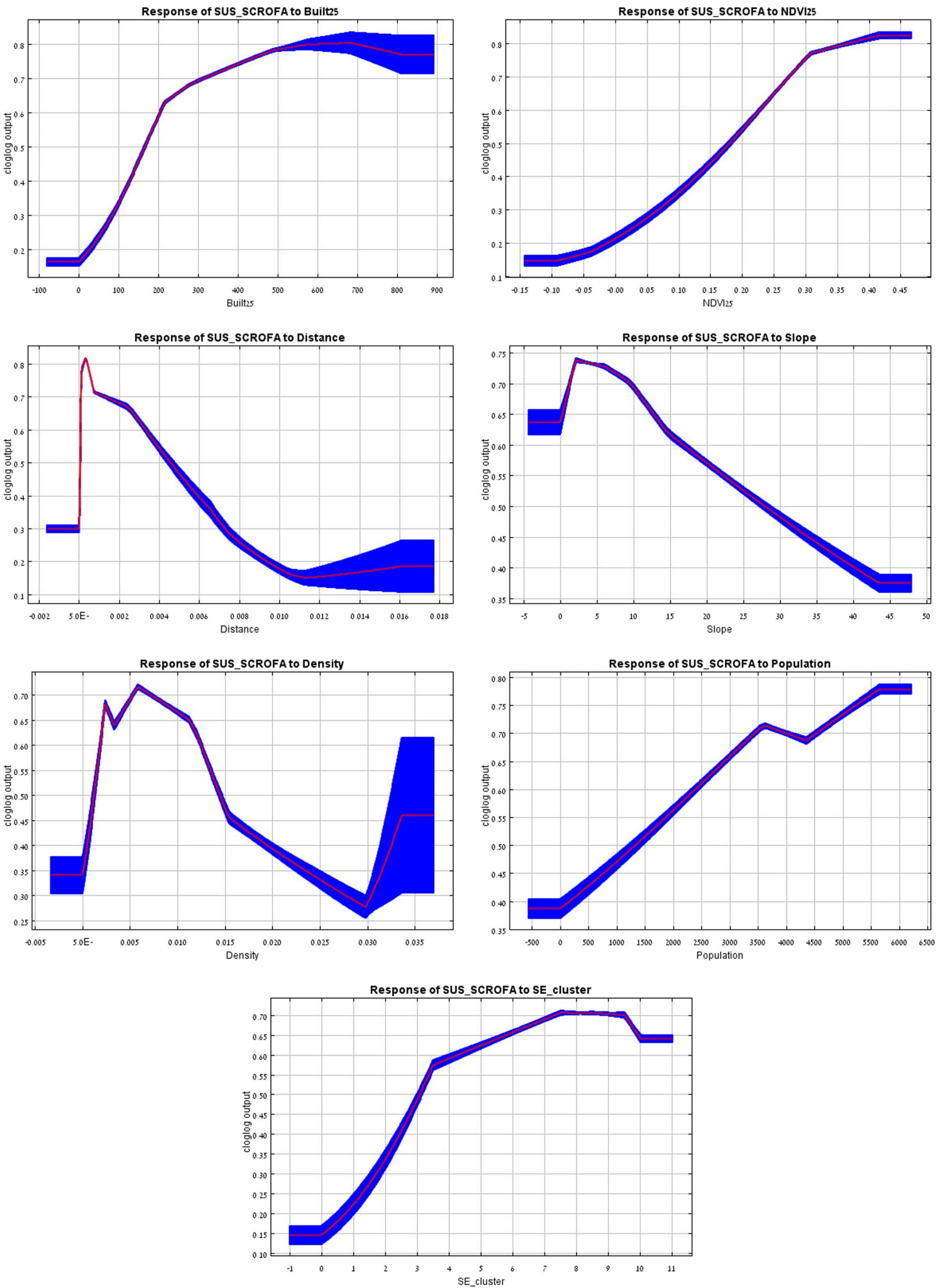
The first differences to explain are between the University of Haifa and the Technion (Israel Institute of Technology). Both universities are located within the area where boars are found, but since families rarely live in their dormitories, they are not included in the conflict reports, as they are less

Fig. 8 Distribution of Haifa's human-wild boar conflict based on the model's maximum training sensitivity plus specificity threshold

frequently reported. Additionally, at the Technion, there is an independent and active effort to control boar entry, which involves better waste storage and collection, electric fences, and repairing holes in the perimeter fence. The institution is addressing boars on its campus but does not report their presence to the call center.

In Neve David, the most likely reason for under-reporting is the socio-economic cluster (3 out of 10). It is possible that although the area is suitable for boars, residents of this neighborhood are less likely to report encounters with them. Another possible explanation is that, despite being a suitable area for boars, it is isolated from other suitable regions within the distribution model maps (Fig. 3). This explanation is less probable because there is a wadi that runs through Neve David, connecting the neighborhood to other urban boar habitats.

Along with Neve David, additional neighborhoods in lower socio-economic clusters also appear as under-reported on the differences map. These include Qiryat Eliezer, Qiryat Eliyahu, Geula, and Ramat Vizhnitz. The last two


Response of SUS_SCROFA to Built25
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Response of SUS_SCROFA to Population
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Response of SUS_SCROFA to SE_cluster
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Fig. 9 Marginal response curves of Haifa's socio-ecological model. These curves show the marginal effect of changing exactly one variable, while the model can also analyze sets of variables changing together. The X axis displays the values of the variables. The Y axis shows the cloglog output – the probability of presence, ranging from 0 to 1

are Ultra-Orthodox, and further research is needed to determine whether cultural perceptions of pigs as impure animals drive the under-reporting (personal communication), or if it is a broader effect of the lower socio-economic status.

A significant area with under-reporting is Neve Sha'anan and its neighboring. They fall into the 5-6th socio-economic clusters, which are less likely to explain the under-reporting. It could be suggested that in these neighborhoods, the actual number of boars is low enough that residents do not complain. However, further research is necessary to determine the causes of under-reporting in each neighborhood discussed in this section.

In the top northwestern part of Haifa, the different patch represents the neighborhood called En Ha'Yam. This is a mixed Jewish-Arab neighborhood, which, although in a middle socio-economic cluster (6), is still perceived as a minority neighborhood. Similarly, other Arab neighborhoods on this map were indicated as non-conflicting with boars – e.g., Abbas and parts of the German Colony. An exception to this pattern is Kababir, which is a mixed Jewish-Arab neighborhood with a relatively high socio-economic cluster (7). As in Ultra-Orthodox neighborhoods, the Muslim population may under-report boars' presence since they perceive pigs as impure. However, these neighborhoods also include an Arab-Christian population.

Other areas identified as under-reporting include Stella Maris Monastery and the Bahá'í Hanging Gardens, likely because of their social isolation from the city and the municipality. Few residents live there, and they probably have effective barriers like walls and fences.

The sites identified as under-reporting boars despite being within their known range are promising areas for further research. In this study, we cannot determine what makes these locations different or how their populations view boars. They might be places where humans and wildlife coexist peacefully, or they could be areas where conflicts are managed by local residents without involving municipal authorities (e.g., Technion).

Discussion

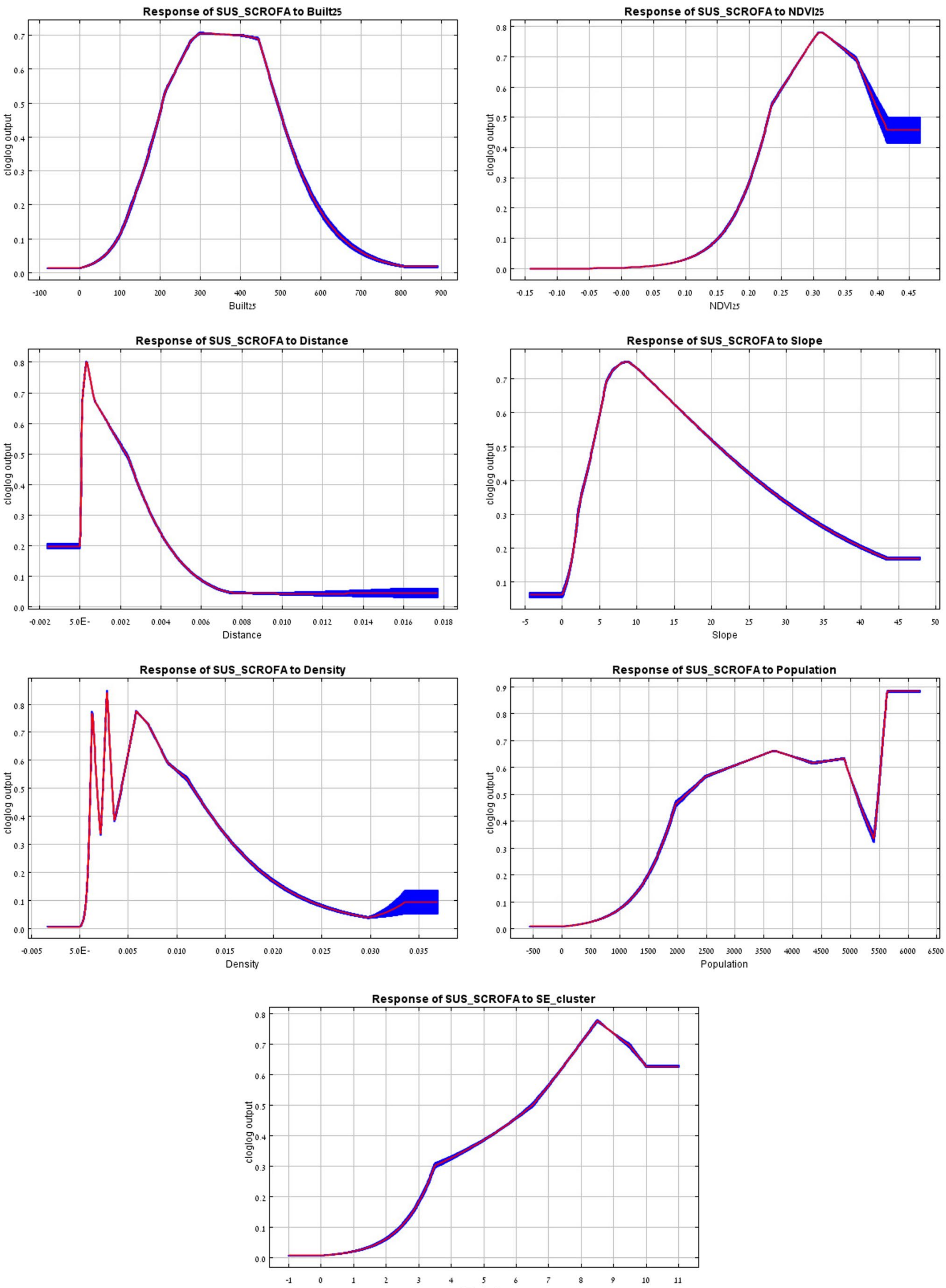
We aimed to explore the ecological and social aspects of urban human-wildlife conflict, recognizing that such conflicts cannot be understood or managed without a thorough knowledge of the local environment and its social, cultural, and ecological factors. The need for interdisciplinary research in managing and making decisions about human-wildlife interactions is already emphasized in the IUCN (2020) recommendation for human-wildlife conflict management and is widely discussed in the literature on human-wildlife conflicts and conservation (Alberti et al., 2003; Liu et al., 2007; Manfredo, 2008; Mascia et al., 2003; Miller & Hobbs, 2002; Madden, 2004; Baruch-Mordo et al., 2009, Inskip & Zimmerman, 2009, Dickman, 2010, Peterson et al., 2013, Madden & McQuinn, 2014).

Previous studies that included social factors in their analysis differ from this study in several key ways. Davis et al. (2012) and Ben-Moshe and Iwamura's (2020) studies did not focus on conflict itself but rather on social disparities and wildlife presence. Baruch-Mordo et al. (2011) and Marley et al. (2017), although strongly disagreeing with each other (Dietsch et al. 2017), both only considered education and enforcement as management tools, without examining the role of underlying social factors influencing the conflict. This study's main contribution is showing that those factors are not just important as "external" management tools but are actually a vital part of how those conflicts are constructed.

Here, we demonstrate how all these issues are interconnected and cannot be separated. Social disparities affect wildlife presence (as in Davis et al., 2012 and Ben-Moshe & Iwamura, 2020), but they also interact with factors like the urbanization gradient (Gilleland, 2010), education level (Baruch-Mordo et al., 2011; Marley et al., 2017), and willingness to coexist with wildlife (Vogel et al., 2022), with those less willing to do so submitting more reports to municipal authorities. As a feedback loop, green areas and wildlife presence may influence housing prices (as suggested by Broitman et al., 2017, 2019), and a high occurrence of wildlife can lead to conflicts. Therefore, social and ecological factors interact reciprocally.

More specifically, the material and social nature of wealthier neighborhoods could not be separated to determine whether residents' complaints stem from over-sensitivity to the mere presence of boars, whether the neighborhood is more attractive to boars, or both. This ambiguity could not be resolved with our data, and answering this question would likely require qualitative studies that focus on residents' attitudes and perceptions. Nonetheless, the ambiguity remains a key aspect of the urban human-wildlife conflict (Fig. 13).

This work is still in progress. First, we only examined representations of representations (i.e., models of citizen reports rather than field data). The lack of access to more reliable and accurate data (such as a bias map of all calls to the call center, a more detailed description of wildlife sightings, etc.) is a main limitation of this study. For instance, a layer



Response of SUS_SCROFA to Built25
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Fig. 10 Response curves of Haifa's socio-ecological model. These curves illustrate the impact of each variable on the prediction when used individually. Therefore, the graph of one variable may reflect correlations with other variables, which can alter the results of the Marginal response curves. The X-axis shows the values of the variables, while the Y-axis displays the cloglog output—the probability of presence, ranging from 0 to 1

showing garbage cans could have significantly improved the model, but we were unable to obtain it. Garbage cans likely had a notable impact on the model, as they are a common food source for synurbic species (Luniak, 2004, Adams, 2016). Instead of this layer, we present a careful interpretation of the population size results, which may indicate the amount of garbage in different neighborhood areas (Wowrzeczka, 2021).

However, in many areas, high-quality data are unavailable. Many studies have attempted to address this issue by using proxies instead of precise data, such as Castillo Contreras et al. (2018), who used a cat colony layer as a proxy for available urban food resources, or Davidson et al. (unpublished), who used local call center reports of overturned garbage cans as a proxy for garbage can distribution. The methods we employed to overcome the lack of reliable data can be applied to explore and manage similar conflicts worldwide, especially where data are incomplete or problematic, as is the case here. Despite limited data, our results are fairly consistent, robust, and intuitive, as certain trends repeatedly emerged (e.g., NDVI, socio-economic clusters, and other impacts), and for each trend, a reasonable explanation was identified.

Table 5 Haifa's socio-ecological model's environmental variables contributions table. Values are the averages over 10 replicate runs

Variable	Percent contribution	Permutation importance
SE cluster	66.3	25.3
Population	9.8	10.2
Built25	7.8	16.1
Distance	7	17.8
NDVI25	4.3	15.7
Slope	2.5	3.2
Density	2.3	11.7

Recommendations

Applicational management recommendations based on the results of this study mainly address the problematic nature of the methods usually used for measuring the distribution of urban human-wildlife conflicts. The biases discussed in this article are crucial when a local authority seeks to adjust the conventional methods to assess conflict within its area. Here, we propose a more comprehensive (and complex) method that is better suited to urban environments; it may help identify, for each case, which factors are most important for selecting management tools. It is important to emphasize that the results of this study show that urban human-wildlife conflicts are highly localized, and there is no single solution that fits all conflicts (as stated by the IUCN, 2020).

In particular, we recommend that Haifa's municipality investigate the areas included in the wild boar distribution, not just those in the conflict's distribution. These areas may shed light on the details of the conflict and offer management tools to replicate the "success" of these areas in reducing conflicts. Additionally, the municipality should recognize that focusing on the "hot spots" of the conflict, as identified by conventional methods, might overlook minorities and underprivileged neighborhoods, which may not complain as much as wealthier and more prosperous neighborhoods. Therefore, Haifa's municipality should concentrate

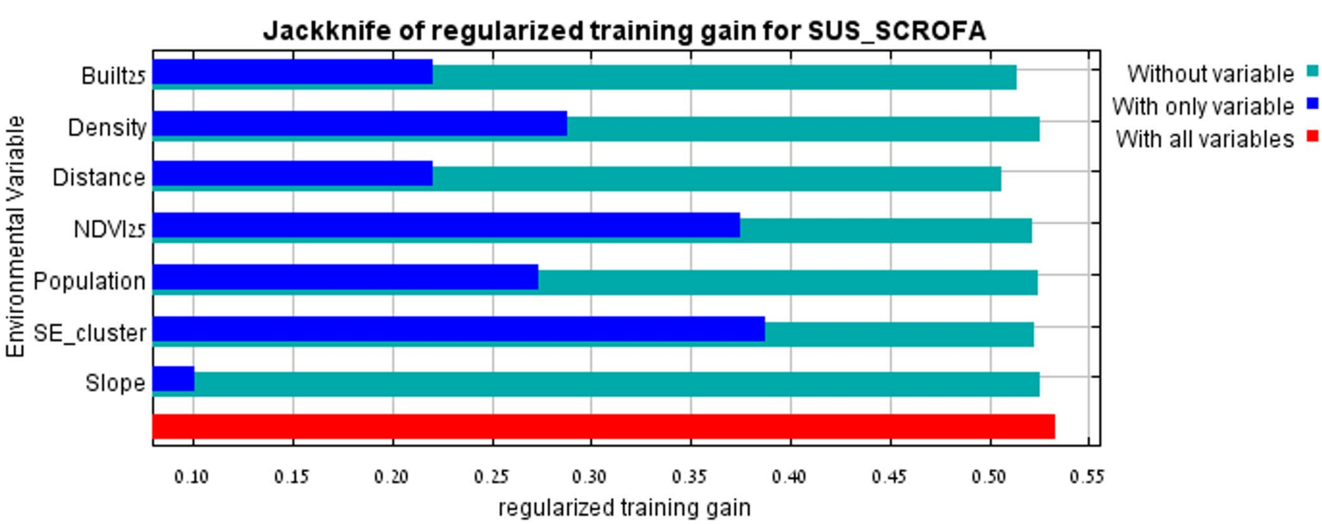

Fig. 11 Haifa's socio-ecological model jackknife test of variable importance. Values shown are the averages across 10 replicate runs

Fig. 12 Map showing the differences in distribution between the ecological and the socio-ecological models. In yellow: areas part of the wild boar's range but not in the human-boar conflict range. In red: areas included in the human-boar conflict range but not in the wild boar's range

on addressing social disparities and their connection to the conflict.

Further research is necessary to validate our findings, clarify finer details, and understand their underlying mechanisms. Field surveys, public questionnaires, and qualitative methods could help verify species and conflict distributions, explore cultural dimensions, and examine diverse community perspectives on urban wildlife interactions (Drury et al., 2011; Kimmig et al., 2020; Vogel et al., 2022). Quantitative ecological approaches are also important for testing species distribution models and investigating potential factors driving human-wildlife conflict linked to species' life histories, such as group behaviors or seasonal and circadian patterns. Ultimately, an interdisciplinary

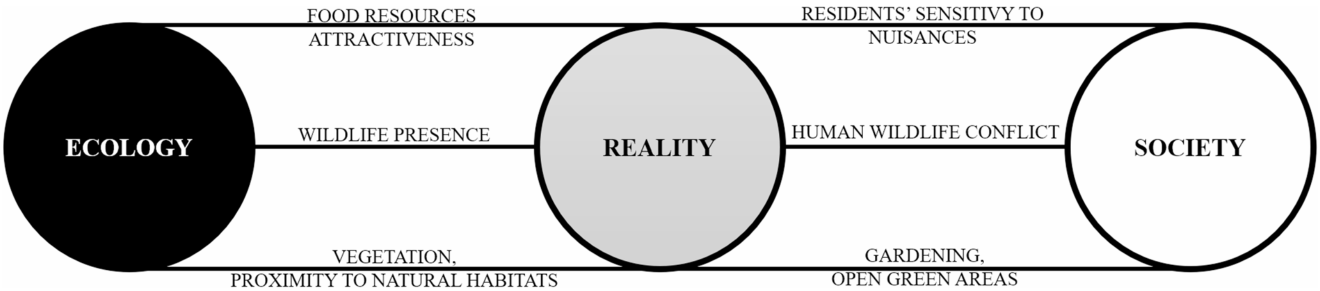

Fig. 13 Visualization of the intertwining of the ecological and the social in synurbic species. Ecology and Society are represented here as two aspects of reality. Each can adequately explain the variable's effect, but they do not explain each other (for further discussion: Latour, 1991). Here, we demonstrated four variables: socio-economic cluster, presence data, NDVI, and distance from a nature reserve

approach that combines sociological, ecological, and potentially political factors (Beeri et al., 2025) would improve our understanding of this complex issue.

Urban expansion is an increasing global trend (UN, 2018, Ritchie & Roser, 2018), threatening open landscapes and affecting biodiversity. At the same time, cities serve as crucial habitats for synurbic species, which are on the rise (Luniak, 2004). As urban areas keep growing, we can expect more synurbic species to flourish and for human-wildlife conflicts within cities to increase (Luniak, 2004, Adams, 2016). Studies that combine ecological and social methods, like this one, will be increasingly important for effective urban planning, coexistence, and "Conservation where people live and work" (Miller & Hobbs, 2002).

Conclusion

The deep entanglement of social and ecological realms in urban areas, which creates hybrid zones, attracts hybrid entities we refer to as "urban wildlife"—a somewhat oxymoronic term. We cannot ignore the social aspect when studying the ecological in these hybrids, as they incorporate both. Nature-culture hybrid entities and zones, which are a major part of living in the Anthropocene era, are becoming increasingly visible and critical for sustainable development (Tsing et al., 2017). Their visibility compels us to rethink our scientific approaches and conduct more comprehensive, interdisciplinary research that integrates both social and ecological perspectives.

The findings of this research, along with its conceptual implications, should motivate researchers, local authorities, and nature conservation groups to give social factors as much importance as ecological factors when studying and managing human-wildlife conflicts. Social factors are not only vital for addressing the human side of these conflicts but also essential for understanding how wildlife issues unfold in urban settings.

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Data Availability Our research is based on data obtained from Haifa Municipality, and we are unable to share it publicly due to the city policy. All other open data sources are cited within the article and in the bibliography.

Declarations

Competing interests The authors declare no competing interests.

References

Adams, C. E. (2016). *Urban wildlife management (third edition).* CRC press.

Alberti, M. (2005). The effects of urban patterns on ecosystem function. *International Regional Science Review, 28*(2), 168–192.

Alberti, M., Marzluff, J. M., Shulenberger, E., Bradley, G., Ryan, C., & Zumbrunnen, C. (2003). Integrating humans into ecology: Opportunities and challenges for studying urban ecosystems. *BioScience, 53*(12), 1169–1179.

Apollonio, M., Andersen, R., & Putman, R. (Eds.). (2010). *European ungulates and their management in the 21st century*. Cambridge University Press.

Baruch-Mordo, S., Breck, S. W., Wilson, K. R., & Broderick, J. (2009). A toolbox half full: How social science can help solve human–wildlife conflict. *Human Dimensions of Wildlife, 14*(3), 219–223.

Baruch-Mordo, S., Breck, S. W., Wilson, K. R., & Broderick, J. (2011). The Carrot or the stick? Evaluation of education and enforcement as management tools for human-wildlife conflicts. *PLoS ONE*, 6(1), e15681.

Beeri, I., Sadetzki, Y., & Hirsch-Matsioulas, O. (2025). Urban conflict management, human-wild animal interactions, local environmental governance and political participation. *Public Administration Review, 85*(3), 698–716. https://doi.org/10.1111/puar.13858

Ben-Moshe, N., & Iwamura, T. (2020). Shelter availability and human attitudes as drivers of rock hyrax (Procavia capensis) expansion along a rural–urban gradient. *Ecology and Evolution, 10*(9), 4044–4065.

Bieber, C., & Ruf, T. (2005). Population dynamics in wild Boar Sus scrofa: Ecology, elasticity of growth rate and implications for the management of pulsed resource consumers. *Journal of Applied Ecology, 42*(6), 1203–1213.

Bradsworth, N., White, J. G., Rendall, A. R., Carter, N., & Cooke, R. (2021). Where to sleep in the city? How urbanisation impacts roosting habitat availability for an apex predator. *Global Ecology and Conservation, 26*, e01494.

Broitman, D., Czamanski, D., & Toger, M. (2017). The complex interactions between cities and nature. *Quality Innovation Prosperity, 21*(1), 92–105.

Broitman, D., Griskin, V., & Czamanski, D. (2019). Unbundling negative and positive externalities of nature in cities: The influence of wild animals on housing prices. *Urban Studies, 56*(13), 2820–2836.

Castillo-Contreras, R., Carvalho, J., Serrano, E., Mentaberre, G., Fernández-Aguilar, X., Colom, A., & López-Olvera, J. R. (2018). Urban wild boars prefer fragmented areas with food resources near natural corridors. *Science of the Total Environment, 615*, 282–288.

Castillo-Contreras, R., Mentaberre, G., Aguilar, X. F., Conejero, C., Colom-Cadena, A., Ráez-Bravo, A., & López-Olvera, J. R. (2021). Wild Boar in the city: Phenotypic responses to urbanisation. *Science of the Total Environment, 773*, 145593.

CBS, Israel Central Bureau of Statistics (2019). *Characterization and Classification of Geographical Units by the Socio-Economic Level of the Population, 2015*. Retrieved from: https://www.cbs.gov.il/en/publications/Pages/2019/Characterization-and-Classification-of-Geographical-Units-by-the-Socio-Economic-Level-of-the-Population-2015.aspx

CBS, Israel Central Bureau of Statistics (2021a). *File of Local Authorities in Israel– 2019*. Retrieved from: https://www.cbs.gov.il/he/publications/doclib/2019/hamakomiot1999_2017/2019.xlsx

CBS, Israel Central Bureau of Statistics (2021b). *Statistic areas layer 2011 with demographic data of 2019*. Retrieved from: https://www.cbs.gov.il/he/Documents/%D7%A9%D7%9B%D7%91%D7%95%D7%AA%20%D7%92%D7%99%D7%90%D7%95%D7%92%D7%A8%D7%A4%D7%99%D7%95%D7%AA/statisticalareas_demography2019.gdb.zip

Collins, J. P., Kinzig, A., Grimm, N. B., Fagan, W. F., Hope, D., Wu, J., & Borer, E. T. (2000). A new urban ecology: Modeling human communities as integral parts of ecosystems poses special problems for the development and testing of ecological theory. *American Scientist, 88*(5), 416–425.

Davidson, A. (2021). *The effects of hunting and landscape structure on wild boar behavior, social structure and physiology in urban, agricultural and natural areas in Israel* (Doctoral dissertation, University of Haifa, Israel).

Davidson, A., Malkinson, D., Schonblum, A., Koren, L., & Shanas, U. (2021). Do boars compensate for hunting with higher reproductive hormones? *Conservation Physiology, 9*(1), coab068.

Davis, A. Y., Belaire, J. A., Farfan, M. A., Milz, D., Sweeney, E. R., Loss, S. R., & Minor, E. S. (2012). Green infrastructure and bird diversity across an urban socioeconomic gradient. *Ecosphere, 3*(11), 1–18.

Dickman, A. J. (2010). Complexities of conflict: The importance of considering social factors for effectively resolving human–wildlife conflict. *Animal Conservation, 13*(5), 458–466.

Dietsch, A. M., Slagle, K. M., Baruch-Mordo, S., Breck, S. W., & Ciarniello, L. M. (2017). Education is not a panacea for reducing human–black bear conflicts. *Ecological Modelling, 367*, 10–12.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., & Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and A simulation study evaluating their performance. *Ecography, 36*(1), 27–46.

Drury, R., Homewood, K., & Randall, S. (2011). Less is more: The potential of qualitative approaches in conservation research. *Animal Conservation, 14*(1), 18–24.

Elith, J., Graham, H., Anderson, C. P., Dudík, R., Ferrier, M., Guisan, S., & Zimmermann, A. E., N (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography, 29*(2), 129–151.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of maxent for ecologists. *Diversity and Distributions, 17*(1), 43–57.

ESRI– Environmental Systems Research Institute (2019). *ArcGIS Pro*, version 2.7.

Feng, X., Park, D. S., Liang, Y., Pandey, R., & Papeş, M. (2019). Collinearity in ecological niche modeling: Confusions and challenges. *Ecology and Evolution, 9*(18), 10365–10376.

Gilleland, A. H. (2010). *Human-wildlife conflict across urbanization gradients: spatial, social, and ecological factors*. Ph.D. Theses, University of South Florida. Retrieved from: https://digitalcommons.usf.edu/etd/3489

Giménez-Anaya, A., Herrero, J., Rosell, C., Couto, S., & García-Serrano, A. (2008). Food habits of wild boars (Sus scrofa) in a mediterranean coastal wetland. *Wetlands, 28*(1), 197–203.

Gras, P., Knuth, S., Börner, K., Marescot, L., Benhaiem, S., Aue, A., & Kramer-Schadt, S. (2018). Landscape structures affect risk of canine distemper in urban wildlife. *Frontiers in Ecology and Evolution, 6*, 136.

Hengl, T. (2006). Finding the right pixel size. *Computers & Geosciences, 32*(9), 1283–1298.

Hof, A. R., Jansson, R., & Nilsson, C. (2012). The usefulness of elevation as a predictor variable in species distribution modelling. *Ecological Modelling, 246*, 86–90.

Hysen, L., Nayeri, D., Cushman, S., & Wan, H. Y. (2022). Background sampling for multi-scale ensemble habitat selection modeling: Does the number of points matter?. *Ecological Informatics, 72*, 101914. https://doi.org/10.1016/j.ecoinf.2022.101914

Inskip, C., & Zimmermann, A. (2009). Human-felid conflict: A review of patterns and priorities worldwide. *Oryx, 43*(1), 18–34.

IUCN (2020). What is human-wildlife conflict. *Briefing Paper by the IUCN SSC Human-Wildlife Conflict Task Force.* Retrieved from: https://www.hwctf.org/_files/ugd/7acc16_c026ab9ffce44ea7900580771cba1cb4.pdf

Jaman, M. F., Sarker, A. R., Alam, M., Rahman, M., Rabbe, F., Rana, A. S., & Hossain, S. (2021). Species diversity, distribution, and habitat utilization of urban wildlife in a megacity of Bangladesh. *Biodiversity Journal, 12*(3), 635–653.

Jefford, M., Black, C., Grogan, S., Yeoman, G., White, V., & Akkerman, D. (2005). Information and support needs of callers to the Cancer helpline, the Cancer Council Victoria. *European Journal of Cancer Care, 14*(2), 113–123.

Keuling, O. & Leus, K. (2019). *Sus scrofa*. *The IUCN Red List of Threatened Species*. e.T41775A44141833. Retrieved at: https://doi.org/10.2305/IUCN.UK.2019-3.RLTS.T41775A44141833.en

Kimmig, S. E., Flemming, D., Kimmerle, J., Cress, U., & Brandt, M. (2020). Elucidating the socio-demographics of wildlife tolerance using the example of the red Fox (Vulpes vulpes) in Germany. *Conservation Science and Practice*, 2(7), e212.

König, H. J., Kiffner, C., Kramer-Schadt, S., Fürst, C., Keuling, O., & Ford, A. T. (2020). Human–wildlife coexistence in a changing world. *Conservation Biology, 34*(4), 786–794.

Kotulski, Y., & König, A. (2008). Conflicts, crises and challenges: Wild Boar in the Berlin City–a social empirical and statistical survey. *Natura Croatica: Periodicum Musei Historiae Naturalis Croatici, 17*(4), 233–246.

Latour, B. (1991). *We Have Never Been Modern*, translation: C. Porter, Cambridge: Harvard University Press, 1993.

Licoppe, A., Prévot, C., Heymans, M., Bovy, C., Casaer, J., & Cahill, S. (2013, August). Wild boar/feral pig in (peri-) urban areas. In *Managing wild boar in human-dominated landscapes. International Union of Game Biologists—Congress IUGB* (Vol. 2013, pp. 1–31).

Linnell, J. D., Cretois, B., Nilsen, E. B., Rolandsen, C. M., Solberg, E. J., Veiberg, V., ... & Kaltenborn, B. (2020). The challenges and opportunities of coexisting with wild ungulates in the human-dominated landscapes of Europe's Anthropocene. *Biological Conservation, 244*, 108500. https://doi.org/10.1016/j.biocon.2020.108500

Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography, 28*(3), 385–393.

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., & Taylor, W. W. (2007). Complexity of coupled human and natural systems. *Science, 317*(5844), 1513–1516.

Luniak, M. (2004, July). Synurbization–adaptation of animal wildlife to urban development. *In Proceedings 4th international urban wildlife symposium* (pp. 50–55). University of Arizona.

Madden, F. (2004). Creating coexistence between humans and wildlife: Global perspectives on local efforts to address human–wildlife conflict. *Human Dimensions of Wildlife, 9*(4), 247–257.

Madden, F., & McQuinn, B. (2014). Conservation's blind spot: The case for conflict transformation in wildlife conservation. *Biological Conservation, 178*, 97–106.

Magle, S. B., Hunt, V. M., Vernon, M., & Crooks, K. R. (2012). Urban wildlife research: Past, present, and future. *Biological Conservation, 155*, 23–32.

Manfredo, M. J. (2008). *Who cares about wildlife?* Springer.

Marley, J., Hyde, A., Salkeld, J. H., Prima, M. C., Parrott, L., Senger, S. E., & Tyson, R. C. (2017). Does human education reduce conflicts between humans and bears? An agent-based modelling approach. *Ecological Modelling, 343*, 15–24.

Mascia, M. B., Brosius, J. P., Dobson, T. A., Forbes, B. C., Horowitz, L., McKean, M. A., & Turner, N. J. (2003). Conservation and the social sciences. *Conservation Biology, 17*(3), 649–650.

Maselli, V., Rippa, D., Russo, G., Ligrone, R., Soppelsa, O., D'Aniello, B., & Fulgione, D. (2014). Wild boars' social structure in the mediterranean habitat. *Italian Journal of Zoology, 81*(4), 610–617.

Massei, G., Kindberg, J., Licoppe, A., Gačić, D., Šprem, N., Kamler, J., & Náhlik, A. (2015). Wild Boar populations up, numbers of hunters down? A review of trends and implications for Europe. *Pest Management Science, 71*(4), 492–500.

Mendelson, H., & Yom-Tov, Y. (1987). [Hebrew]. *Plants and Animals of the Land of Israel, Vol. 7, Mammals.* Ministry of Defense Publishing House and Society for Protection of Nature, Tel Aviv, Israel.

Merow, C., Smith, M. J., & SilanderJr, J. A. (2013). A practical guide to maxent for modeling species' distributions: What it does, and why inputs and settings matter. *Ecography, 36*(10), 1058–1069.

Miller, J. R., & Hobbs, R. J. (2002). Conservation where people live and work. *Conservation Biology, 16*(2), 330–337.

Nelli, L., Schehl, B., Stewart, R. A., Scott, C., Ferguson, S., MacMillan, S., & McCafferty, D. J. (2022). Predicting habitat suitability and connectivity for management and conservation of urban wildlife: A real-time web application for grassland water voles. *Journal of Applied Ecology, 59*(4), 1072–1085.

Nyhus, P. J. (2016). Human–wildlife conflict and coexistence. *Annual Review of Environment and Resources, 41*, 143–171.

OpenStreetMap (2022). *Israel and Palestine*. Retrieved from: http://download.geofabrik.de/asia/israel-and-palestine-latest-free.shp.zip

Parker, T. S., & Nilon, C. H. (2012). Urban landscape characteristics correlated with the synurbization of wildlife. *Landscape and Urban Planning, 106*(4), 316–325.

Peterson, M. N., Birckhead, J. L., Leong, K., Peterson, M. J., & Peterson, T. R. (2010). Rearticulating the myth of human–wildlife conflict. *Conservation Letters, 3*(2), 74–82.

Peterson, M. N., Peterson, M. J., Peterson, T. R., & Leong, K. (2013). Why transforming biodiversity conservation conflict is essential and how to begin. *Pacific Conservation Biology, 19*(2), 94–103.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2004). A maximum entropy approach to species distribution modeling. In *Proceedings of the twenty-first international conference on Machine learning* (p. 83).

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3–4), 231–259.

Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: An open-source release of maxent. *Ecography, 40*(7), 887–893.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2022). *Maxent software for modeling species niches and distributions* Version 3.4.4. Retrieved from: http://biodiversityinformatics.amnh.org/open_source/maxent/

R Core Team (2022). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*, version 4.2.1 Vienna, Austria. Retrieved from: https://www.R-project.org/

Redpath, S. M., Young, J., Evely, A., Adams, W. M., Sutherland, W. J., Whitehouse, A., & Gutierrez, R. J. (2013). Understanding and managing conservation conflicts. *Trends in Ecology & Evolution, 28*(2), 100–109.

Redpath, S. M., Bhatia, S., & Young, J. (2015). Tilting at wildlife: Reconsidering human–wildlife conflict. *Oryx, 49*(2), 222–225.

Ritchie, H., & Roser, M. (2018). Urbanization. Published online at *OurWorldInData.org.* Retrieved from: https://ourworldindata.org/urbanization

Soulsbury, C. D., & White, P. C. (2016). Human–wildlife interactions in urban areas: A review of conflicts, benefits, and opportunities. *Wildlife Research, 42*(7), 541–553.

Stillfried, M., Gras, P., Busch, M., Börner, K., Kramer-Schadt, S., & Ortmann, S. (2017). Wild inside: Urban wild Boar select natural, not anthropogenic food resources. *PLoS ONE*, 12(4), e0175127.

Toger, M., Malkinson, D., Benenson, I., & Czamanski, D. (2016). The connectivity of Haifa urban open space network. *Environment and Planning B: Planning and Design, 43*(5), 848–870.

Toger, M., Benenson, I., Wang, Y., Czamanski, D., & Malkinson, D. (2018). Pigs in space: An agent-based model of wild Boar (*Sus scrofa*) movement into cities. *Landscape and Urban Planning, 173*, 70–80.

Tsing, A. L., Bubandt, N., Gan, E., & Swanson, H. A. (Eds.). (2017). *Arts of living on a damaged planet: Ghosts and monsters of the anthropocene*. University of Minnesota Press.

United Nations, Population Division (2018). World Urbanization Prospects: The 2018 Revision, Published Online, Retrieved from: https://population.un.org/wup/publications/Files/WUP2018-Report.pdf

Vogel, S. M., Vasudev, D., Ogutu, J. O., Taek, P., Berti, E., Goswami, V. R., & Svenning, J. C. (2022). Identifying the potential for sustainable human wildlife coexistence by integrating willingness to coexist with habitat suitability models. *bioRxiv*.

Wowrzeczka, B. (2021). City of waste—importance of scale. *Sustainability, 13*(7), 3909.

Yang, X. Q., Kushwaha, S. P. S., Saran, S., Xu, J., & Roy, P. S. (2013). Maxent modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda L.* in Lesser Himalayan foothills. *Ecological Engineering, 51*, 83–87.

Zurell, D., Franklin, J., König, C., Bouchet, P. J., Dormann, C. F., Elith, J., & Merow, C. (2020). A standard protocol for reporting species distribution models. *Ecography, 43*(9), 1261–1277.

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