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María Escobar-González [1,*], Miguel Ibáñez-Álvarez [2], Irene Torres-Blas [1], Stefania Tampach [1], Aser Clavero [3], Santiago Lavín [1], Gregorio Mentaberre [4], Jorge Ramón López-Olvera [1] and Emanuel Serrano [1,*]

[1] Wildlife Ecology & Health group (WE&H) and Servei d'Ecopatologia de Fauna Salvatge (SEFaS), Departament de Medicina i Cirurgia Animals, Universitat Autònoma de Barcelona, (UAB), Bellaterra, Barcelona, Spain

[2] Forest Research, Northern Research Station, Roslin, United Kingdom

[3] Animal Rights Services, Barcelona City Council, Barcelona, Spain

[4] Departament de Ciència Animal, Wildlife Ecology & Health group (WE&H), Escola Tècnica Superior d'Enginyeria Agroalimentària i Forestal i de Ve-terinària (ETSEAFiIV), Lleida, Spain

* Correspondence: maria.escobar@uab.cat (M.E.-G.); Emmanuel.Serrano@uab.cat (E.S.)

Abstract

Urbanisation is reshaping ecosystems and increasing human–wildlife interactions. Wild boar (*Sus scrofa*), a highly adaptable species, is increasingly common in European cities, where it exploits natural and anthropogenic resources, often leading to conflict. Predicting when and where wild boar enters urban areas remains challenging, particularly using scalable tools such as remote sensing. Here we show that temporal and spatial drivers of urban presence are decoupled in Barcelona over a 14-year period. Seasonal vegetation dynamics influenced the timing of urban incursions, with peaks in spring and late summer associated with changes in vegetation moisture and likely reinforced by increased energetic demands during reproduction and early lactation. However, remotely sensed vegetation indices captured these dynamics only partially, limiting their predictive power when used alone. Spatial variation in urban green area use was primarily explained by landscape structure, with proximity to streams and habitat fragmentation contributing similarly. Green areas near natural corridors concentrated higher and more variable presence, while heterogeneous landscapes likely facilitated repeated use by increasing access to foraging and refuge. Integrating remote sensing with landscape metrics can improve anticipation and management of human–wildlife conflicts.

Keywords: wild boar; urban ecology; landscape structure; human–wildlife conflict; Mediterranean ecosystems

1. Introduction

Human-driven environmental changes affect ecosystems across the globe [1]. Among these changes, urbanisation stands out as a dominant trend. Urban areas currently account for approximately 3% of the total land area of Earth, and yet they contain about half of the world's human population [2], a figure expected to peak in the 2080s [3]. This expansion alters land use and disrupts ecological processes, leading to biotic and genetic homogenisation [4–7]. Altogether, urban settlements expand into natural areas, reducing the habitat availability for wildlife [8], which must adapt their life cycles to the new scenario, relocate, or disappear [9].

Despite its ecological impacts, urbanisation has also created novel opportunities for highly adaptable and generalist species [10–12]. In Europe, for instance, wild boars (Sus scrofa) and medium-sized carnivores such as red foxes (Vulpes vulpes) and Eurasian badgers (Meles meles) successfully

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exploit these urban habitats [8,13]. Synurbic wildlife may not reside permanently in cities but benefit from the refuge and resources in urbanised areas, particularly those close to peri-urban natural habitats or green spaces [8,13,14].

Wild boar has become a leading example of urban wildlife adaptation [15–17]. This mammal is characterised by the highest reproductive rate among ungulates and a broad ecological, demographic and behavioural flexibility [18,19]. These traits, coupled with broad environmental and socio-economic changes, such as rural abandonment, shifts in crop types, milder winters, and declining predator and hunting pressures, have supported its expansion into urban habitats [20–22]. Wild boars have increasingly established synurbic populations across European cities, where they behave as urban exploiters [15,16,23–27]. This has heightened the reciprocal habituation with humans, leading to increased interactions and conflicts [15,28–30], including traffic accidents, aggressions, damage to green areas and infrastructure, and increased zoonotic disease risk [31–36].

In urban environments, synurbic wild boars exploit anthropogenic food sources such as garbage, pet food, or intentional feeding by humans [16,29]. They also actively seek urban green areas and areas of high vegetation productivity throughout the year [17,33,37,38], which can offer shelter, food and water [15]. Nevertheless, they may remain ecologically tied to forested habitats and show a strong preference for natural food resources and landscapes [23,39–42]. Seasonal events, such as spring and summer farrowing or summer droughts (particularly intense in Mediterranean climates), trigger wild boar use of urban areas in search of food and water [16,24,43,44]. The spatial behaviour and daily activities of wild boars in urban environments are shaped by human disturbances, landscape structure, and the distribution of resources [17,24,33,38,42,45,46].

In Barcelona, the wild boar population inhabiting Collserola Natural Park (CNP) has increased tenfold over the last 20 years [44]. The CNP is largely isolated from other natural areas due to intense infrastructure pressure on its periphery [43,47], and the CNP wild boars maintain reduced genetic flow with neighbouring populations [26]. Therefore, during the summer natural resource scarcity period, wild boar presence increases in urban landscapes [16,24]. To manage this growing challenge, local authorities have been allocating increasing amounts of public resources to different strategies [48–51]. These include reducing the attractiveness of the city limiting anthropogenic food resources, conducting vegetation clearings in the urban-forest ecotone, reducing population numbers, and raising public awareness [52]. Despite these efforts, effectively anticipating wild boar presence and managing conflicts in such complex and dynamic urban contexts remains challenging.

Statistical models have been developed to predict wild boar presence and human–wildlife conflicts (HWC) across rural and peri-urban landscapes [24,34,46,53,54]. These models typically incorporate environmental factors such as proximity to natural habitats, landscape structure, and resource distribution. However, the role of primary production in predicting wild boar occurrence has been only limitedly investigated in rural or agricultural contexts, but not in urban and peri-urban settings [41,55].

Satellite remote sensing (SRS) is a cost-effective, long-term monitoring tool that can provide consistent data on vegetation dynamics [56]. Vegetation indices (VI) derived from spectral reflectance data include the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalised Difference Water Index (NDWI), and Global Vegetation Moisture Index (GVMI), which reflect primary production, vegetation health, and water content in both vegetation and soil [57–61]. These indices are widely applied in agriculture and conservation to infer ecological processes and habitat conditions [56,62,63]. However, the use of vegetation indices for predicting urban wildlife conflict remains limited, with few studies focusing on large mammals in urban environments [37]. Thus, a significant gap remains in integrating remotely sensed vegetation indices (RS-VI) with predictive models for addressing wild boar-related conflicts in complex urban contexts. The present study evaluates the relationship between wild boar occurrence in Barcelona and multiple RS-VI across both natural and urban green areas. Additionally, given the need for fine-scale ecological understanding [17], the study also identifies the urban green area characteristics best predicting wild boar presence. We hypothesised that RS-VI could serve as a cost-effective and scalable tool to

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anticipate conflict hotspots and inform adaptive management for improved planning and resource allocation. Finally, we predicted that, due to continuous irrigation, RS-VI values in urban parks would be higher than those of CNP during the summer scarcity period, which would help to explain the occurrence of wild boar presence in urban settings.

2. Materials and Methods

2.1. Study Area and Plot Selection

The study area included the CNP and 32 urban green areas located in the Barcelona districts bordering the Collserola massif (Figure 1). The Collserola massif covers approximately 11,100 ha, including the 8,295 hectares of the CNP (Parc de Collserola, 2024a). The relief is gentle and asymmetrical, with ridges facing inland long and gently sloping and short and steep slopes facing the sea.

The study area included the CNP and 32 urban parks and green areas (hereafter "green areas") located in the Barcelona districts bordering the Collserola massif (Figure 1). The Collserola massif covers approximately 11,100 ha, including the 8,295 hectares of the CNP [64]. The relief is gentle and asymmetrical, with ridges facing inland long and gently sloping and short and steep slopes facing the sea.

Collserola has a typical Mediterranean climate, with an average annual temperature of 14°C. Winters are generally mild, with temperatures typically above 5 °C, while summers are hot and dry, with an average temperature of 21 °C. Spring and autumn are transition seasons characterised by concentrated and irregular rainfall. These two seasons constitute the two wet periods, with an average rainfall of 83.1 mm in October and 60.4 mm in May, followed by intense summer drought in July (10.6 mm). Despite these generalities, there are significant local climatic variations, influenced by the topography, the thermoregulatory effect of the sea, altitudinal variations, the sun exposure on the slopes and the vegetation cover, among others [65].

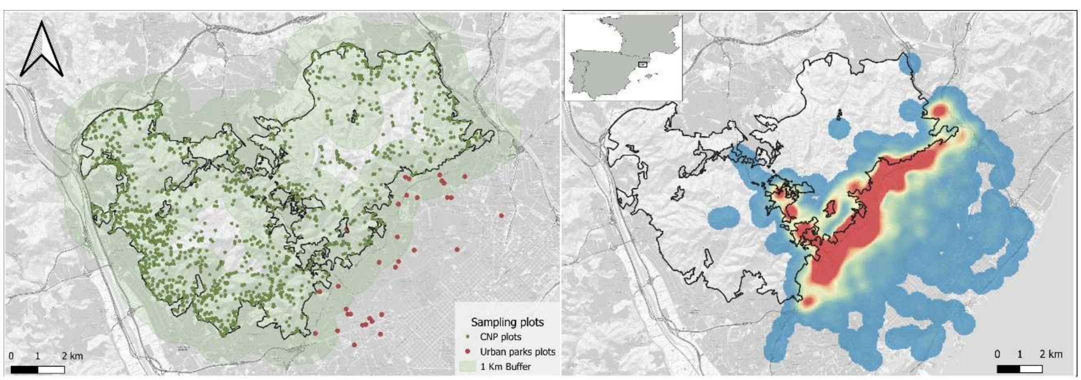

Figure 1. *Left*: Map of the study area showing the sampling points for remotely sensed vegetation indices (RS-VI) in Collserola Natural Park (CNP; green dots) and in Barcelona urban green areas (red dots). The urban green areas located within a 1 km buffer from the CNP boundary (green shading) were included in the PLSR analysis. *Right*: Kernel density map of wild boar-related incidences in Barcelona, supporting the selection of urban green areas within the buffer zone as focal areas for analysis.

The landscape consists of a complex, dynamic mosaic of natural habitats, with meadows, grasslands, scrublands, and croplands, predominated by Mediterranean forests. The most abundant forest type is a mixed woodland of Holm oaks (Quercus ilex) with an upper canopy of Aleppo pine (Pinus halepensis) and interspersed Quercus × cerrioides. The Holm oak woodland is a dense and humid forest further characterised by a tall shrub stratum (1.5-3 m), and a whole host of creeping and climbing plants that sometimes make the wood impenetrable. Secondary pine forests, dominated by Aleppo pine with smaller numbers of stone pine (Pinus pinea), normally occupy abandoned

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farmland. In this habitat, oaks are also found among the pines, which also have an undergrowth consisting of plants from open environments, like cistus (Cistus spp.), rosemary (Rosmarinus officinalis) and gorse (Ulex parviflorus) [64].

We selected the urban green areas that met two criteria: (1) previously reported wild boar presence and/or (2) the existence of irrigation systems to maintain green spaces and vegetation during the dry summer months. These green areas differ in vegetation, size, and proximity to CNP.

We selected one sampling plot in each green area within a >30 m2 vegetation area to minimise interference from paths, concrete, and bare soil. In the CNP, we selected 1,492 sampling plots representing nine land cover types from the 41 categories in the ICGC (Institut Cartogràfic i Geològic de Catalunya) land cover dataset, focusing on natural and agricultural areas. Pine and oak forests were excluded since EVI and NDVI are not reliable indicators of leaf photosynthetic rates or drought events in evergreen Mediterranean forests [66,67]. We defined each sampling location as a 30m-side pixel (corresponding to 900m2) extending from the UTM coordinates of the centroid using QGIS 3.10.0 [68].

2.2. Wild Boar Presence

Wild boar presence refers to at least one alive, wounded or dead wild boar in the city of Barcelona [24]. These were reported by citizens to the Local Police of Barcelona, who registered the location, date, and time of each event. To avoid pseudo-replication, we processed these data, retaining only one presence if multiple events occurred within a 500 m buffer in a two-hour timeframe, following Castillo-Contreras et al. [24]. From 2010 to 2024, we registered a total of 8,321 refined presences.

2.3. Satellite Images and Extraction of Vegetation Indices

To characterise vegetation dynamics, we obtained surface reflectance Landsat imagery through Google Earth Engine [69]. We selected images based on their availability and temporal coverage of the study area, covering the period from 2010 to 2024. The datasets, accessible under the LANDSAT/LT05/C02/T1_L2, LANDSAT/LE07/C02/T1_L2, and LANDSAT/LC08/C02/T1_L2 collections, provide atmospherically corrected surface reflectance products standardised under the Collection 2 framework [70–72]. The Collection 2 ensures high geometric accuracy, radiometric calibration, and consistent preprocessing across different Landsat missions, facilitating reliable multi-temporal and cross-sensor comparisons.

We filtered the imagery to match the extent of our study area using a custom shapefile. The images were clipped to this region and exported as multispectral images with a spatial resolution of 30 meters. These geoprocessing steps were automated through a custom Earth Engine script. Only images with minimal cloud cover were considered, and further cloud masking steps were performed during subsequent preprocessing stages. Further imagery processing was conducted in R statistical software [73]. We used the “terra” package [74] to combine the different spectral bands from the images and generate vegetation indices, including NDVI [57], EVI2 [75] (Enhanced Vegetation Index 2, equivalent to EVI from modern sensors), NDWI [58], and GVMI [59,60,76].

We then extracted the VI values for each sampling plot using the “terra” package [74] and a shapefile mask of the selected sampling plots. Since low or negative VI values are typically associated with areas of bare soil, concrete, water, snow, or clouds [70], we identified and removed anomalous observations by applying a vegetation threshold based on NDVI values within the study area (NDVI > 0.1 and NDVI < 1). The observations falling outside this range were discarded. After correlation analysis confirming high correlation between EVI2 and NDVI, we selected EVI2 for further analyses because it is less sensitive to soil and atmospheric noise, and NDVI saturates in evergreen vegetation [78,79].

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To obtain monthly VI values for each urban green area while minimising sensitivity to outliers, we first calculated the median. For the CNP, we explored EVI2 phenology across different land uses and aggregated them into four broader categories: arable land, permanent crops (olives and vineyards), scrubland, and meadows and pastures. For each of these new combined land-use categories, we also calculated the median VI values. Then, for both the urban green areas and CNP, we aggregated the data by averaging the monthly medians across individual green areas or land-use categories. This resulted in a single VI value per month for urban green areas and CNP, which was subsequently used to construct harmonised and consistent regular time series (TS). We used linear interpolation between adjacent values as a gap-filling method to estimate missing VI data (two observations in the CNP and four observations in the urban green areas).

2.4. Statistical Analyses

All the statistical analyses were conducted in R statistical software 4.3.1 [73].

2.4.1. Analysis of Long-Term Temporal Trends

To evaluate the long-term temporal trends and dynamics in both presences and VI in the urban green areas and CNP, we followed the protocol proposed by Verbesselt et al. [80] using the "bfast" analysis. BFAST, which stands for "Breaks For Additive Season and Trend", detected and characterised "breakpoints" or structural changes in the time series (TS) by iteratively decomposing it into three different components: trend, seasonal, and remainder [80].

The analysis followed an iterative procedure, beginning with seasonal trend decomposition using the LOESS method (STL) [81]. STL subtracted the trend from the observed values, resulting in a detrended TS that represents seasonality alone (St). This detrended TS was then averaged to obtain a representative seasonal component. The remainder component (or noise) captured residual variation not explained by trend or seasonality. Afterwards, BFAST applied the Ordinary Least Squares residuals-based Moving Sum test (OLS-MOSUM), which identified significant shifts or "breakpoints" in the trend component. Breakpoints were determined iteratively, minimising the Bayesian Information Criterion (BIC) and optimising their position through reduction of the Residual Sum of Squares (RSS). This process was repeated until both the number and placement of breakpoints were stable.

BFAST transformed the TS into a piecewise linear regression model in which the maximum number of regressions was influenced by the parameter "h". This parameter defines the minimum segment size between potential breaks in the trend model, expressed as a fraction of the total sample size [80]. By setting the minimum segment size, h determines the potential number of breaks [80,82]. For our analysis, each TS included 168 observations (14 years at a monthly frequency). We set the significant trend periods at $h = 1/8$ following the recommendations of Watts et al. (2014), which corresponded to a minimum segment size of 21 observations (21 months), allowing the detection of up to seven breakpoints.

After extracting the temporal and seasonal trends from the BFAST models, we investigated whether the long-term trends of VI from the urban green areas, CNP, and wild boar presence were correlated. We obtained the predicted monthly values of the trend component (i.e., the piecewise model) from the BFAST models, and then conducted Kendall correlation analysis, since they are well-suited for handling ties. Additionally, to test whether the VI trends statistically predicted the presence trend, we fitted a set of linear models. We used the predicted number of presences as the response variable and the predicted VI of the CNP and urban green areas as the predictors. To account for autocorrelation, we applied Newey-West standard errors to adjust the inference [83].

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2.4.2. Evaluation of the Relationship Between Seasonal Trends

To evaluate the relationship between VI seasonal variation and wild boar presences, we fitted Generalised Additive Mixed Models (GAMMs) using the "mgcv" package [84,85]. We fitted these seasonal models separately for the urban green areas and the CNP. The models included month as a cyclic smoothing function to account for seasonal patterns [86]. The maximum of knots was below the number of months to prevent model overfitting [86]. We included year as a random term to account for interannual variability. We used Gaussian family with an identity link function for the VI, and Poisson family with log link for wild boar presence, or a negative binomial distribution if the model showed overdispersion. Subsequently, we assessed model fit using standard residual diagnostics following Zuur et al. [87] and Wood [85]. We conducted Levene's test for homogeneity of variance [88] and tests for temporal autocorrelation (e.g., Durbin–Watson), using the "mgcViz" and "DHARMa" packages to validate the wild boar urban presence GAMM [89,90].

We then extracted the predicted values and the standardised residuals. Predicted values represented within-year cyclic seasonal variation adjusted for interannual variability, whereas the residuals no longer contained the seasonal cycle, reflecting the unexplained variation. After exploring the residual distribution, we conducted Kendall correlation tests between the standardised residuals of the set of GAMMs. This analysis aimed to identify whether short-term anomalies (e.g., sudden droughts, unseasonal green-ups) in vegetation indices were linked to unexpected increases or decreases in wild boar presence. We repeated the correlations between the predicted values to compare the general seasonal co-fluctuation of vegetation indices and wild boar presence.

To quantify the relationship between monthly vegetation in the urban green areas and CNP and the presence of wild boar in urban areas, we fitted a set of Generalised Linear Mixed Models (GLMMs) using the glmmTMB package [91]. Monthly wild boar incidences were modelled as negative binomial counts with a log link to account for overdispersion. All the models included year as a random intercept to account for interannual variability, and month as linear, quadratic, and cubic terms to represent seasonal dynamics identified in preliminary GAMM exploration. The RS-VI (EVI2, NDWI, GVMI) were included as predictors separately for the urban green areas (subscript p) and Collserola (subscript c). To improve interpretability and reduce collinearity, each index was centred before modelling. Since several indices were strongly correlated within habitat type, we compared a structured set of candidate models, including: (i) seasonality only, (ii) single-index models for each habitat, (iii) combined habitat models (e.g., GVMIc + GVMIp), (iv) a PCA-based model, using the first principal component from each habitat, (v) a Δ-model using differences between the urban green areas and the CNP (e.g., ΔEVI2 = EVI2p – EVI2c), (vi) a full model including all the indices, and (vii) zero-inflated versions of the key models to account for potential excess zeros. The models were compared using AIC and AICc, and the model with the lowest AICc was selected as the best-supported model. Model assumptions were evaluated using DHARMa simulation-based diagnostics [90]. We assessed multicollinearity using variance inflation factors (VIFs), and model explanatory power was quantified using Nakagawa's marginal and conditional R^2 [92]. Partial effect plots were produced using the ggeffects package [93].

2.4.3. Evaluation of the Relationship Between Wild Boar Presence and Urban Green Area Characteristics

Lastly, to identify local predictors for wild boar presence in the urban area of Barcelona we evaluated the relationship between the number of presences during the peak period (May to October, n=6189) and the values of VIs and landscape metrics of each green area. Because most presences (5752/8321, 69.13%) occurred within a 1-km buffer from the CNP perimeter (Figure 1), we selected only those green areas located within this range (n=14).

For each selected green area, we computed the mean VI values during this period and then calculated the total number of presences and derived environmental and urban landscape metrics within a 300 m buffer from the green area perimeter. We obtained environmental variables and urban landscape metrics reflecting landscape fragmentation using QGIS 3.10.0 [94]. These metrics included street length, street density, number of intersections, intersection density, Euclidean distance to the

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closest stream, and the total area of the urban green area plus its buffer. Because all the urban green areas analysed in this section were located within a similar range from CNP (the source population) [24], we excluded this variable from the analysis. For the landscape ecology analysis, we utilised the ICGC (Institut Cartogràfic i Geològic de Catalunya) land cover dataset, which comprises 41 categories. Using the LecoS plugin in QGIS [95], we calculated the number of patches, patch density, edge length, edge density, patch cohesion index, and landscape division for each specific land use. To simplify interpretation, we processed these outputs to compute total patch number, total patch density, total edge length, total edge density, mean patch cohesion index (mpci), and mean landscape division (mld).

We then followed the protocol for data exploration proposed by Zuur et al. [87]. Before analysis, we log-transformed all the variables using the base-10 logarithm (log10) to reduce skewness and residual patterns. For the variables containing zero values (e.g., number of presences), we added a constant value of +1. For the variables with negative values, such as GVMI, we subtracted the minimum observed value and added 1 before applying the logarithm to ensure that all the values were positive. We excluded NDVI because this variable was redundant with EVI2 (τ=0.98, p=0.00, Kendall correlation). We did not include fragmentation variables corrected by the urban green area extension, as we did not detect any relationship with the number of presences.

We then applied a Partial Least Squares Regression approach (PLSR) to explore the relationship between the number of presences, urban green area characteristics, and urban fragmentation metrics. This statistical approach is robust to multicollinearity among predictors but can explain complex phenomena that combine different predictors, proving especially useful for determining relevant variables and their magnitudes of influence [96,97]. The transformed number of presences within a 300 m buffer of the park was considered the response PLSR Y component, while the year, the distance to the closest stream, the total area of the park and its buffer, street length, number of intersections, total number of patches, total edge length, mpci, mld, GVMI, NDWI, and EVI2 were considered the explanatory PLSR component. The PLSR analysis was conducted using the "plspm" 0.51 version package [98].

3. Results

3.1. Long-Term Temporal Trends

We obtained a decomposition of both TS, the original presences and VI data into seasonal (St), trend (Tt), and remainder (et) components (Figure 2).

The BFAST decomposition of wild boar urban presence in the urban green areas of Barcelona from 2010 to 2024 (Figure 2A) identified a seasonal component (S_t) with consistent annual cycles and a distinct bimodal pattern, marked by peaks in spring and late summer and troughs in winter and midsummer. The long-term trend component (T_t) comprised four segments, each separated by statistically detected breakpoints (breakpoint dates in Table 1): an initial gradual, non-significant increase from 2010 to approximately April 2015 (β = 1.489, p = 0.228); a subsequent steep and highly significant rise between April 2015 and January 2017 (β = 46.415, p < 0.001), corresponding to the rapid escalation of incursions; a period of near-stabilisation or minimal increase from January 2017 to August 2021 (β = 0.451, p = 0.426); and a sharp, highly significant decline from August 2021 onwards (β = –34.968, p < 0.001), indicating a substantial reduction in urban presence.

For the CNP VI, we identified three breakpoints in the GVMI trend, two in the EVI2 and four in the NDWI (Table 1, Figure 2). On the other hand, for the urban green area VI, we identified two breakpoints in the EVI2 trend, and three in the GVMI and NDWI trends (Table 1, Figure 2). Table 1 presents the dates of abrupt changes, along with their magnitude and direction. It also includes the regression parameters of the piecewise model, depicting the values at the break date (intercept) and the recovery rate (slope).

We detected significant correlations in the long-term trends of all the vegetation indices for the urban green areas and the CNP, suggesting coherent long-term dynamics in vegetation greenness, moisture content, and water-related status (Figure 3). In contrast, the long-term trend in wild boar urban presence was only weak, largely non-significant associated with the vegetation trend components. The strongest (albeit still weak) relationship was a significant negative correlation with vegetation moisture in the CNP (Presence vs. GVMIc: $\tau = –0.22$, $p < 0.001$). The presence of wild boar in urban areas was also weakly associated with long-term trends in urban green area EVI2 and NDWI ($\tau = 0.11$, $p = 0.03$; and $\tau = 0.13$, $p = 0.01$, respectively). However, none of these trends significantly predicted presence trends linearly (Table S1).

Table 1. Results from the BFAST trend component of urban wild boar presence, and vegetation indices of both urban green areas (EVI2p, GVMIp and NDWIp) and CNP (EVI2c, GVMIc and NDWIc).

Variable	Breakpoint	Breakpoint Dates			Change Magnitude (Absolute units)	Linear Regression Parameters of Trend Component	
		2.5% CI limit	Breakpoint timing	97.5% CI limit		Intercept	Slope
Wb presence	1st	2014(12)	**2015(4)**	2015(5)	-16.020	29.996	46.415
	2nd	2016(12)	**2017(1)**	2017(4)	-65.026	42.329	0.451
	3rd	2021(4)	2021(8)	2021(9)	59.265	103.624	-34.968
EVI2c	1st	2012(9)	2012(10)	2013(5)	0.071	0.354	-0.004
	2nd	2017(5)	2018(3)	2018(5)	0.068	0.401	-0.018
GVMIc	1st	2011(3)	2011(9)	2011(10)	-0.029	0.074	0.023
	2nd	2013(5)	2013(6)	2013(11)	-0.031	0.080	0.002
	3rd	2019(10)	2019(12)	2020(1)	0.016	0.109	-0.016
NDWIc	1st	2011(5)	2011(9)	2011(10)	-0.043	0.038	0.043
	2nd	2013(5)	2013(6)	2013(9)	-0.050	0.060	0.014
	3rd	2015(1)	**2015(3)**	2015(6)	-0.032	0.051	0.010
	4th	2020(8)	2020(9)	2020(10)	-0.014	0.089	-0.016
EVI2p	1st	2012(9)	2012(11)	2013(3)	0.060	0.363	-0.006
	2nd	2017(6)	2018(6)	2018(9)	0.045	0.383	-0.012
GVMIp	1st	2012(8)	2012(12)	2013(2)	0.020	0.099	-0.005
	2nd	2016(11)	**2017(1)**	2017(7)	0.009	0.088	0.004
	3rd	2020(8)	2020(10)	2020(12)	-0.006	0.095	-0.010
NDWIp	1st	2012(7)	2013(1)	2013(2)	0.015	0.100	-0.007
	2nd	2016(12)	**2017(1)**	2017(8)	0.017	0.088	0.004
	3rd	2020(2)	2020(4)	2020(5)	0.006	0.107	-0.012

The breakpoint timing indicates the date in which an abrupt change in the trend occurred, expressed in format "Year (Month)". The left and right limits of the breakpoint timing represent the 95% confidence interval of date estimation. The change in magnitude reflects the difference between the variable value at the end of a linear model (previous segment before the breakpoint) and the intercept of the following one. The linear regression parameters correspond to each segment of the trend after the breakpoint. The intercept represents the value of each variable during the breakpoint (starting value of the following segment), whereas the slope reflects the increasing or decreasing trend of that segment. The synchronous breakpoint dates between wild boar presence and RS-VI are shown in bold.

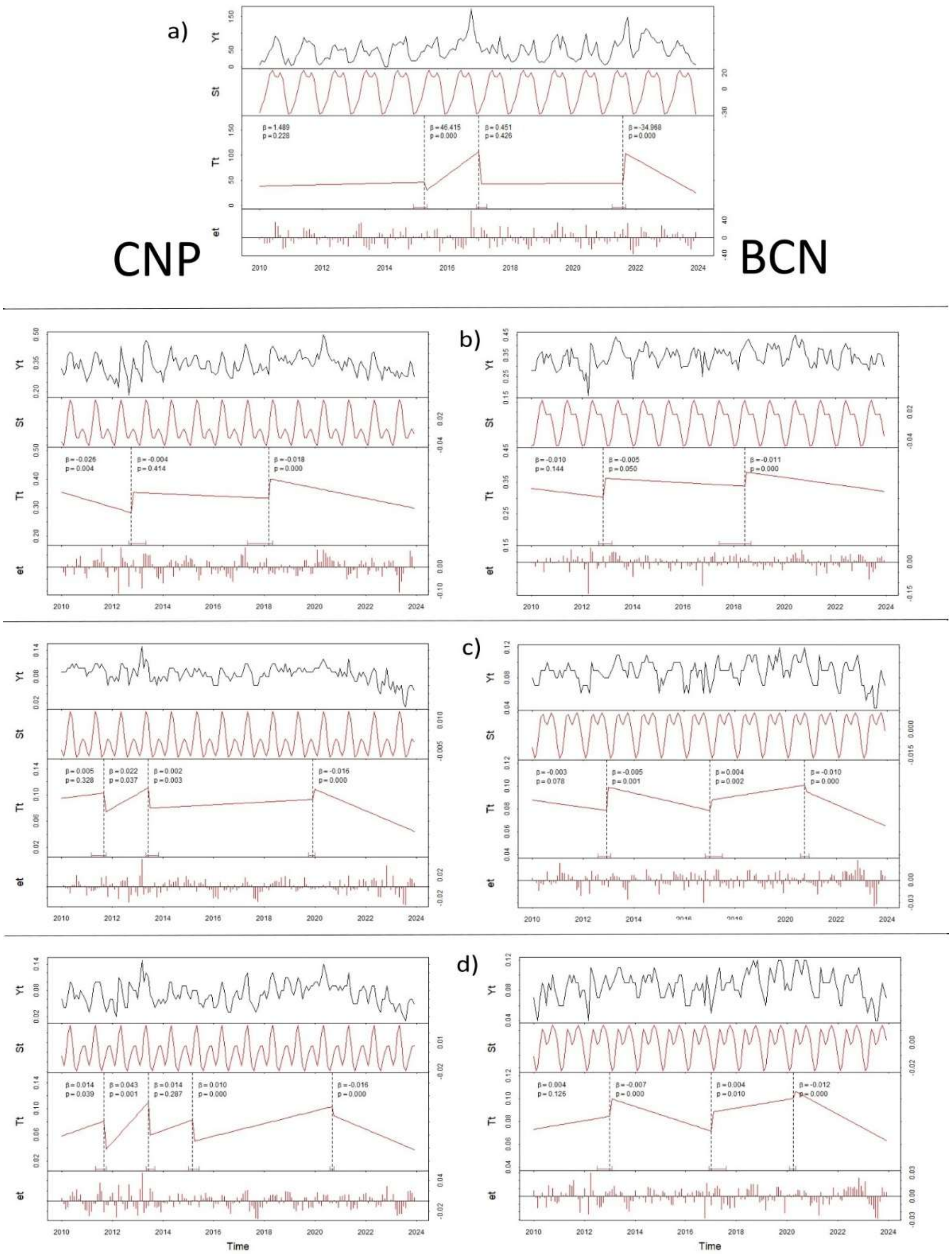

Figure 2. Decomposition of TS (Y_t) using the BFAST method for: (a) wild boar urban presence; and vegetation indices in CNP and urban green areas—(b) EVI2, (c) GVMI, and (d) NDWI, between 2010 and 2023. BFAST separates each series into seasonal (S_t), trend (T_t), and remainder (e_t) components. Slope coefficients (β) and associated p-values are shown for each segmented trend.

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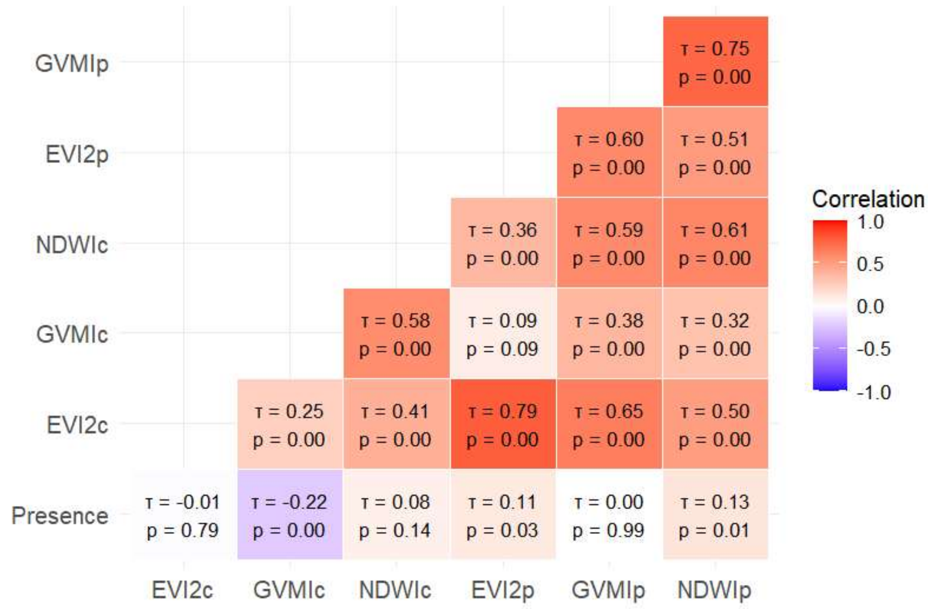

Figure 3. Kendall correlation matrix of long-term trend components from BFAST for wild boar urban presence and RS-VI from urban green areas (EVI2p, GVMIp and NDWIp) and CNP (EVI2c, GVMIc and NDWIc). Colour intensity reflects correlation strength based on Kendall's tau coefficient (τ): dark red indicates strong positive correlations, and dark blue, strong negative correlations. Statistical significance is based on *p*-values.

3.2. Relationship Among Seasonal Trends

The GAMMs (Figure 4) revealed marked seasonal patterns in both the presence of wild boar in urban areas and all the RS-VI. The results from the Kendall correlations between the standardised residuals and the predicted values of the models are represented in Figure 5. The specifications and goodness-of-fit of the GAMM models are presented in Table S2. On average, the models demonstrated moderate to good explanatory power, with a mean pseudo-R^2 of 0.36. However, seasonal variation in VI differed among indices and habitats: seasonality explained a higher proportion of the variance of EVI2 and NDWI in both the urban green areas and CNP (pseudo-$R^2 \approx$ 0.32–0.39; pseudo-$R^2 \approx$ 0.40–0.43, respectively), whereas GVMI seasonality was stronger in the urban green areas (pseudo-R^2 = 0.32) than in the CNP (pseudo-R^2 = 0.14).

The predicted values from the presence model were highly and positively associated with the urban green area EVI2 (τ= 0.66, p=0.00) and moderately associated with the urban green area and CNP GVMI (τ= 0.51, p=0.00; τ= 0.47, p=0.00, respectively; Figure 5a). On the other hand, the standardised residuals of the presence model did not show significant correlations with any of the standardised residuals of the RS-VI GAMMs (Figure 5b).

Among all the candidate GLMMs, the most parsimonious model with the lowest AICc value and the highest Akaike weight was the zero-inflated negative binomial model including GVMI for both habitats (Table 2). Both GVMI predictors (for the urban green areas and the CNP) were retained in the best model and were statistically significant (Table S3). The GVMI in the urban green areas was positively associated ($\beta \approx 24.1$, $p < 0.01$) with urban wild boar presence, whereas the GVMI in the CNP was negatively associated ($\beta \approx -26.2$, $p < 0.05$). The seasonal effects remained important, with a significant linear month term and a marginal quadratic effect, indicating non-linear seasonal variation in wild boar urban presence. The zero-inflation component was significant ($p < 0.00$), supporting the inclusion of a zero-inflated structure. The model achieved a high marginal R^2 (~0.71) and conditional R^2 (~0.93), indicating strong explanatory power after accounting for interannual variability.

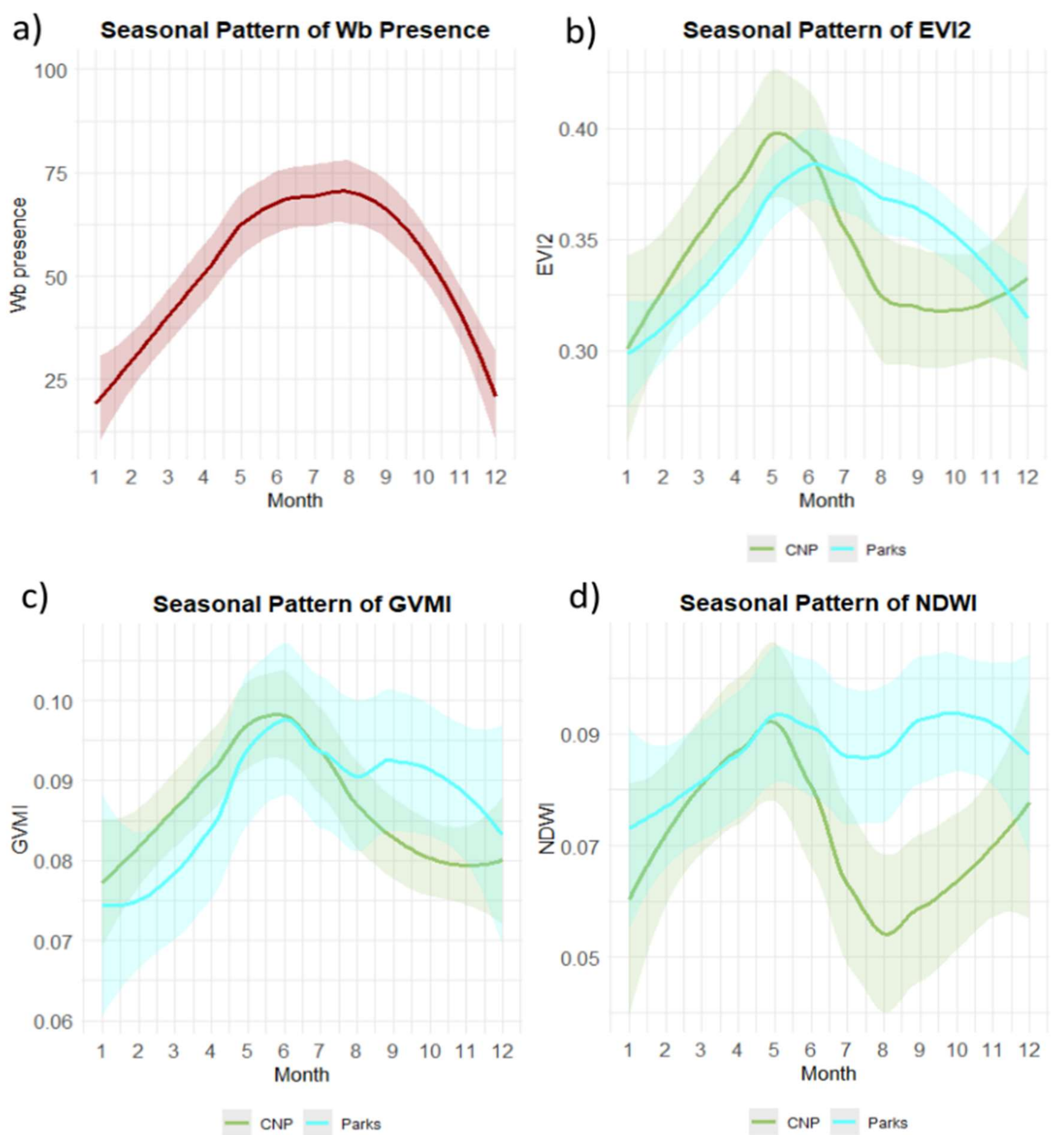

Figure 4. Seasonal trends from Generalised Additive Mixed Models (GAMMs) for (a) wild boar urban presence and (b–d) vegetation indices (EVI2, GVMI, NDWI). Blue lines represent urban green areas and green lines represent CNP. LOESS smoothing was applied to illustrate seasonal variation.

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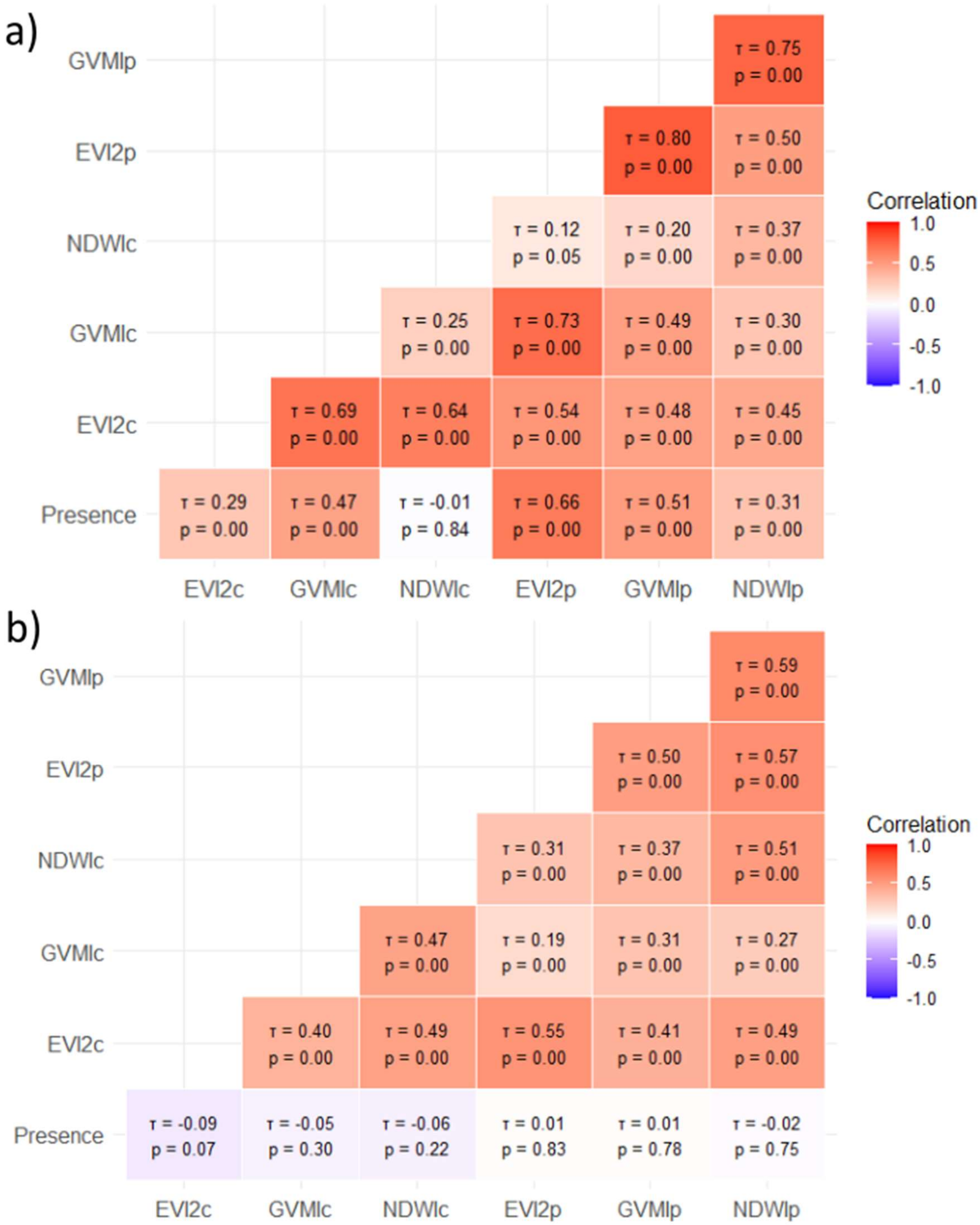

Figure 5. Kendall correlation matrices between (a) predicted values and (b) standardised residuals from the GAMMs. Subscript "p" indicates RS-VI from urban green areas (EVI2p, GVMIp and NDWIp), whereas subscript "c" indicates RS-VI from CNP (EVI2c, GVMIc and NDWIc). Colour intensity reflects correlation strength based on Kendall's tau coefficient (τ): dark red indicates strong positive correlations, and dark blue, strong negative correlations. Statistical significance is based on *p*-values.

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Table 2. Model selection and performance of candidate Generalised Linear Mixed Models (GLMMs) explaining wild boar urban incidences.

Model	Formula	AICc	dAICc	R^2m	R^2c	Weight
GVMIcp_ZI	**Month + I(Month^2) + I(Month^3) + GVMIc + GVMIp + (1 ∣ Year)**	**1502.00**	**0.00**	**0.71**	**0.93**	**0.91**
noGVMI_ZI	Month + I(Month^2) + I(Month^3) + EVI2c + EVI2p + NDWIc + NDWIp + (1 ∣ Year)	1506.99	5.00	0.71	0.93	0.08
GVMIcp	Month + I(Month^2) + I(Month^3) + GVMIc + GVMIp + (1 ∣ Year)	1513.07	11.08	0.48	0.62	0.00
Delta	Month + I(Month^2) + I(Month^3) + d_EVI + d_NDWI + d_GVMI + (1 ∣ Year)	1513.84	11.85	0.48	0.62	0.00
NDWIc	Month + I(Month^2) + I(Month^3) + NDWIc + (1 ∣ Year)	1515.38	13.38	0.47	0.61	0.00
GVMIp	Month + I(Month^2) + I(Month^3) + GVMIp + (1 ∣ Year)	1515.55	13.55	0.47	0.61	0.00
Month	Month + I(Month^2) + I(Month^3) + (1 ∣ Year)	1516.21	14.21	0.46	0.60	0.00
PCA	Month + I(Month^2) + I(Month^3) + CNP_PC1 + PAR_PC1 + (1 ∣ Year)	1516.46	14.47	0.47	0.61	0.00
NDWIcp	Month + I(Month^2) + I(Month^3) + NDWIc + NDWIp + (1 ∣ Year)	1516.56	14.57	0.47	0.61	0.00
NDWIp	Month + I(Month^2) + I(Month^3) + NDWIp + (1 ∣ Year)	1516.83	14.84	0.46	0.60	0.00
Urban	Month + I(Month^2) + I(Month^3) + EVI2p + GVMIp + NDWIp + (1 ∣ Year)	1517.04	15.04	0.47	0.61	0.00
EVIp	Month + I(Month^2) + I(Month^3) + EVI2p + (1 ∣ Year)	1517.20	15.21	0.46	0.60	0.00
EVIc	Month + I(Month^2) + I(Month^3) + EVI2c + (1 ∣ Year)	1517.36	15.36	0.46	0.60	0.00
GVMIc	Month + I(Month^2) + I(Month^3) + GVMIc + (1 ∣ Year)	1518.38	16.38	0.46	0.60	0.00
EVIcp	Month + I(Month^2) + I(Month^3) + EVI2c + EVI2p + (1 ∣ Year)	1519.41	17.41	0.46	0.60	0.00
Full	Month + I(Month^2) + I(Month^3) + EVI2c + EVI2p + NDWIc + NDWIp + GVMIc + GVMIp + (1 ∣ Year)	1520.12	18.12	0.48	0.62	0.00
Null	1 + (1 ∣ Year)	1609.12	107.12	0.00	0.07	0.00

Models are ordered from lowest to highest AICc. All models were fitted using a negative binomial error distribution; zero-inflated models included a constant zero-inflation term (~1). Fixed effects describe seasonal patterns (Month, $Month^2$, $Month^3$) and remotely sensed vegetation indices (EVI2, NDWI, GVMI) for urban green areas (p) and CNP (c). Year was included as a random intercept in all models. AICc = Akaike Information Criterion corrected for small sample size; ΔAICc = difference in AICc relative to the best-supported model; R^2m = marginal Nakagawa R^2; R^2c = conditional Nakagawa R^2; Weight = Akaike weight.

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3.3. Relationship Between Wild Boar Presence and Urban Green Area Features

The results from the PLSR model are shown in Table 3. Only the first latent component (t1) was significant (Q2 > 0.0975), explaining 22% of the variance in the log-transformed number of presences. The most influential predictors for constructing t1, based on their relative importance (derived from squared raw weights), were the log-transformed number of patches (logpatch: 0.33), total edge length (logedge: 0.26), and the distance to the closest stream (logdist_str: 0.24). These were also the variables with the highest loads (logpatch: 0.58; logedge: 0.51; logdist_str: -0.49) and strongest correlations (logpatch: 0.88; logedge: 0.78; logdist_str: -0.61), evidencing their strong association with t1. On the other hand, the effect of the VIs and the remaining landscape metrics was negligible (Table 3). We also detected that the green areas located closer to streams had both higher mean presence and greater interannual variability in wild boar presence, whereas the green areas farther from these corridors consistently recorded fewer incursions (Figure S2).

Table 3. Predictor weights of the Partial Least Squares Regression (PLSR) model explaining the number of wild boar presences within a 300-m buffer of the urban green areas located within a 1-km buffer of Collserola Natural Park (CNP).

PLSR component	**Predictor variables**	**Variable meaning**	**Loads**	**Weights**	**Explained variance**
	logpatch	Total N of patches within the buffer	0.58	0.33	0.77
	logedge	Total edge length within the buffer	0.51	0.26	0.77
	logdist_str	Distance to the closest stream	-0.49	0.24	0.61
	loginters	Total N of intersections within the buffer	0.26	0.07	0.37
	logstreet	Total street length inside the buffer	0.23	0.05	0.16
X	logarea_buf	Total park + 300 m buffer area	0.14	0.02	0.18
	logmpci	Mean patch cohesion index within the buffer	-0.12	0.02	0.16
	logmld	Mean landscape division	0.09	0.01	0.07
	logEVI	Mean EVI2 value for peak period	-0.04	0.00	0.07
	Year		0.02	0.00	0.01
	logNDWI	Mean NDWI value for peak period	-0.01	0.00	0.02
	logGVMI	Mean GVMI value for peak period	-0.01	0.00	0.01
Y	logIncid	N of presences during peak period	-	-	-

The distance to streams and RS vegetation indices (EVI2, NDWI and GVMI) were calculated for the urban green areas, while all other variables were calculated for the park and its buffer. Loads represent the contribution of each original predictor to the X latent components, with positive or negative signs indicating the direction of the relationship. Predictor weights correspond to the squared raw weights, reflecting the relative contribution of each environmental predictor to the PLSR's X-axis. Explained variance reflects the proportion of variance in the predictors (X) accounted for by each PLS component. The variables that contributed the most to constructing the first latent component are shown in bold.

4. Discussion

In this study, we explored whether remotely sensed vegetation indices (RS-VI) and urban landscape characteristics could explain temporal and spatial patterns of wild boar presence in an urban Mediterranean setting. The predictive value of RS-VI depended on the temporal scale analysed, being more informative at the annual scale.

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4.1. Temporal Trends

The breakpoints in the VI temporal evolution at interannual scale could be expected, because most terrestrial biomes follow a non-linear trend related to greening and browning cycles [99]. The negative relationship between wild boar presence and GVMI in the CNP indicates more frequent urban incursions during the dry periods. Drought reduces soil moisture and forage availability, constraining rooting and promoting the use of anthropogenic food and water sources [24,43,44,100]. While vegetation dynamics provided a broad environmental seasonal context, they did not account for interannual and spatial variation in wild boar urban presence.

At the annual scale, the higher VI values in urban green areas than in the CNP during the scarcity period (Figure 4) correspond to a sharp decline under summer Mediterranean drought in the CNP [101], balanced by irrigation in the urban green areas [102]. The higher presence of wild boars in urban areas coinciding with the higher difference in VI between the CNP and the urban green areas is probably explained by wild boar selecting moist soils for rooting during dry periods [24,43]. The association between urban presence and EVI2 in urban green areas further indicates that wild boars tracked vegetation productivity and greenness, likely reflecting increased availability of forage or cover [24].

Although GVMI emerged as the most informative RS-VI in the GLMMs, the seasonal GAMM fitted to GVMI in the CNP explained only a limited proportion of its temporal variability. This suggests that vegetation moisture does not follow a smooth seasonal pattern in the CNP but is influenced by short-term fluctuations such as rainfall pulses or soil heterogeneity [43,101]. Accordingly, the negative GVMIc effect detected in the GLMM should be interpreted as part of broader seasonal conditions rather than a direct predictor of urban presence. The absence of correlations between model residuals further indicates that wild boar presence and vegetation indices vary similarly across seasons, but do not respond in parallel to short-term changes. Together, these results suggest that vegetation dynamics, as assessed by EVI2 and GVMI, represent a significant, but partial, driver of urban wild boar presence.

The seasonal increase in wild boar presence in urban areas when vegetation and moisture conditions in CNP were still improving suggests that incursions are not driven solely by drought, but also by life-history processes [46,103,104]. In Mediterranean populations, farrowing occurs from late winter to spring, with lactation extending into early summer [105–107]. During this period, energetic demands of wild boar females increase markedly due to milk production and the rapid growth of piglets [108,109]. These energetic constraints may promote exploratory movements and the exploitation of resource-rich anthropogenic environments, especially when natural forage is spatially limited or patchily distributed [37,44,46]. Under these conditions, irrigated urban green areas may temporarily provide higher profitable refuge and feeding opportunities than natural environments, even though the dry season is not completely established [24,44]. The subsequent decline in presence from late summer to autumn may reflect the end of lactation and improved natural foraging conditions associated with autumn rainfall and mast production [101], which likely draw individuals back toward natural habitats [39].

4.2. Urban Green Area Features

While seasonal dynamics explain when wild boars are more likely to enter the urban matrix, these processes do not determine how space is used within the city. While proximity to watercourses and landscape fragmentation have already been identified as key spatial predictors of wild boar occurrence in urban settings [24], we refined these findings in two ways. First, by modelling aggregated presence within urban green areas, we captured variation in the intensity of habitat use rather than occurrence probability alone. Second, by explicitly quantifying landscape configuration and integrating RS-VI, we disentangled the relative roles of habitat structure and resource dynamics. Similarly to previous studies, our results consistently indicate that natural corridors and landscape configuration remain the primary drivers of wild boar presence at the local scale. However, in contrast to the strong dominance of connectivity reported by Castillo-Contreras et al. [24], we

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detected a similar contribution of connectivity and fragmentation in explaining variation in wild boar presence across parks. Vegetation productivity and moisture within parks, however, had little influence on spatial patterns. This suggests that wild boar use of urban habitat is driven by the interaction between movement pathways and the spatial arrangement of resources and refuge, rather than by primary production of urban vegetation patches [24,33,46].

The higher wild boar presence in the green areas closer to streams matches their role as natural corridors linking CNP with the urban matrix [24]. This spatial pattern indicates that connectivity regulates the entry of individuals into the urban matrix, while neighbouring green spaces facilitate stepwise movement across the city [37,110]. The higher interannual variation in wild boar presence observed in highly connected urban green areas likely reflected fluctuations in the number of individuals entering the city, driven by changes in population size and dispersal [46]. Once within the city, local habitat structure determines whether these individuals remain and use these areas [42]. Management interventions such as fencing or restricting anthropogenic food can reduce accessibility and habitat attractiveness [52], while human disturbance and lethal control create a “landscape of fear” that modifies habitat selection [49,51,111–113]. Together, these processes can limit site fidelity and promote avoidance or displacement responses [37,45,114].

The higher wild boar presence in the urban green areas embedded in more heterogeneous landscapes (Figure S1) suggests that fragmentation increases the spatial proximity and connectivity of resources and refuge, key factors shaping movement in urban environments [24,33,115]. Such configurations can promote efficient foraging while maintaining access to cover, reducing movement costs and favouring repeated use [37,42]. This interpretation is consistent with previous findings showing increased displacement where resources are dispersed [45], but reduced home ranges where they are predictable and concentrated [27]. In contrast, wild boars tend to avoid less fragmented areas dominated by homogeneous urban land uses and densely built-up areas (Figure S1) [17]. The absence of fragmentation effects in studies using alternative metrics, such as “effective mesh size” [27,116], further suggests that its influence depends on how resources and risk are arranged within the urban matrix [24,33,46].

Several limitations should be considered when interpreting these patterns. The absence of explicit data on anthropogenic food sources likely underestimated fine-scale drivers of urban green area use [24,33,44]. In addition, although emergency calls can be used for the assessment of human-wildlife conflict [117], reliance on citizen-reported data may bias observations towards areas with higher human presence or conflict perception, potentially inflating apparent use in highly frequented parks [28,29,33]. Behavioural adaptations such as increased nocturnality further reduce detectability, reinforcing this bias [44,118,119]. Despite reported presences may represent only a subset of actual habitat use, the consistent effects of connectivity and landscape structure across parks suggest that the main patterns identified are robust to these sources of uncertainty.

5. Conclusions

Wild boar presence in urban settings likely emerges from the interaction of processes operating at different scales: seasonal resource dynamics influence when incursions occur, and landscape connectivity and configuration constrain where animals access and use space within the urban landscape. RS-VI captured Mediterranean vegetation dynamic differences between urban versus natural habitats, which influence the timing of urban presence. However, RS-VI only partially represent these processes, limiting their predictive power. From a management perspective, our results highlight the importance of targeting highly connected areas that facilitate entry into the city. Because irrigated urban green spaces act as seasonal attractants, reducing irrigation intensity or promoting xerophytic vegetation in parks located near corridors could lower their attractiveness during peak incursion periods [52]. Our findings also highlight the need to further develop remote sensing approaches in urban systems, particularly through the integration of high-resolution movement data to better capture fine-scale habitat use.

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Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org, **Figure S1**: Land cover composition within a 300 m buffer surrounding each selected urban green area; **Figure S2**: Conditional boxplots showing variation in wild boar urban presence across individual urban green areas located within 1 km of the CNP boundary; **Table S1**: Results from the Linear Regression of the long-term trends (BFAST trend component) of wild boar urban presence and vegetation indices of both urban green areas and CNP, with Newey-West standard errors; **Table S2**: Summary of the Generalised Additive Mixed Models (GAMMs) fitted for seasonal patterns of vegetation indices and urban wild boar presence, including model specifications and pseudo-R^2 as an indicator of goodness of fit; **Table S3**: Summary of the best Generalised Linear Mixed Model (GLMM); **Table S4**: Structural, compositional, and management characteristics of urban green areas included in this study.

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Abbreviations

The following abbreviations are used in this manuscript:

CNP	Collserola Natural Park
EVI2	Enhanced Vegetation Index 2
GVMI	Global Vegetation Moisture Index
NDWI	Normalised Difference Water Index
RS-VI	Remotely Sensed Vegetation Indices
TS	Time Series

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