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EVI and NDVI as proxies for multifaceted avian diversity in urban areas

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Abstract

Most ecological studies use remote sensing to analyze broad-scale biodiversity patterns, focusing mainly on taxonomic diversity in natural landscapes. One of the most important effects of high levels of urbanization is species loss (i.e., biotic homogenization). Therefore, cost-effective and more efficient methods to monitor biological communities' distribution are essential. This study explores whether the Enhanced Vegetation Index (EVI) and the Normalized Difference

Vegetation Index (NDVI) can predict multifaceted avian diversity, urban tolerance, and specialization in urban landscapes. We sampled bird communities among 15 European cities and extracted Landsat 30-meter resolution EVI and NDVI values of the pixels within a 50-m buffer of bird sample points using Google Earth Engine (32-day Landsat 8 Collection Tier 1). Mixed models were used to find the best associations of EVI and NDVI, predicting multiple avian diversity facets: Taxonomic diversity, functional diversity, phylogenetic diversity, specialization levels, and urban tolerance. A total of 113 bird species across 15 cities from 10 different European countries were detected. EVI mean was the best predictor for foraging substrate specialization. NDVI mean was the best predictor for most avian diversity facets: taxonomic diversity, functional richness and evenness, phylogenetic diversity, phylogenetic species variability, community evolutionary distinctiveness, urban tolerance, diet foraging behavior, and habitat richness specialists. Finally, EVI and NDVI standard deviation were not the best predictors for any avian diversity facets studied. Our findings expand previous knowledge about EVI and NDVI as surrogates of avian diversity at a continental scale. Considering the European Commission's proposal for a Nature Restoration Law calling for expanding green urban space areas by 2050, we propose NDVI as a proxy of multiple facets of avian diversity to efficiently monitor bird community responses to land use changes in the cities.

KEYWORDS
avian specialization, biodiversity, bird, enhanced vegetation index, normalized difference vegetation index, remote sensing, urban tolerance, VIIRS night-time lights

INTRODUCTION

Worldwide urbanization is rising, and approximately 60% of the world's population is expected to live in cities by 2030 (United Nations, 2017). Urbanization is a significant threat to biodiversity, modifying biotic and abiotic ecosystem characteristics (Grimm et al., 2008) through fragmentation or replacing natural habitats (Sklenicka, 2016; Williams et al., 2009). At the same time, urbanization generates new habitats suitable for a few species capable of adapting to novel urban environments (McKinney, 2002, 2006). Unsurprisingly then, taxonomic (Marzluff, 2001), functional (Devictor et al., 2007), and phylogenetic (Ibáñez-Álamo et al., 2016; Morelli et al., 2016; Sol et al., 2014) diversity decreased in urban environments compared with their rural or natural counterparts. More specifically, along an urbanization gradient, species richness generally decreases (e.g., Melles et al., 2003). However, it may peak at intermediate levels of urbanization (Batáry et al., 2018; Blair, 1996; Jokimäki & Suhonen, 1993; Leveau & Leveau, 2005). Although even some urban areas show increased taxonomic diversity (Blair, 1996), it usually consists of the replacement of local native species, also called "urban avoiders" (Blair, 1996), by increasingly spreading non-natives (Devictor et al., 2008; McKinney, 2002, 2006), and the predominance of generalist species, generally more tolerant to high urbanized areas (Devictor et al., 2008). Consequently, urbanization leads to biotic homogenization (McKinney, 2002, 2006).

Bird assemblages are affected by local resources and how they use suitable habitats (Croci et al., 2008). Therefore, local environmental factors better explain bird species richness (BSR) and composition than regional and landscape factors, suggesting that site-specific management strategies can improve avian diversity in cities (Croci et al., 2008; Evans et al., 2009). Managing green areas within cities could increase avian diversity (Croci et al., 2008). For example, there are a greater number of native bird species, less urban-tolerant species, in those areas composed predominantly of native vegetation (Blair, 1996). Conversely, few species, principally non-native ones, more urban tolerant, dominate areas at higher built-up land cover levels (Blair, 1996). At intermediate levels of urbanization, avian assemblages can be composed of native and non-native species. Therefore, an important first step in urban development planning is understanding factors influencing avian diversity (Stagoll et al., 2012). Moreover, to successfully carry out land management plans, it is

necessary to quantify the relationship between avian diversity and habitat features (Mcfarland et al., 2012).

The decline of biodiversity affects species richness and functional richness, increasing taxonomic and functional biotic homogenization (Ibarra et al., 2015). Indeed, the biotic homogenization process substitutes specialists with generalist species, both spatially and temporally (McKinney, 2006; Sol et al., 2014). Specialist species occupy narrower niches. For example, they exploit particular habitats and limited portions of available resources (Clavel et al., 2011). In contrast, generalist species use a wider range of habitats and greater diversity of available resources (Ducatez et al., 2015; Irschick et al., 2005). Thus, species responses to habitat loss would depend on the degree of specialization (Webb, 2010), favoring those with wider niche breadths to survive in more degraded habitats and increasing the risk of extinction of those with a high degree of specialization (Davies et al., 2004; McKinney & Lockwood, 1999). Recently, Callaghan, Benedetti, et al. (2020) highlighted a negative association between avian species specialization and their urban tolerance. Thus, considering that biodiversity involves many facets (Carmona et al., 2012), conservation ecologists claimed to apply a more integrative approach to estimate biodiversity by disentangling different facets of species assemblages (Carmona et al., 2012; Zupan et al., 2014), mainly in urbanized landscapes (Devictor et al., 2007; Morelli, Benedetti, Ibáñez-Álamo, et al., 2021). The different responses of taxonomic diversity, functional diversity, and phylogenetic diversity to environmental gradients lead to different patterns in their spatial distribution (Bässler et al., 2016; Devictor et al., 2010; Tucker & Cadotte, 2013). For these reasons, conserving different facets of biodiversity, such as taxonomic, functional, and phylogenetic diversity, including also, specialization and urban tolerance assessments, are relevant for a comprehensive understanding of biodiversity drivers (Dehling et al., 2014; Grass et al., 2015), and applying more effective conservation strategies (Brooks et al., 2006; Lee & Jetz, 2008).

Monitoring species distribution using traditional field surveys is challenging and logistically expensive. Thus, standardized evaluations of the environmental conditions with an adequate spatial resolution (Seto et al., 2004). In addition, species distribution surveys in large areas are challenging for ecologists and fieldworkers since they require high sampling effort (Palmer, 1995). Therefore, developing new methods of assessing species diversity using environmental variables could easily provide more insights into the anthropogenic and natural disturbances affecting biodiversity (Rocchini et al., 2010, 2016). In recent years, the constant availability of multispectral remote-sensed imagery has led to the widespread use of imagery with a growing resolution and quality (Huang et al., 2021).

The quality of images is adequate for the evaluation of various vegetation aspects such as canopy phenology, seasonal changes in the leaf area, and gross primary production (Liu et al., 2011; Muraoka et al., 2013; Turner et al., 2005), as well as the floristic composition, vegetation height, and structure, vitality and age (Lausch et al., 2016). So, the use of remote sensing tools largely improved the ability to monitor biodiversity and ecosystem functioning at large scales providing useful information on the species distribution, reproductive fitness (Regos et al., 2021), and population abundance (Arenas-Castro et al., 2019) when facing spatial and temporal changes (Lausch et al., 2016). Among many vegetation indices, Normalized Difference Vegetation Index (NDVI hereafter) and Landsat-derived Enhanced Vegetation Index (EVI hereafter) are the most commonly used to obtain vegetation information (Huete, Didan, Miura, & Rodriguez, 2002; Mildrexler et al., 2009; Peckham et al., 2008). Many studies demonstrated the capacity of EVI and NDVI global-based vegetation indices to track vegetation characteristics and changes at different spatial scales (Dobson et al., 2015; Gonsamo, 2010; Nieto et al., 2015; Turner et al., 2001) and across long time series (Dutrieux et al., 2015; Pettorelli et al., 2005; Semeraro et al., 2019). Both vegetation indices share many spectral-domain attributes. For this reason, they are complementary in identifying vegetation changes and canopy biophysical parameters (Huete & Justice, 1999; Semeraro et al., 2019). EVI and NDVI values are calculated based on the visible red and near-infrared spectral reflectance (top-of-atmosphere—TOA or surface reflectance). Specifically, the NDVI value calculation uses the visible red and near-infrared spectral reflectance from all land surface types, including vegetated surfaces (Huete & Justice, 1999). The index varies between −1 and 1, indicating different vegetation levels from vegetation-free cover up to high vegetation biomass (Pettorelli, 2013; Tucker, 1979). Several studies showed that NDVI value is positively related to the biomass of vegetation (Matsushita et al., 2007), vegetation structure (Caruso et al., 2017), as well as, the amount of leaf chlorophyll (Lausch et al., 2016), and leaf area coverage (Wang et al., 2005). NDVI is one of the most used global-based vegetation index. NDVI is characterized by removing the noise produced by ever-changing sun angles, topography, clouds or shadow, and atmospheric conditions (Huete, 1988; Zhengxing et al., 2003). EVI is an "optimized" vegetation index from NDVI developed to reduce some atmospheric conditions and canopy background noise and is more receptive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy architecture (Huete, Didan, Miura, & Rodriguez, 2002; Huete & Justice, 1999). Similarly to NDVI, EVI values calculation uses spectral reflectance, either TOA or surface, in the visible red and near-infrared spectra. However, unlike NDVI, EVI uses the blue band for the atmospheric

correction and constant soil factor (Liu & Huete, 2019). For these reasons, EVI is demonstrated to be more reliable in low and high vegetation cover and adjusts to soil influence, canopy background signals, and atmospheric effects on vegetation index values (Gao et al., 2000; Liu & Huete, 2019). Thus, many researchers have preferred the EVI index in their studies (e.g., Boles et al., 2004; Nagler et al., 2005; Soudani et al., 2006; Waring et al., 2006). However, both vegetation indices have different constraints and do not provide direct measures of the vegetation attributes but act as proxies (Son et al., 2014). Other studies focusing on NDVI and EVI comparisons showed contrasting results in their capacities to obtain information on the vegetation attributes (Son et al., 2014). One commonly recognized obstacle with NDVI is its lower sensitivity at high vegetation biomass (Huete, 1988; Zhengxing et al., 2003) and the effects of atmospheric and background soil reflectance (Huang et al., 2021; Huete & Justice, 1999). Conversely, EVI surpasses these constraints, increasing the detection accuracy in regions at high biomass (Semeraro et al., 2019). However, EVI is more affected by the topography, becoming a challenge in hilly terrains (Matsushita et al., 2007).

NDVI and EVI are the most common vegetation indices used in ornithological studies (Bae et al., 2018; Bonthoux et al., 2018; Cooper et al., 2020; Hobi et al., 2017; Leveau et al., 2020; Pettorelli et al., 2011; Wu et al., 2013). Both vegetation indices have been documented as excellent proxies for primary productivity (e.g., Box et al., 1989; Cramer et al., 1999) and the spatiotemporal distribution of vegetation (Pettorelli et al., 2005). Because primary productivity influences the diversity and distribution of species (Wright, 1983), EVI and NDVI were identified as good predictors of avian diversity in several studies. Specifically, several authors found a positive relationship between EVI and NDVI with avian species richness in both natural (Bae et al., 2018; Cooper et al., 2020; Hobi et al., 2017; Hurlbert & Haskell, 2003; Mcfarland et al., 2012; St-Louis et al., 2009) and urban areas (Bino et al., 2008; Callaghan, Major, et al., 2020; Leveau, 2019; Leveau et al., 2018, 2020). Some studies on urban areas found contrasting associations between NDVI and avian diversity (Bae et al., 2018; Leveau et al., 2020). For example, Bae et al., 2018, found a positive association between NDVI and species richness, displaying a concave curve. While for functional and phylogenetic diversity, the association was negative and characterized by a convex curve. These results (Hawkins, Porter, & Diniz-Filho, 2003) demonstrated that the productivity–diversity correlation has not had a universal form (Hawkins, Porter, & Diniz-Filho, 2003). In addition, most of the urban studies were mainly conducted in single or few urbanized localities (e.g., cities, towns) (Argentina: Leveau et al., 2018, 2020; Leveau, 2019; Brazil: Souza et al., 2019; Jerusalem: Bino et al., 2008; Taiwan: Lin et al., 2008), potentially

limiting the transferability of such results to different cities at a national or continental scale. Therefore, more studies on a larger geographical scale (e.g., Callaghan, Major, et al., 2020) are needed to discover EVI or NDVI potential in tracking multifaceted avian diversity changes in urban areas.

The spectral heterogeneity hypothesis argued for a positive correlation between habitat heterogeneity and species diversity (Palmer et al., 2002; Rocchini et al., 2010). It was demonstrated in several taxa, for example, vascular plants (Foody & Cutler, 2006; Gould, 2000; Levin et al., 2007), lichens (Waser et al., 2004), ants (Lassau et al., 2005), birds (Bino et al., 2008; St-Louis et al., 2009), and mammals (Oindo & Skidmore, 2002). Accordingly, many studies demonstrated a positive association between the spatial heterogeneity of vegetation (assessed by EVI and NDVI spatial standard deviation) with species richness (Bacaro et al., 2011; Bergen et al., 2007; Coops et al., 2009; Culbert et al., 2012; Price et al., 2013) by monitoring and quantifying significant vegetation characteristics (e.g., change of broadleaf vegetation LAI or the phenological heterogeneity of vegetation layers) (Davi et al., 2006; Qiao et al., 2019). However, many mechanisms can change these associations when focusing on different facets of avian diversity or habitats (e.g., urban areas). Consequently, more studies are essential to understand better the associations between surrogates of habitat heterogeneity (as EVI or NDVI standard deviations) with each facet of avian diversity in cities.

Since each diversity component discloses different attributes of avian communities, more efficient monitoring across large regions in a short period should be essential to support urban avian diversity. Accordingly, more specific vegetation indices as proxies for each facet of avian diversity metrics can help to indicate potential vulnerabilities of avian communities facing climatic and land uses changes. Therefore, in this study, we investigated and compared the capacity of EVI and NDVI (as most common proxies of primary productivity and vegetation heterogeneity proxies) to determine the best-fitted surrogate of every single facet composing avian diversity (e.g., taxonomic, functional, and phylogenetic diversity, urban tolerance, and avian specialization) in 15 different European cities. We hypothesized that increasing primary productivity and vegetation heterogeneity should increase levels of avian taxonomic, functional, and phylogenetic diversity according to the (1) productivity-diversity relationship (Wright, 1983) and (2) habitat-heterogeneity hypothesis (MacArthur & MacArthur, 1961). Regarding avian specialization, we hypothesized that increasing the cover of vegetation biomass (primary productivity) and vegetation heterogeneity could be associated with a higher number of avian species that are less urban tolerant and more specialized.

METHODS

Bird data collection

Data on bird presence and abundance were collected during the breeding season along a continent-wide latitudinal gradient in 15 European cities (Figure 1; Appendix S1: Table S1). The bird survey period was performed between early April and late July 2018. The field surveys started by considering the differences in the study areas' seasons to mitigate potential issues associated with avian detectability (e.g., early April in southern Spain and the end or late May
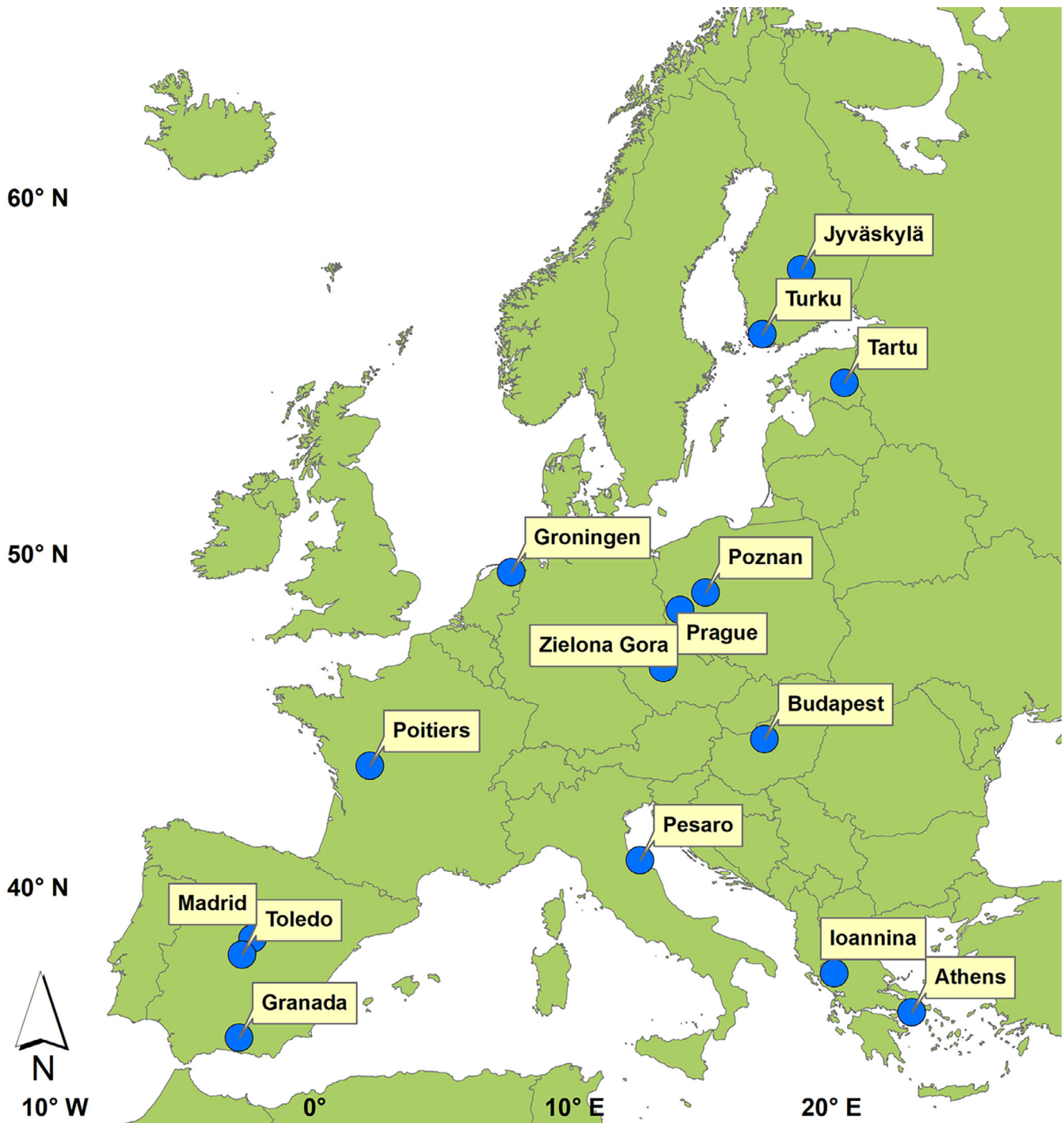

FIGURE 1 Location of the 15 different European cities used in this study: Prague (Czech Republic); Tartu (Estonia); Jyväskylä (Finland); Turku (Finland); Poitiers (France); Athens and Ioannina (Greece); Budapest (Hungary); Pesaro (Italy); Groningen (Netherlands); Poznań and Zielona Góra (Poland); Granada, Madrid, and Toledo (Spain). See detailed results in Benedetti & Morelli (2022).

in northern Finland) (Kéry et al., 2005). Local expert ornithologists performed avian surveys to reduce potential bias due to different skills.

One observer (the same local expert ornithologists for each city) surveyed the avian composition early morning (from 6:00 to 10:00) only during good weather conditions (no rain and heavy winds). Approximately one hundred 5-min single-visit point counts (hereafter referred to as "sample site") per city distributed evenly along an urbanization gradient. All birds, visually or acoustically identified to the species level, were recorded. More specifically, the sample sites consisted of a fixed area with a 50-m radius. Sample sites were located in urbanized areas and were recorded with a GPS in decimal degrees (DD). According to GPS technical specifications from the manufacturer (Garmin), the horizontal GPS accuracy was within ±5–10 m, and the vertical accuracy was within ±15–38 m under normal conditions. All sample sites were distanced by at least 200 m, a standardized method in ecology (Bibby et al., 1992). This survey was designed to obtain data about the distribution and abundance of diurnal songbirds (Bibby et al., 1992). Additionally, we excluded the raptors, nocturnal species, and aerial feeders (i.e., swallows and swifts) from the analysis because the sample site method is inappropriate for estimating their abundance.

EVI and NDVI estimation

We calculated the EVI and NDVI. EVI is an extension of NDVI, which approximates vegetation and canopy structure with improved sensitivity in high biomass regions (Huete, Didan, Miura, Rodriguez, Gao, & Ferreira, 2002; Jiang et al., 2008). The EVI and NDVI values fluctuate from −1 to 1, where positive values correspond to the cover of vegetated areas, while negative ones are for water bodies, snow, clouds, and non-vegetated surfaces (Holben, 1986; Vermote, 2013). To calculate EVI and NDVI, we used Google Earth Engine (Gorelick et al., 2017) to conduct our analysis, using the USGS Landsat 8 Collection 1 Tier 1 imagery (see details in the Google Earth Engine catalog here: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_RT_TOA). Landsat 8 provides 30-m resolution data, with a temporal resolution of one image in ~16 days. Therefore, 2 or 3 images per month were obtained for each sample site (i.e., bird survey). To overcome the potentially limited number of images for a given sample site, we used scenes from 2017, 2018, and 2019 (expanding 1 year to either side of the bird surveys), averaging any potential interannual variation in vegetation changes. This expanded time scale was also necessary as we filtered for cloud cover on a per-pixel basis, meaning that if only 1 year was used, some pixels could potentially have no imagery for a given month. We filtered the data using the BQA bit 4, filtering out pixels associated with cloud cover—this is a quality assessment variable provided by the USGS, associated with the Landsat 8 imagery. We also removed pixels with low cloud shadow confidence. After this filtering, we collapsed the remaining scenes for each pixel by taking the median EVI and NDVI at each pixel, minimizing the potential of outliers in the imagery. For each sampling site (i.e., bird survey), we calculated the mean and standard deviation value of the pixels within a 50-m buffer (corresponding to the bird survey 50-m sample site) separately for April, May, June, and July (corresponding to the bird survey period). We tested this robustness by calculating the mean and standard deviation of the pixels with a 150-m buffer but found that the values were strongly correlated with the 50-m buffer values (Appendix S1: Figure S1).

Finally, using monthly EVI and NDVI values (considering April to July period to match the bird survey period), we calculated the average (EVI mean and NDVI mean) and standard deviation (EVI sd and NDVI sd). As detailed above, these mean values are the median pixel values within each buffer. EVI and NDVI mean values were strongly correlated with monthly values of EVI (Appendix S1: Figure S2) and NDVI (Appendix S1: Figure S3).

Facets of avian diversity assessment

A bird community is the total list of bird species present in each sample site. We assessed each bird community's different facets of avian diversity: taxonomic, functional, and phylogenetic diversity (Appendix S1: Table S2). The first facet corresponds to taxonomic diversity regarding BSR (Magurran, 2004). The second facet includes three metrics related to functional diversity: functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv) (Villéger et al., 2008). All functional diversity metrics were calculated through the "FD" package in R (Laliberté et al., 2015; Laliberté & Legendre, 2010) by using the avian niche database comprising 73 different traits (Pearman et al., 2014) (Appendix S1: Table S3). The third facet involves three metrics related to phylogenetic diversity: phylogenetic diversity (PD) (Faith, 1992), phylogenetic species variability (PSV) (Helmus et al., 2007), and community evolutionary distinctiveness (CED). We built the phylogenetic tree with the relationships among the species in each sample site, using genetic data from a total of 6663 taxa (Jetz et al., 2012), provided in BirdTree (https://birdtree.org/subsets/). PD and PSV metrics were estimated using the "picante"

package for R (Kembel et al., 2010). Finally, CED was assessed to determine the mean ED score for each bird community considering all species present (see details in Benedetti & Morelli, 2022) in a community (sample site) (Morelli et al., 2016; Tucker et al., 2016). We obtained the species ED score (Isaac et al., 2007; Redding et al., 2008) from the following online database: from https://www.edgeofexistence.org/edge-lists/ (Zoological Society of London, 2008).

Then, we calculated an urban tolerance mean (UTM) for every community (i.e., sample site) as species generally show responses to urbanization along a continuum. We used species-specific urban tolerance scores from Callaghan, Benedetti, et al., 2020. This method uses eBird citizen science data and VIIRS night-time lights to provide species-specific preferences for or against urbanization (for more details, see Callaghan, Major, et al., 2020). Then, we took the mean of the species-specific urban tolerance scores (UTM) across all species at that sample site (Appendix S1: Table S2).

Finally, we assessed avian specialization richness for each avian community (i.e., sample site). We used the avian species-specific specialization index estimated by Morelli et al., 2019 for different ecological traits: diet, foraging behavior, foraging substrate, and habitat (see details in Appendix S1: Table S3). The specialization richness in each sample site is estimated by the number of bird species with a specialization value equal to 1 (Benedetti et al., 2022; Morelli et al., 2019; Morelli, Benedetti, Hanson, & Fuller, 2021), see more details in Benedetti & Morelli, 2022. Thus, avian specialization richness types estimated were diet specialization richness (Diet), foraging behavior specialization richness (Forb), foraging substrate specialization richness (Forsub), and habitat specialization richness (Hab).

Statistical analyses

We explored EVI and NDVI values (mean and sd) associations with taxonomic, functional, and phylogenetic diversity, specialization types, and UTM. These associations were examined using Generalized Linear Mixed Models (GLMMs). Models were fitted by maximum likelihood using the package "nlme" and "lme4" in R (Bates et al., 2015; Pinheiro et al., 2019). Each diversity facet (Taxonomic diversity: Species richness; Functional diversity: Functional diversity, functional evenness, and functional divergence; Phylogenetic diversity: Phylogenetic diversity, phylogenetic species variability, and community evolutionary distinctiveness; UTM; and four specialization types: Diet, foraging behavior, foraging substrate, and habitat) (see detailed description in Appendix S1: Table S2) was established as a response variable and was

modeled separately. EVI and NDVI (mean and sd) were designated as predictors individually. They were modeled separately (each predictor for each response variable) since we aimed to evaluate the single capacity of EVI and NDVI (mean and sd) as surrogates of each avian diversity facet. EVI and NDVI mean showed a high level of collinearity (Appendix S1: Figure S3). The city was included as a random factor in the models. Geographical coordinates were not included as predictors, considering the redundancy of using cities as a random factor.

The response variables based on count data (e.g., BSR and all specialization richness types) were tested for overdispersion by employing the "aods3" package in R (Lesnoff & Lancelot, 2018). Therefore, a ratio between the sum of squared Pearson residuals and the residual degrees of freedom lower than one (<1) indicates no overdispersion issues (Agresti, 1990). Then, BSR and each type of specialization richness were modeled following a Poisson distribution. The normality assumptions of response variables based on continuous data (e.g., UTM, phylogenetic and functional diversity facets) were tested employing the "MASS" package (Venables & Ripley, 2002) in R. To normalize data not following a normal distribution, we log-transformed using the "rcompanion" package in R (Salvatore Mangiafico, 2021). Finally, the variables were modeled following a Gaussian distribution (Box & Cox, 1964).

The Akaike information criterion (AIC) was used to determine the "best" model explaining variation in the data of each significant model when exploring EVI or NDVI predictors (Burnham & Anderson, 2002). The model selection and multimodel inference were performed using the package "AICcmodavg" in R (Mazerolle, 2016). The model with the lowest AIC and greater Akaike information criterion weighted (AICWt) is considered the best model (Mazerolle, 2016). Thus, this study evaluated the best proxies' avian diversity facets among all EVI or NDVI indices explored.

Finally, the goodness of fit of each model was assessed by assessing the conditional R^2 (which considers the variance by the fixed and random effects) and marginal R^2 (which considers the variance by the fixed effects) using the function "rsquared" from the package "piecewiseSEM" (Lefcheck, 2016).

The correlation between predictors was performed using the "corrgram" function in R (Wright, 2018) to produce a matrix correlogram including the correlation value obtained by the Pearson correlation coefficient.

Confidence intervals for the significant variables selected in the best model were calculated by the Wald method using the "MASS" package in R (Venables & Ripley, 2002).

All modeling procedures, statistical tests, and data explorations were performed with R software v. 4.1.3

(R Development Core Team, 2019) and considered results statistically significant when the p-value was lower than 0.05.

RESULTS

In this study, 1382 sample sites were surveyed in 15 different European cities (Figure 1, Appendix S1: Table S1). A total of 113 avian species (see details in Benedetti & Morelli, 2022) and 31,760 individuals were recorded. The mean of total BSR across all 1382 sample sites was 7.23 species (minimum: 1, maximum: 24 species). The EVI mean values in 50-m buffers vary between 0.040 and 0.734, considering all sample sites. In contrast, the EVI sd values fluctuate between 0.006 and 0.248. NDVI mean values fluctuate between 0.048 and 0.684. At the same time, the NDVI sd values vary from 0.007 to 0.292. Considering only significant predictors, the values of conditional R^2 vary from 0.540 (for NDVI mean as a predictor of phylogenetic diversity [PD]) to 0.155 (for NDVI sd as a predictor of community evolutionary distinctiveness [CED]). The values of marginal R^2 ranged from 0.22 (for NDVI mean as a predictor of urban tolerance [UTM]) to 0.004 (for EVI sd and NDVI sd as predictors for habitat specialization richness [Hab]) (Appendix S1: Table S4).

EVI and NDVI as proxies of avian diversity

The number of species (BSR), functional richness (FRic), community evolutionary distinctiveness (CED), and phylogenetic diversity (PD) values of avian communities were positively associated with all indices investigated (e.g., EVI mean, EVI sd, NDVI mean, and NDVI sd). Conversely, phylogenetic species variability (PSV) was negatively associated (Table 1, Figure 2, Appendix S1: Figures S3–S6). In addition, functional divergence (FDiv) was not related to any EVI and NDVI indices used in this study, and functional evenness (FEve) was significantly related only to EVI and NDVI mean (Table 1, Figure 2, Appendix S1: Figures S3–S6). NDVI mean was the best proxy for BSR, FRic, FEve, CED, PD, and PSV as it carries between 99% and 67% of the cumulative model weight and has the lowest AIC (Table 1, Figure 2, Appendix S1: Figures S3–S6).

EVI and NDVI as proxies of avian urban tolerance

The UTM values were negatively associated with all indices, EVI and NDVI (both mean and sd). NDVI mean is

the selected best model, as it carries 99% of the cumulative model weight and has the lowest AIC score (Table 2, Figure 2, Appendix S1: Figures S3–S6).

EVI and NDVI as proxies of avian specialization

Bird assemblages characterized by a high number of diet (Diet), Foraging behavior (Forb), and Habitat (Hab) specialist species were positively associated with all indices investigated (e.g., EVI mean, EVI standard deviation, NDVI mean, and NDVI sd) (Table 3, Figure 2, Appendix S1: Figures S3–S6). Those areas characterized by the greater number of foraging substrate specialists (Forsub) were negatively related to EVI, and NDVI mean. NDVI mean was the best proxy for Diet, Forb, and Hab specialist species as it carries between 77 and 55% of the cumulative model weight and has the lowest AIC (Table 1, Figure 2, Appendix S1: Figures S3–S6). Finally, both EVI mean was the selected best model for Forsub, as it carries 69% of the cumulative model weight and has the lowest AIC score (Table 3, Figure 2, Appendix S1: Figures S3–S6).

DISCUSSION

Our analysis provides the first assessment investigating the ability of Landsat-derived EVI and NDVI as proxies of different facets of avian diversity (e.g., taxonomic, functional, and phylogenetic diversity, urban tolerance, and avian specialization) in urban landscapes across 15 European cities. We found that EVI mean as a surrogate of primary productivity was associated significantly with most avian diversity facets. However, EVI was the best predictor only for foraging substrate specialization. Specifically, EVI mean was negatively correlated to the number of bird species specialized in foraging substrate. Indicating a lower number of birds specialized in a particular foraging substrate are likely found in areas characterized by higher values of EVI mean. This finding could indicate a lower availability of potential foraging substrates (e.g., bare soil, artificial surfaces, and/or body water characterized) at higher cover vegetation. Most previous studies focused on the association between EVI (mean and standard deviation) and BSR (e.g., Callaghan, Major, et al., 2020; Cooper et al., 2020; Farwell et al., 2020; Hobi et al., 2017). Such studies were performed mainly in forest and rural areas (e.g., grassland and farmland). Instead, our findings are the first evidence that the EVI is significantly associated with multiple facets of avian diversity in urban areas and, most importantly, is the best predictor of foraging substrate specialization.

TABLE 1 Results of fixed-effect parameters in the GLMM model performed in this study, accounting for variations in the following diversity metrics: Bird species richness (BSR), Functional richness (FRic), Functional evenness (FEve), Functional divergence (FDiv), Community evolutionary distinctiveness (CED), Phylogenetic diversity (PD), and Phylogenetic species variability (PSV), concerning the following predictors: EVI mean, EVI standard deviation (EVI sd), NDVI mean, NDVI standard deviation (NDVI sd). Model = Individual models.

Model	ES	SE	t/z	p-value	AIC	Delta AIC	AICWt
Response variable: Bird species richness							
EVI mean	1.384	0.109	12.75	<0.001	3845.91	10.38	0.01
EVI sd	2.731	0.354	7.71	<0.001	3949.75	114.22	0
NDVI mean	**1.481**	**0.113**	**13.10**	**<0.001**	**3835.53**	**0**	**0.99**
NDVI sd	2.975	0.389	7.65	<0.001	3950.98	115.45	0
Response variable: Functional richness							
EVI mean	1.454	0.238	6.110	<0.001	2142.16	4.74	0.09
EVI sd	3.891	0.840	4.630	<0.001	2157.56	20.15	0
NDVI mean	**1.581**	**0.243**	**6.504**	**<0.001**	**2137.41**	**0**	**0.91**
NDVI sd	4.544	0.928	4.894	<0.001	2155.12	17.7	0
Response variable: Functional evenness							
EVI mean	0.437	0.052	8.458	<0.001	−598.88	5.86	0.05
EVI sd	0.459	0.177	2.587	0.0098	−537.29	67.45	0
NDVI mean	**0.467**	**0.053**	**8.834**	**<0.001**	**−604.77**	**0**	0.95
NDVI sd	0.306	0.197	1.558	0.1195	−533.07	71.67	0
Response variable: Functional divergence							
EVI mean	0.007	0.004	1.648	0.100	−4767.79	0.45	0.25
EVI sd	0.017	0.014	1.202	0.230	−4766.59	1.65	0.14
NDVI mean	**0.008**	**0.004**	**1.802**	**0.072**	**−4768.24**	**0**	**0.31**
NDVI sd	0.028	0.016	1.731	0.0839	−4768.11	0.13	0.30
Response variable: Community evolutionary distinctiveness							
EVI mean	0.073	0.006	12.815	<0.001	−4184.500	1.4	0.33
EVI sd	0.100	0.022	4.616	<0.001	−4055.203	130.7	0
NDVI mean	**0.075**	**0.006**	**12.880**	**<0.001**	**−4185.899**	**0**	**0.67**
NDVI sd	0.087	0.024	3.620	<0.001	−4047.140	138.8	0
Response variable: Phylogenetic diversity							
EVI mean	2.318	0.248	9.340	<0.001	2217.973	4.28	0.11
EVI sd	5.243	0.895	5.861	<0.001	2267.243	53.55	0
NDVI mean	**2.433**	**0.254**	**9.593**	**<0.001**	**2213.690**	**0**	**0.89**
NDVI sd	5.738	0.990	5.796	<0.001	2267.969	54.28	0
Response variable: Phylogenetic species variability							
EVI mean	−0.328	0.026	−12.550	<0.001	−1603.509	6.94	0.03
EVI sd	−0.459	0.098	−4.665	<0.001	−1480.491	129.95	0
NDVI mean	**−0.343**	**0.027**	**−12.877**	**<0.001**	**−1610.445**	**0**	**0.97**
NDVI sd	−0.391	0.110	−3.573	<0.001	−1471.652	138.79	0

Note: Each predictor was modeled separately for each response variable. The significant and selected model—according to the lowest AIC value and higher AICWt—is evidenced in bold. Additionally, conditional R^2 (variance explained by fixed and random effects) and marginal R^2 (variance explained by the fixed effects) assessed for each model are reported in Appendix S1: Table S4.

Abbreviations: AIC, Akaike information criterion; AICWt, Akaike information criterion weighted; ES, estimate; SE, standard error.

On the other hand, NDVI mean was significantly associated with most avian diversity facets. Specifically, it was positively correlated with BSR, functional richness, functional evenness, community evolutionary distinctiveness, phylogenetic diversity, and the number of diet and habitat specialists in urbanized areas. However, NDVI
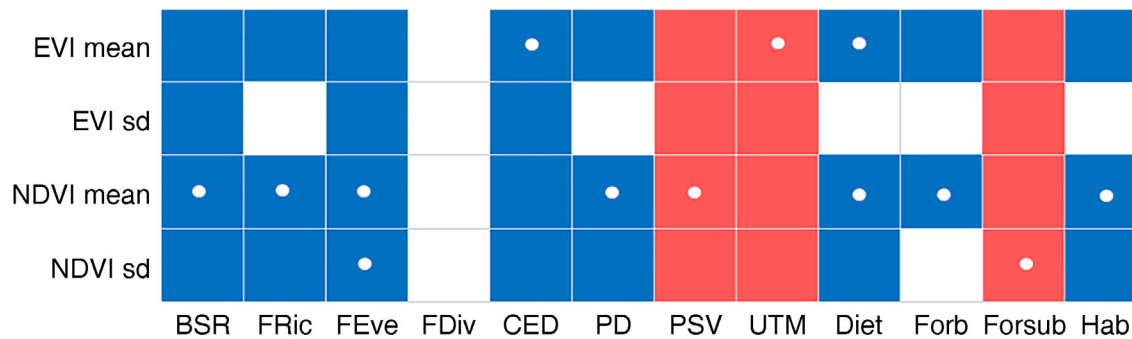
FIGURE 2 Matrix representing the GLMM association types between avian diversity and community metrics and Landsat-derived indices. In the columns, the following responses variables are: Bird species richness (BSR), Functional richness (FRic), Functional evenness (FEve), Functional divergence (FDiv), Community evolutionary distinctiveness (CED), Phylogenetic diversity (PD), Phylogenetic species variability (PSV), Urban Tolerance mean (UTM), Diet specialization richness (Diet), Foraging behavior specialization richness (Forb), Foraging substrate specialization richness (Forsub), Habitat specialization richness (Hab). In the rows, the following predictive variables are: EVI mean, EVI standard deviation (EVI sd), NDVI mean, and NDVI standard deviation (NDVI sd). Each predictive variable was assessed in separate models. Blue squares represent positive and significant associations. Red squares represent negative and significant associations. White squares represent non-significant associations. The selected best models—according to the lowest AIC and greater AICWt values—are indicated with a white dot. See detailed results in Tables 1–3.

TABLE 2 Results of fixed-effect parameters in the GLMM model performed in this study, accounting for variations in Urban Tolerance mean (UTM), concerning the following predictors: EVI mean, EVI standard deviation (EVI sd), NDVI mean, NDVI standard deviation (NDVI sd).

Model	ES	SE	t/z	p-value	AIC	Delta AIC	AICWt
Response variable: Urban tolerance mean							
EVI mean	−4.380	0.221	−19.854	<0.001	3961.821	9.70	0.01
EVI sd	−7.251	0.855	−8.479	<0.001	4237.844	285.72	0
NDVI mean	**−4.605**	**0.228**	**−20.176**	**<0.001**	**3952.123**	**0**	**0.99**
NDVI sd	−6.394	0.980	−6.524	<0.001	4265.989	313.87	0

Note: Model, Individual models. Each predictor was modeled separately for each response variable. The significant and selected model—according to the lowest AIC value and higher AICWt—is evidenced in bold. Additionally, conditional R^2 (variance explained by fixed and random effects) and marginal R^2 (variance explained by the fixed effects) assessed for each model are reported in Appendix S1: Table S4.

Abbreviations: AIC, Akaike information criterion; AICWt, Akaike information criterion weighted; ES, estimate; SE, standard error.

mean was correlated negatively to phylogenetic species variability, urban tolerance, and foraging substrate specialism. Simultaneously, except for foraging substrate specialization, NDVI mean was the best predictor of all avian diversity metrics explored in this study. Hence, urban areas with high NDVI mean values were characterized by a greater number of bird species (Ibáñez-Álamo et al., 2016), high functional richness, and phylogenetical diversity (Morelli, Benedetti, Ibáñez-Álamo, et al., 2021), and also a greater number of avian specialists. In agreement, previous studies found higher species richness and phylogenetic diversity associated with low-density urban areas, which we can assume greater NDVI mean values (Ibáñez-Álamo et al., 2016; Morelli et al., 2016; Morelli, Benedetti, Ibáñez-Álamo, et al., 2021). Conversely, in areas with high values of NDVI mean, avian assemblages were barely correlated phylogenetically and with few urban

tolerant species and foraging substrate specialists. Our results show that a greater vegetation cover supports urban areas with avian assemblages taxonomically less related and with a greater number of native species. Therefore, greater NDVI mean values can identify urban areas with lower avian biotic homogenization (Morelli, Benedetti, Ibáñez-Álamo, et al., 2021). Accordingly, most studies focused on NDVI as a proxy of avian diversity found positive associations between NDVI and BSR and functional diversity (Bailey et al., 2004; Gillespie, 2005; Hurlbert & Haskell, 2003; Levin et al., 2007; Seto et al., 2004). Leveau et al. (2020) found a negative correlation between NDVI and community evolutionary distinctiveness in Argentine, contrasting our findings. Such discrepancies could be associated with the sampling size differences between both studies or the bird species composing such avian assemblages. For example, the overall

TABLE 3 Results of fixed-effect parameters in the GLMM model performed in this study, accounting for variations in each category of specialization richness: Diet (Diet), Foraging behavior (Forb), Foraging substrate (Forsub), and Habitat (Hab) concerning the following predictors: EVI mean, EVI standard deviation (EVI sd), NDVI mean, NDVI standard deviation (NDVI sd).

Model	ES	SE	t/z	p-Value	AIC	Delta AIC	AICWt
Response variable: Diet richness							
EVI mean	0.857	0.180	4.750	<0.001	3823.02	0.46	0.44
EVI sd	2.276	0.610	3.735	<0.001	3831.9	9.34	0.01
NDVI mean	**0.905**	**0.189**	**4.784**	**<0.001**	**3822.56**	**0**	**0.55**
NDVI sd	2.405	0.688	3.498	<0.001	3833.59	11.03	0
Response variable: Foraging behavior richness							
EVI mean	0.696	0.133	5.123	<0.001	4678.76	0.48	0.28
EVI sd	2.197	0.430	5.110	<0.001	4680.38	2.11	0.12
NDVI mean	**0.733**	**0.140**	**5.248**	**<0.001**	**4678.28**	**0**	**0.35**
NDVI sd	2.555	0.486	5.255	<0.001	4679.02	0.74	0.24
Response variable: Foraging substrate richness							
EVI mean	**−0.694**	**0.182**	**−3.806**	**<0.001**	**3715.79**	**0**	**0.69**
EVI sd	−0.517	0.616	−0.840	0.4008	3729.63	13.84	0
NDVI mean	−0.678	0.189	−3.595	<0.001	3717.42	1.63	0.31
NDVI sd	0.006	0.691	0.009	0.993	3730.34	14.55	0
Response variable: Habitat richness							
EVI mean	1.424	0.294	4.844	<0.001	2356.12	2.41	0.23
EVI sd	3.358	0.880	3.815	<0.001	2365.31	11.59	0
NDVI mean	**1.590**	**0.314**	**5.072**	**<0.001**	**2353.72**	**0**	**0.77**
NDVI sd	3.817	1.001	3.795	<0.001	2365.5	11.79	0

Note: Model, Individual models. Each predictor was modeled separately for each response variable. The significant and selected model—according to the lowest AIC value and higher AICWt—is evidenced in bold. Additionally, conditional R^2 (variance explained by fixed and random effects) and marginal R^2 (variance explained by the fixed effects) assessed for each model are reported in Appendix S1: Table S4.

Abbreviations: AIC, Akaike information criterion; AICWt, Akaike information criterion weighted; ES, estimate; SE, standard error.

avian assemblages in European cities can be characterized by higher community evolutionary distinctiveness than those found in Argentine (Ibáñez-Álamo et al., 2016; Morelli et al., 2016). These differences can be related to the presence of *Upupa epops* in some urban areas, a species characterized by a high evolutionary distinctiveness score.

Our findings indicate that the mean values of NDVI and EVI are suitable as proxies for monitoring different facets of avian diversity in urban areas. However, NDVI mean was the best predictor for most avian diversity metrics. Considering that both vegetation indices are surrogates of primary productivity (Huete, Didan, Miura, Rodriguez, Gao, & Ferreira, 2002), these findings are consistent with the species-energy hypothesis (Wright, 1983). Such a hypothesis claims that the species diversity of vertebrates (including birds) and invertebrates should increase with energy availability (Evans & Gaston, 2005; Hawkins, Field, et al., 2003; Lennon et al., 2004). Accordingly, our results show that areas at high productivity levels (greater vegetation biomass), represented by high EVI and NDVI values, support avian assemblages with a high number of native species, more diverse functionally, less related phylogenetically, and more distinctive species. Therefore, in such areas, we can expect a greater number of avian specialist species, particularly in diet and foraging behavior.

Regarding vegetation heterogeneity, several studies demonstrated the ability of EVI sd and NDVI sd to represent vegetation heterogeneity (Seto et al., 2004). Similar to EVI and NDVI mean, our results showed that EVI sd and NDVI sd were significantly and positively associated with most avian diversity facets. Instead, they were negatively correlated to phylogenetic species variability and urban tolerance. We expected such results because heterogeneous environments provide a greater diversity of microhabitats and niches potentially suitable as refugia, substrate, and other resources for the organisms (Keppel et al., 2011; Stein et al., 2014; Tews et al., 2004). Nonetheless, EVI sd and NDVI sd were not the best predictors for any avian diversity facets studied since they exhibited an overall lower performance than the other predictors.

CONCLUDING REMARKS AND PERSPECTIVES

Previous studies demonstrated that each satellite sensor (e.g., Landsat, Sentinel, or Gaofen) provides different vegetation indices values. Such differences can affect the accuracy of the assessment of the vegetation attributes (Wu et al., 2020; Zhao et al., 2018). The search for the "best" proxy should consider the trade-offs among vegetation index effectiveness, economic costs, and spatiotemporal resolution for each band and sensor type. Therefore, further studies could apply this framework by exploring other potential proxies of avian diversity metrics by using spectral indices based on other bands such as SWIR band (e.g., NDWI, Normalized Difference Water Index) or linear band transformations (e.g., TCT, Tasseled Caps Transformation), and by also examining different satellite sensors (e.g., Sentinel-2A, Sentinel-2B, WorldView-2). Additionally, we encourage that upcoming studies should expand the temporal monitoring scheme to detect changes in avian assemblages of urban areas.

The World Cities Report 2020 (United Nations Human Settlements Programme, 2022), jointly with the New Urban Agenda (United Nations, 2017) and the European Biodiversity Strategy for 2030 (EC, 2020), recognizes the value of urban green areas in removing carbon from the atmosphere and safeguarding biodiversity. Such programs call for different measures to promote green space areas, increasing environmental resilience in human settlements. Accordingly, our results indicate that greater cover of green areas can support different facets of urban avian diversity. For this reason, efficient conservation strategies in cities should be considered: (1) Maintaining different types of green-area habitats, not only forests and urban parks (Nguyen et al., 2020), but also larger urban greenspaces to preserve connectivity in the city (Callaghan et al., 2018; EC, 2020; Nguyen et al., 2020; United Nations, 2017); and (2) Restoring vegetation cover to support avian communities confronting climate change (EC, 2020). Additionally, we recommend long-term and broader spatial monitoring of different avian diversity metrics in urban areas using NDVI mean to detect temporal and spatial changes in avian assemblages. Therefore, such approaches can help to explore the potential vulnerabilities of bird assemblages facing climatic and land-use changes and promote more efficient landscape restoration and urban planning, congruently with biodiversity conservation.

In summary, we tested the efficiency of remote sensing measurements as proxies' of multiple facets of avian diversity using data from several European cities, considering that: (1) most articles focusing on vegetation indices and avian diversity metrics are based on single-city studies; (2) assess proxies of avian diversity in urban areas is essential given that the spectral indices can find different technical limitations (e.g., higher reflectance from different material types) if compared to natural or rural areas (Xue & Su, 2017); and (3) several facets of avian diversity were not previously assessed (e.g., phylogenetic relatedness, urban tolerance, and different specialization traits of avian assemblages) even though they can mirror undetected biotic homogenization (Petchey & Gaston, 2006). Our findings showed that although all vegetation indices explored in this study were significantly related to most avian diversity facets, NDVI mean was the best explanatory vegetation index for avian diversity in urban areas.

CONFLICT OF INTEREST STATEMENT

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

DATA AVAILABILITY STATEMENT

EVI and NDVI data were calculated using the USGS Landsat 8 Collection 1 Tier 1 imagery from the Google Earth Engine catalog: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_RT_TOA. The avian niche database, comprising 73 different traits, was obtained from Pearman et al. (2014) and is available in the supplementary material at https://onlinelibrary.wiley.com/doi/10.1111/geb.12127. Phylogeny data for birds were downloaded from BirdTree https://birdtree.org/subsets/ using the list avian species subset from Benedetti and Morelli (2022) in Figshare at https://doi.org/10.6084/m9.figshare.19780285.v1. Evolutionary distinctiveness score for birds were downloaded from https://www.edgeofexistence.org/edge-lists/ by searching for "ED scores–birds". Species specific urban tolerance scores were

downloaded from Callaghan, Benedetti, et al. (2020) and are available in the supplementary material provided at https://www.oikosjournal.org/appendix/oik-07356. Bird specialization data was extracted from Morelli et al. (2019) and are also available in Benedetti and Morelli (2022) in Figshare at https://doi.org/10.6084/m9.figshare.19780285.v1.

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SUPPORTING INFORMATION

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