Linking ecosystem functioning diversity and passerine species richness with application to landscape monitoring

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Todas as correções determinadas pelo júri, e só essas, foram efetuadas.
O Presidente do Júri,

Porto, ______/______/_________

"To see the world, things dangerous to come to,
to see behind walls, draw closer, to find each
other, and to feel. That is the purpose of life."

The Secret Life of Walter Mitty

Agradecimentos

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Resumo

A alteração da paisagem é um dos promotores de mudança mais importantes que afetam a biodiversidade e os serviços de ecossistema na bacia do Mediterrâneo. Analisar a heterogeneidade espacial da paisagem e suas mudanças ao longo do tempo melhora a capacidade de entender a magnitude dos impactos humanos nos ecossistemas terrestres. A heterogeneidade é mais frequentemente medida enfatizando as respostas espectrais composicionais, estruturais e físicas, enquanto negligencia a diversidade funcional. Portanto, há um interesse em testar se a heterogeneidade espacial e temporal no funcionamento do ecossistema ou da paisagem pode atuar como um preditor robusto para padrões de diversidade de espécies.

Neste estudo, foi compilada uma série temporal de 35 anos do Enhanced Vegetation Index (EVI) detectado remotamente para a bacia do rio Vez, para analisar a dinâmica da Diversidade de Funcionamento do Ecossistema. Preditores calculados a partir da série temporal EVI foram usados para explicar a riqueza específica de vários grupos funcionais de passeriformes através de um modelo GLM Elasticnet. Esse modelo forneceu informações sobre o desempenho preditivo de variáveis baseadas no EVI, e as variáveis com melhor desempenho foram usadas para realizar uma análise de tendências durante o período de tempo focal.

A paisagem da área de estudo foi considerada bastante heterogénea, e espécies de aves passeriformes com comportamento mais diverso e de maior tamanho alcançaram a explicação mais alta dos modelos. Para variáveis baseadas no EVI, os melhores resultados foram obtidos para dois preditores que mantinham uma relação linear positiva com a riqueza de espécies de aves: uma variável contínua (desvio padrão do EVI máximo) e uma variável discreta (riqueza dos tipos de funcionamento do ecossistema). As análises de tendências revelaram um cenário bastante dinâmico, em constante mudança ao longo do período focal.

Os resultados sugerem que várias características da dinâmica do ciclo de vida dos passeriformes dependem da diversidade de funcionamento do ecossistema. Recursos alimentares, diversidade de habitats, refúgio, recursos de nidificação e sincronismo do ciclo de vida estão profundamente conectados aos padrões e processos da paisagem. A diversidade funcional mostrou ter o potencial de prever tendências de riqueza específica, pelo menos para aves passeriformes na bacia do Vez, mas provavelmente também para outros táxon ou áreas de interesse. Uma compreensão mais profunda dos processos ecológicos e dinâmicas que caracterizam paisagens heterogéneas permitirá a definição de estratégias mais robustas de conservação da biodiversidade.

Palavras-chave: Diversidade funcional de ecossistemas; Atributos funcionais de ecossistemas; Tipos funcionais de ecossistemas; Heterogeneidade da paisagem; Detecção remota; Alteração da paisagem; Monitorização de biodiversidade

Abstract

Landscape change is one of the most important drivers of biodiversity and ecosystem services change on the Mediterranean basin. Analysing landscape spatial heterogeneity and its change over time improves our capacity to understand the magnitude of human impacts on land ecosystems. Heterogeneity is most often measured emphasizing the compositional, structural and physical spectral responses, while overlooking functioning diversity. Therefore there is an interest in testing whether the spatial and temporal heterogeneity in ecosystem or landscape functioning can act as a robust predictor for patterns of species diversity.

In this study, we compiled a 35-year time series of the remotely sensed Enhanced Vegetation Index (EVI) for the Vez river watershed, to analyse Ecosystem Functioning Diversity dynamics. Predictors computed from the EVI time series were used to explain species richness of various passerine functional groups in a GLM Elasticnet model. That model provided information on the predictive performance of EVI-based variables, and the best performing variables were used to perform a trend analysis during the focal time period.

The landscape of the study area was found to be quite heterogeneous, and passerine bird species with more diverse behaviour and of larger size attained the highest explanation of models. For EVI-based variables, the best results were obtained for two predictors both holding a positive linear relation with passerine species richness - a continuous variable (standard-deviation of maximum EVI) and a discrete variable (richness of ecosystem functioning types). Trend analyses revealed a rather dynamic landscape in constant change throughout the focal time frame.

Our results suggest that several features of passerine life cycle dynamics depend on ecosystem functioning diversity - feding resources, diversity of habitats, refuge from disturbances, nesting resources and life cycle synchronism are deeply connected to landscape patterns and processes. We hence show that ecosystem functioning diversity holds the potential to predict trends in species richness, at least for passerine birds in the Vez watershed but likely also for other taxa or areas of interest. A deeper understanding of the ecological processes that characterise heterogeneous and dynamic landscapes will allow the definition of more robust strategies of biodiversity conservation.

Keywords: Ecosystem Functioning Diversity; Ecosystem Functioning Attributes; Ecosystem Functioning Types; Landscape heterogeneity; Passerine functional traits; Remote sensing; Landscape change; Biodiversity monitoring.

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Note: *All photographs were taken by the author*

List of acronyms

VI – Vegetation index

EVI – Enhanced Vegetation Index

EFAs – Ecosystem Functioning Attributes

EFD – Ecosystem Functioning Diversity

EFTs – Ecosystem Functioning Types

VIF – Variance Inflation Factor

PSU – Primary Sampling Unit

SSU – Secondary Sampling Unit

GEE – Google Earth Engine

GLM - Generalized Linear Model

SRS – Satellite Remote Sensing

LRT – Likelihood Ratio Test

1. Introduction

1.1. Landscape changes and its effects on biodiversity

In a world of constant transformation, landscape and land use change is one of the most important drivers that affect biodiversity and ecosystem services. It depends on several factors, including ecological, geographical, sociological, and economical aspects, and can have both positive and negative impacts for different species (Rindfuss et al., 2004; Fletcher and Fortin, 2018).

Another important factor for understanding biodiversity patterns is scale. If we are referring to the global scale, one of the major drivers of change is related to modifications in climate, which potentially causes the aggravation of other drivers. It is estimated that in the last 30 years temperatures rose 0,2ºC per decade and in the last 50 years extreme weather events became more frequent and intense (e.g. fires, floods and droughts) (Díaz et al., 2019). Temperature increase for example can affect species distribution, phenology (migrations, breeding time, etc.) and morphology, which ultimately affects communities structure and composition (Schneider and Root, 2002; Root et al., 2003; Masson-Delmotte et al., 2018).

The most common consequences of landscape change at the regional and local scales are habitat loss, degradation and fragmentation, constituting a generalized threat to the biodiversity of the planet. There are many causes for these types of landscape modifications, such as the construction of infrastructures (e.g. roads and buildings), wildfires (Figure 1) or the clearing of forests for agriculture (Jaeger, 2000).

Figure 1 - Fires of 2017 in Centre Portugal, images of pre and post fire (burnt area highlighted) (Google LLC, n.d.)

Fragmentation and habitat loss may seem the same but there are some differences. While habitat loss is the destruction of an area for a new type of use, habitat fragmentation causes both the destruction (e.g., the building of the new infrastructure or the deforestation/fire that divides the area) and over time changes the characteristics of the initial environment (van den Berg et al., 2001). When there is fragmentation or loss of habitat, the resources are less available for the biological community on the area, and the community itself becomes more isolated, leading to a decrease of species' populations size or on more severe cases to the disappearance of entire populations (Fahrig, 2003; Ewers and Didham, 2005). Fragmentation is also shown to increase edge habitats and causing the dispersion of animals from their habitat into the matrix, leading to a higher mortality rate (Fahrig, 2002)

In order to feed a growing human society many areas are also being converted from extensive to intensive agricultural areas, where the use of agrochemicals is often high and the monotony of the landscape caused by monocultures tends to reduce its diversity, weakening the system and causing a negative impact on biodiversity. For example, agriculture intensification is linked to the decline of farmland bird populations (Gregory et al., 2005; Tscharntke et al., 2005).

Surprisingly many areas of past human influence are being abandoned, such as traditional agriculture lands, especially on the Mediterranean region and Iberian Peninsula (Figure 2) (Plieninger et al., 2014). Extensive farmland abandonment is a complex and gradual process which leads to the progression of natural succession (Keenleyside et al., 2010) and is caused by a conjuncture of aspects: lack of suitability for agricultural activity; low stability of farms; negative factors from regional influence (age of farmers, lack of qualifications, rural exodus, policies, etc.) (Terres et al., 2013; Leal Filho et al., 2017).

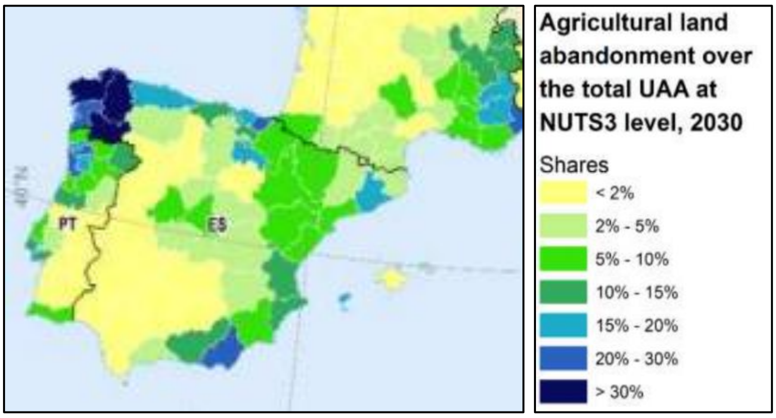


Figure 2 – Predicted agricultural land abandonment on the utilised agricultural area (UAA) on the Iberian Peninsula for 2030 (Perpina Castillo et al., 2018) -

These low intensity farming areas are typically very heterogeneous, with numerous land cover types, from crops to orchards and more naturalized areas like hedgerows and woodlands, forming a very complex mosaic that creates countless opportunities for numerous species (Falcucci et al., 2007; Fahrig et al., 2011; Fischer et al., 2012).

By allowing these areas to return to a natural regime, ecological succession occurs over the course of time giving way to shrub areas and on a later stage to reforestation which potentially leads to a reduction in landscape heterogeneity (Tasser et al., 2007; Chemini and Rizzoli, 2014). This homogenization effect can have both negative effects with potential loss of habitat availability for certain species (e.g. farmland species), favouring shrub or woodland species (Chemini and Rizzoli, 2014; Gámez-Virués et al., 2015); and positive effects, with the rewilding of the landscape to a state previous to agricultural use.

Wildfires also play an important role in shaping vegetation and landscape patterns as well as the resistance and resilience of ecosystems. When a fire occurs the wildlife of the affected region suffers strong impacts, scaring the landscape, modifying vegetation patterns and ecological processes (Sugihara et al., 2006). Post-fire conditions make landscapes more prone to erosion, and leaving a poorer soil behind thus making the recovery of an area more difficult and weakening its ability to provide ecosystem services (Butler et al., 2018; DeLong et al., 2018). This leads to habitat modifications with consequences on future fire regime, and the proliferation of fire-prone species (Viedma et al., 2006; van Mantgem et al., 2015).

1.2. Passerine species as bioindicators of change

To understand how a landscape is evolving, either disturbed or undisturbed, we can use ecological indicators to evaluate the trajectory of an ecological system. The importance of measuring species diversity as an indicator of ecosystem “health” has been recognized by major initiatives worldwide (Skidmore et al., 2015). This information can be used to guide decision makers to implement policies that improve monitoring and conservation of biodiversity efforts of a region (Canterbury et al., 2000).

Taking that in consideration, modifications of the landscape can also be monitored through bioindicators, such has the analysis of bird communities. Birds are a good indicator considering that they are easy to detect, identify, census, and respond quickly to changes; and the ecological/taxonomic knowledge of the group is high (Gregory et al., 2005). They also have a wide-ranging habitat and are generally abundant. All these traits make the group a very good response variable to analyse landscape changes temporally and spatially (Padoa-Schioppa et al., 2006). Passerine birds in particular represent an interesting group as pointed out by Santos and Cabral (2004) and again by Mulatu et al. (2016). This happens because they usually occur in high densities in a large number of habitats (using them for nesting and feeding) and are at an intermediate level on the food web (having different types of feeding), they provide cheap/easy measurements and are sensitive to landscape changes from microhabitat to landscape level, and they are able to recover population effectives in response to good management practices in previously disturbed landscapes.

Landscape disturbances like fire can pose a challenge to passerine communities. While some species benefit from the new opportunities created by the modification of the landscape others face a more difficult environment, depending on the fire regime (larger fires typically have greater negative impacts). Those changes caused by fires can be monitored by evaluating the bird community taxonomic and spatiotemporal changes (Herrando and Brotons, 2002; Herrando et al., 2003; Moreira and Russo, 2007).

The monitoring of individual species can prove to be a difficult task mainly because there can be too much data thus making it harder to analyse and identify generalized trends. A solution to this issue can be the aggregation of species into functional groups, for example by nesting or feeding habits (Finch, 1991; M Block et al., 1995), or by analysing total species richness which has been proven to have a significant relationship with the landscape (Pino et al., 2000).

1.3. Remote sensing in ecology

Remote Sensing Fundamentals

Birds' communities can function as indicators of the ecosystem "health" and to link those indicators with the evaluation of the dynamics of the landscape we need instruments such as remote sensing tools (O'Connell et al., 2000).

During the late mid-19th century the first aerial pictures were taken using balloons. In the 1910's airplanes substituted the balloons, playing a crucial role of aerial reconnaissance during World War I. We have come a long way from the launch of the first satellites in the 50's and the 60's. With these technological innovations Earth Observation, and its application to ecological and biodiversity monitoring, became easier and now there is a great deal of data available to public use (Campbell and Wynne, 2011).

Images captured by remote sensing satellites are used to investigate and analyse the relation between natural phenomena and electromagnetic radiation (EMR) emitted from the Earth's surface (Tatem et al., 2008). EMR spectrum is divided into distinct wavelength regions, from Radio to Gamma rays, and including the visible and infrared portions of EMR, often used for vegetation mapping and monitoring.

Not all wavelengths are equally used for environmental remote sensing, and the ones that are, can be divided into two major groups: Multispectral Visible/Infrared Satellite Remote Sensing (Optical SRS), which uses SRS passive sensors that do not emit radiation and measure the amount of radiation reflected from a surface area, and can only detect a few regions of electromagnetic radiation; and Radar Satellite Remote Sensing (Radar SRS) which uses SRS active sensors that emit radiation and measure the strength and time delay of the returning signal (Radar SRS) (Lavender and Lavender, 2015; Pettorelli et al., 2018).

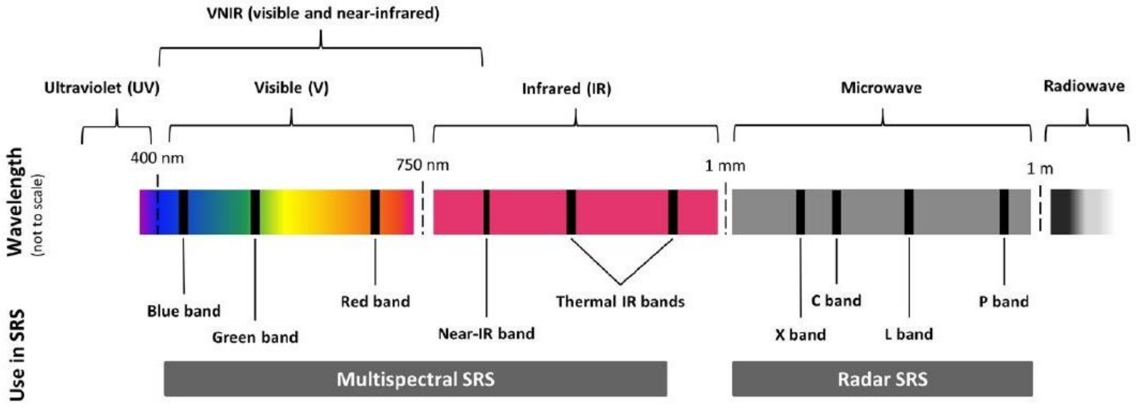


Figure 3 - Electromagnetic spectrum in SRS (Pettorelli et al., 2018).

Intervals of the electromagnetic spectrum (Figure 3) can also be called bands. In Optical SRS, which is the type we explored in this work, this uses Ultraviolet Light (10–400nm); Visible Light (380–740nm) with blue band (450–485 nm), green band (500–565 nm) and red (625–740 nm) band together forming RGB images or true colour images; and Infrared Light (700nm – 1mm) with Near Infrared – NIR (750–1400 nm); Shortwave Infrared – SWIR (1400–3000nm); and Thermal Infrared – TIR(3000nm – 1mm) (Bruno and Svoronos, 2005; Byrnes, 2009; European Space Agency, 2016).

There are a few key concepts when it comes to describe satellites images in terms of different types of resolutions as shown on Table 1.

Table 1 – Key concepts and properties of satellite images (Pettorelli et al., 2018).

Concept	Meaning
Spatial resolution	Size of an individual pixel (usually measured in meters)
Temporal resolution	Overpass frequency of the satellite (usually measured in hours or days)
Spectral resolution	Smallest difference between wavelengths that can be recognized (usually measured in nanometres referring to the electromagnetic spectrum
Radiometric resolution	Smallest difference in the intensity of the radiation (usually measured in bits)

Vegetation Indices

Remote sensing data can be used to evaluate a system dynamics with the help of Spectral Vegetation Indices (VI), which are, put simply, arithmetic calculations (often in the form of normalized ratios) based on reflectance values of the visible and NIR parts of the EMR spectrum (Xue and Su, 2017). When used systematically and repetitively to monitor a certain area (i.e., image time series) VI's can indirectly translate the status and the change in landscape composition, structure and functioning (Figure 4). The most commonly used of these VI's is NDVI (Normalized Difference Vegetation Index) (Matsushita et al., 2007). But this isn't the only index used, there are others that have been showing interesting results such has EVI (Enhanced Vegetation Index) (Jiang et al., 2008). Both indices provide a measure related to vegetation greenness that varies between $-1<VI<1$, and that can be used to predict net primary production. There are some limitations related to satellites historic archive, reducing the availably of data. For example Sentinel-2 was launched in 2015 and MODIS in 1999, that means Sentinel-2 has a smaller time series when compared to MODIS which may prove inadequate for analysis of longer-term dynamics (Gurung et al., 2009). EVI is known to be more reliable in both low and high vegetation cover situations, and resistant to both soil influences and canopy background signals, and atmospheric effects on vegetation index values (it corrects distortions caused by aerosols) (Huete, 1997; Gao et al., 2000). Overall, these characteristics of EVI make it a more desirable index to be used.

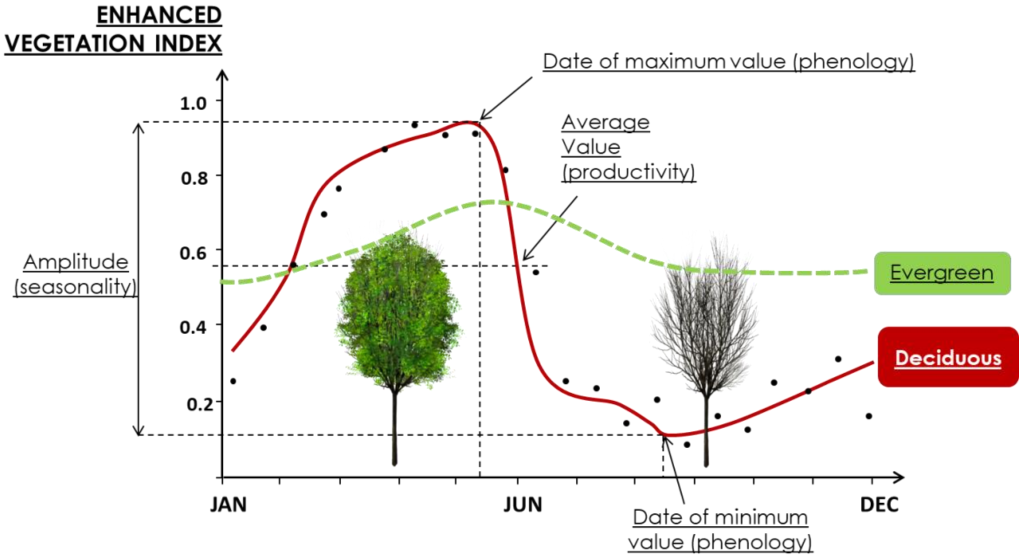


Figure 4 - EVI annual curve and vegetation phenology

EVI is calculated using three bands: Red band, Blue band and Near Infrared Red (NIR) band.

$$EVI = G\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L}$$

For each band a corrected surface reflectance value *ρ* is applied. C_1 and C_2 are the coefficients of the aerosol resistance, that uses the blue band to correct aerosol influences in the red band, and *L* is the canopy background adjustment that addresses nonlinear, differential NIR and red radiant transfer through a canopy. G is the gain factor and equals 2.5. For EVI, the coefficients adopted are: G = 2,5; *L* = 1; C_1 = 6; C_2 = 7,5 (Huete et al., 2002).

Ecosystem Functioning Attributes, Types and their Diversity

Detecting changes in the balance of an ecosystem is a key step to understand how species are affected by the variation and change of environmental and ecological conditions. Biodiversity can be measured in three components: structural (e.g. landscape pattern, habitat structure, population structure, etc); compositional (e.g. land cover types, ecosystem types, etc.); and functioning (landscape/ecosystem process and disturbances, demographic processes, etc.) (Noss, 1990) Taking that into consideration, Ecosystem Functioning Attributes (EFAs) are interesting remotely-sensed indicators that provide a response to ecological and evolutionary process including vegetation feedback towards environmental drivers, detecting changes and shifts in biomes and ecosystems (Noss, 1990; Lausch et al., 2016; Alcaraz-Segura et al., 2017). EFAs related to phenology, productivity and seasonality show the processes of exchange of matter and energy between the physical environment and the biota, quantifying and qualifying changes and linking species responses to the ecosystem overall functioning. These indicators have the advantage of being able to be monitored through remote sensing, being quicker to respond than compositional and structural attributes and are able to characterize ecosystem heterogeneity (Paruelo et al., 2001; Alcaraz-Segura et al., 2006; Mouillot et al., 2013).

Another important concept is Ecosystem Functioning Types (EFTs). These are based on EFAs, grouping similar functioning ecosystems through satellite data (derived from flows of matter and energy that relate to carbon and water cycles), having similar productivity, seasonality and phenology dynamics (Paruelo et al., 2001; Alcaraz-Segura et al., 2006). The concept was developed based on Plant Functional Types but upscaled to a higher level of biological complexity. Instead of grouping plant species into functional groups, ecosystems are grouped based on their functioning behaviour (Paruelo et al., 2001). As so, this allow to describe ecosystem heterogeneity and responses to spatio-temporal environmental change (Pérez-Hoyos et al., 2014).

Analysing landscape heterogeneity improves our capacity to understand the magnitude of human impacts on terrestrial ecosystems (Fernández et al., 2010). Environmental heterogeneity is often appointed as a major predictor of species richness. The basis for the idea is not novel. There are studies, namely Rocchini et al. (2010), that link species richness and spectral diversity, hypothesising that highly heterogeneous environments can host more species due to their higher number of available niches. However we found that most commonly, heterogeneity is measured in the compositional and structural components (Stein et al., 2014) or, in the case of remotely-sensed variables, they often use the diversity of physical spectral response (i.e., spectral diversity) to assess these relations.

In this context, and using this background to frame the research done in this thesis, there is an interest in testing how the diversity or heterogeneity in ecosystem or landscape functioning can also act as an important predictor for species richness. Landscape functioning diversity has shown to have a positive relation with avian species richness (an increase in functioning diversity will lead to an increase of species richness) (Lee and Martin, 2017). This can be addressed by using remotely sensed variables linked to ecosystem functioning and by measuring the heterogeneity in continuous EFAs (standard-deviation) or discrete/categorical EFTs (richness, Shannon, Simpson, etc.) to obtain a spatial measure of how diverse or heterogeneous an area is.

1.4. Aims

Understanding how ecosystems function is an essential step to compute meaningful variables that allow to recognize ecosystem changes as well as their drivers, and thus to improve efforts for conservation purposes. This work focused on applying this rationale to analyse regional biodiversity patterns, by combining remote sensing tools, field surveys of passerine diversity, and predictive modelling in the watershed of river Vez, in northwest Portugal.

Three sequential research goals were established:

1) To test Ecosystem Functioning Attributes (EFA) and Ecosystem Functioning Types (EFT) diversity as predictors of fine-scale passerine species richness patterns;

2) To determine which are the best predictive EFA/EFT diversity variables and to assess if the predictive performance of those variables differs across passerine functional groups;

3) To assess spatiotemporal trends in selected EFA/EFT diversity indicators as a surrogate of predict passerine species richness changes.

2. Material and methods

2.1. Study area

The study area consists of the Vez river watershed located in northwest of Portugal, with an area of 262 km^2 (Figure 5). It runs 36 kilometres from Serra do Soajo to Milhundos-Souto draining in river Lima. This basin presents a complex elevation gradient ranging from 23 m to1418 m that has an influence on climate, ranging from Mediterranean (1000mm/year) in lowlands to Temperate Atlantic (3000 mm/year) in highlands (Mesquita and Sousa, 2009). Regarding geology, the area presents granites and schists, and predominantly Humic Regosols (Highlands) and Dystric Antrosols (Lowlands). Shrublands dominate the highlands; agriculture and forest dominate the lowlands. The upper section of the river is inserted in the Peneda-Gerês National Park (PNPG) (Carvalho-Santos et al., 2016). The natural heterogeneity of the landscape is also affected by decades scattered low-density settlements and of extensive agricultural and livestock grazing. These traditional practices have been changing over the course of recent decades, with an exodus to population centres and afforestation of previously explored land (Moreira et al., 2001; Honrado et al., 2017). Frequent wildfires with some extreme years in terms of burnt area also shape current vegetation and landscape patterns. Plantation of forest exotic tree-species (such as eucalypt) often forming monocultures or in combination with maritime pine as well as invasive tree species (mainly from the *Acacia* genus) are also common in the area.

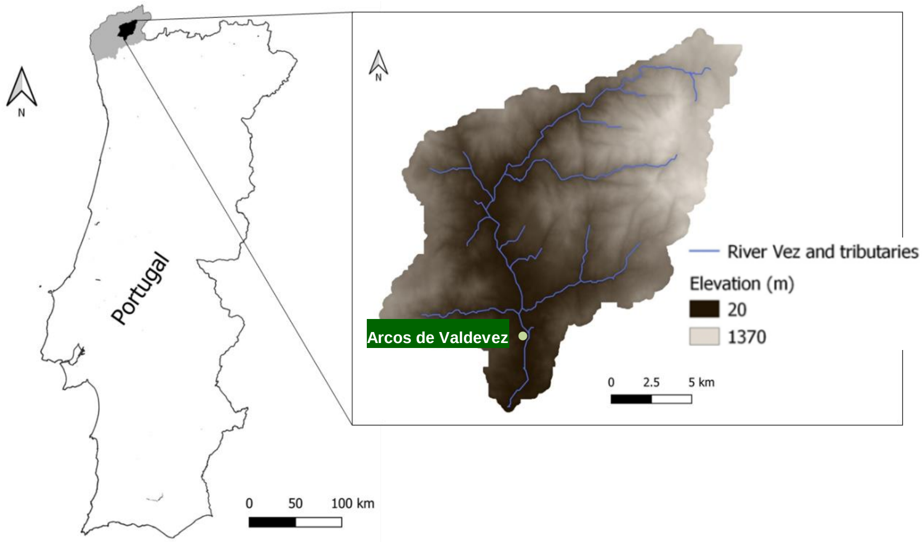


Figure 5 - Location of the study area

2.2. General workflow

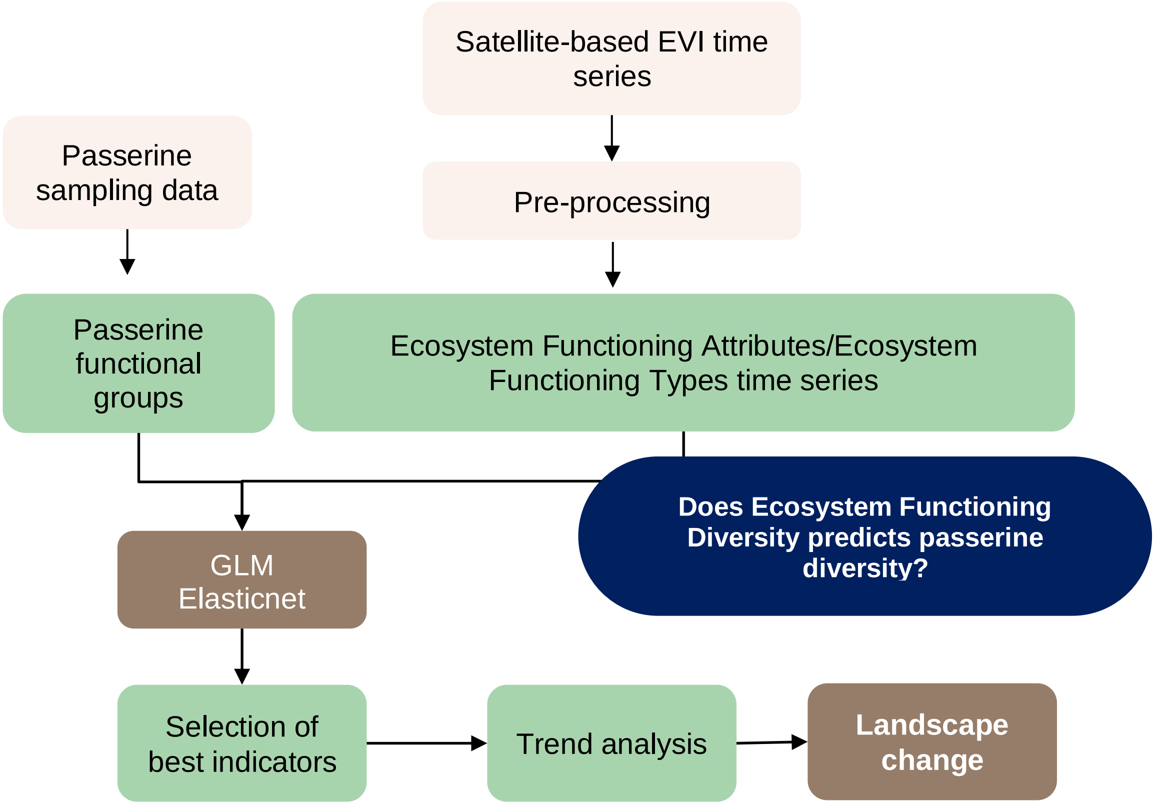


Figure 6 – General workflow followed for research development in the thesis

The general workflow is described in Figure 6, containing both input datasets and the analysis performed. Overall we compiled 35 years of remotely sensed EVI time series to analyse Ecosystem Functioning Diversity (EFD)dynamics. Later those dynamics were combined with passerine functional groups in a GLM Elasticnet model. That model provides information regarding the predictive performance of EFA/EFT indicators to explain passerine diversity patterns. Once selected the best indicators we were able to do a trend analysis to assess landscape changes.

For the purposes of pre-processing and analysing satellite image time series, statistical analysis and modelling, the R software (version 3.6.0) was employed. A full list of packages used can be consulted on Appendix Table A1. To see further detailed and complete code, please consult the online GitHub repository: https://github.com/zepedro96/MSc-Thesis_Jose-Pedro-Silva

2.3. Spatial sampling design and bird surveys

Spatial sampling design

The development of the spatial sampling scheme as well as the field protocol to collect in situ passerine records was conducted during the IND_CHANGE project in 2014.

The IND_CHANGE project was aimed to provide an integrative view, by applying multiple modelling tools under a common theoretical and computational framework and from a spatially and temporally explicit approach. The focus was to improve the existing capacity to accurately forecast responses of standard ecological indicators to landscape change under alternative management scenarios.

This collaborative project involving scientists and stakeholders addressed three sequential questions: (1) How fit are pre-existing data to inform on relevant indicators of socialecological change, and which are the key data gaps? (2) Which modelling frameworks are more suitable to predict and forecast estimates of such indicators under current and future conditions? And (3) Can integrative and collaborative computational tools improve and disseminate the application of model-based social-ecological research in adaptive land planning and management?

IND_CHANGE was conducted by experienced researchers in the study of biodiversity, landscape ecology, and environmental and social-ecological change. A consortium of five national research institutions led by CIBIO/ICETA (InBio Associate Lab) was advised by three top international experts on social-ecological system analysis, spatial planning and natural resource management, and international reporting. Excellence training and mobility opportunities were thus awarded to six young researchers who were hired to support specific tasks. Two administration stakeholders provided the context and requirements for developing and testing the new tools while ensuring post-project system sustainability. A stakeholder advisory commission with representatives from relevant regional administration and private stakeholders was also organized.

In the project the sampling design followed a two-step approach. Firstly, the study area was divided into 1 km^2 plots – i.e., Primary Sample Units (PSU), as in Figure 7. From this grid, there was a stratified selection of PSUs that represented the spatial heterogeneity of the landscape using four layers (climate, topography, soil types, and protection regime protected areas) combined in the Partition Around Medoids clustering algorithm (Mächler et al., 2012). Six strata were obtained after checking clustering validity indices used to select an adequate number of clusters (Rousseeuw, 1987). The result was a selection of 24 PSU (with a minimum of three on each stratum and proportional to each stratum area).

Since the area for each PSU was rather large a second step was needed to diminish the sampling effort. Each 1 km^2 PSU was divided into five 0,04 km^2 Secondary Sample Units (SSU), located at each one of the four corners and one in the centre.

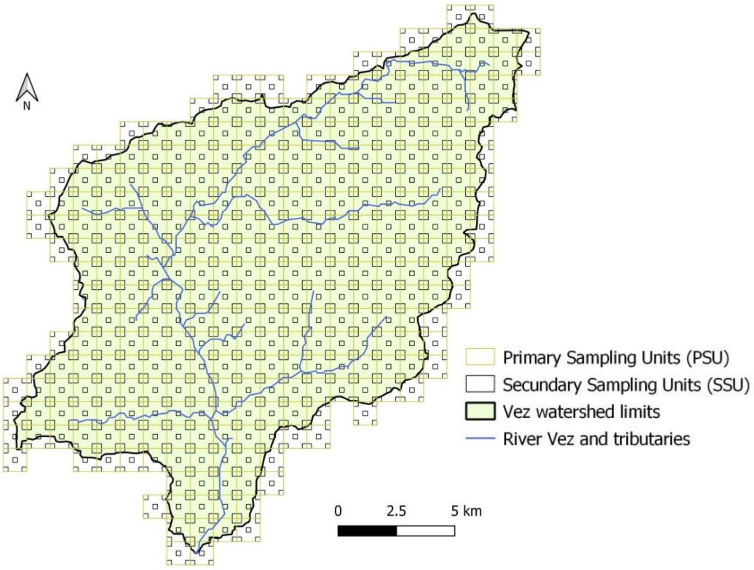


Figure 7 - Representation of the grids: 1000x1000m and 200x200m (restricted to selected stage 2 units) in the Vez watershed.

This design was key to maximize the distance between SSUs and to avert overlapping of birds count. This means that there were a total of 120 secondary units. The number decreased to 111 units due to complications in accessibility to the plot area (Figure 8) (Civantos et al., 2018).

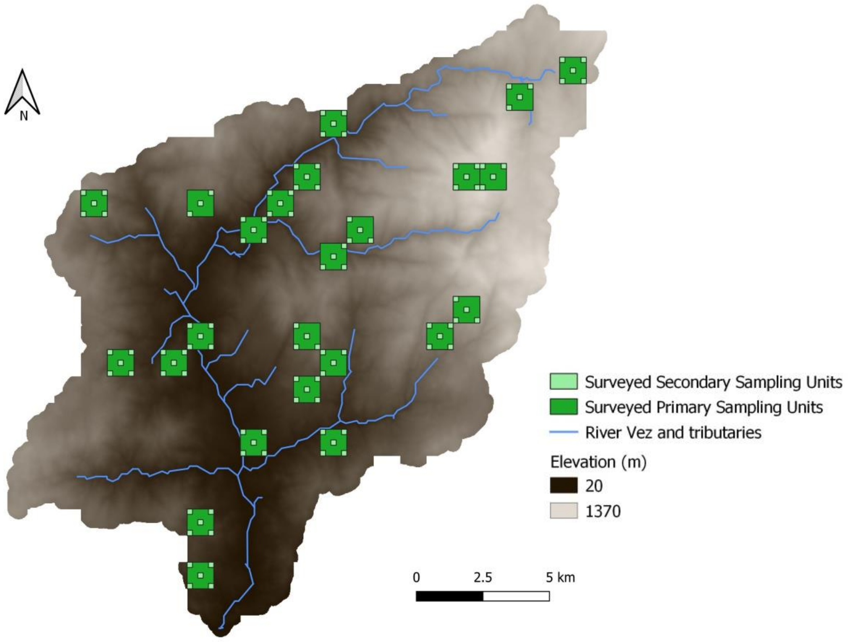


Figure 8 - Surveyed units (PSU and SSU).

Bird surveys

Species richness of passerine birds was evaluated over the 111 plots (separated at least 400m from each other) using a 100m fixed radius point-count approach (Bibby et al., 2000). The surveys were performed from May until mid-June of 2014, during the breeding season. Surveys were executed within the first 3 hours in the morning or the 2 hours before sunset. Days with strong wind, rain or cold weather were avoided. Species richness was then obtained by estimating the total number of passerine species per 10 minutes per SSU plot (Civantos et al., 2018). The total and the per group species richness by PSU was calculated by adding up the number of recorded species in the nested SSUs. Species richness values calculated this way, at the PSU level (1km^2 units), were used as the response variables in subsequent analyses.

2.4. Trait-based bird classification

To facilitate the analysis of species data and instead of investigating individual species responses to EFA/EFT diversity/heterogeneity, an a priori classification and grouping of species based on functional traits was performed. Species grouping also allowed assessing if the predictive performance of EFA/EFTs varied across passerine functional groups. This process used various bibliography sources, namely: Svensson et al. (2012) Guia de Aves. *Assírio & Alvim, Porto Editora Lda: Porto;* Peterson et al. (2004) Birds of Britain and Europe*. HarperCollins;* HBW Alive: Handbook of the Birds of the World Alive*;* Sterry et al. (2003) Field Guide to the Birds of Britain and Europe. *AA Publishing.*

The observed species were categorized according to feeding type, habitat type, nest type, and size (Table 2). This classification is not mutually exclusive (with the exception of size classification), which means that a species can belong simultaneously to more than one class (e.g., a species can be both Frugivorous and Insectivorous if its diet is consistent with this dual classification). This often happens because species exhibit different habits depending on the season of the year, and are conditioned by abiotic and biotic factors (Yoshikawa and Osada, 2015).

Table 3 – Classification for passerine traits.

Types	Class	Notes
Feeding	Omnivorous	*Species with more than 3 feeding types, plus appearing in the bibliography as omnivorous*
	Frugivorous	*Feeding on fruit*
	Granivorous	*Feeding on seeds or grain*
	Insectivorous	*Feeding on insects*
Habitat	Urban and suburban	*Includes cities, towns, rural villages, urban parks and gardens*
	Woodland	*Areas where the dominant vegetation is trees*
	Farmland	*Land specifically used for agricultural purposes in the raising of crops or livestock.*
	Wetlands	*Areas covered by water, including river banks, marshes and ponds*
	Meadows and grassland	*Open habitat dominated by grasses*
	Upland	*Altitude habitat with shrubs and rocky areas*
	Heathland	*Open landscapes dominated by plants such as Heathers, Gorse and heathland grasses and punctuated by scattered trees*
Nest	Artificial urban	*In man-made structures*
	Cliff	*In vertical rock faces*
	Tree	*In branches of trees*
	Tree cavity	*Holes in trees*
	Cavity	*All sort of cavities except tree cavities*
	Shrub	*In shrubby vegetation*
	Ground	*On the ground*
Size	S	*[9.1 – 13.3[cm*
	M	*[13.3 – 14.9[cm*
	L	*[14.9 – 18.4[cm*
	XL	*[18.4 – 63] cm*

Regarding the species that were only able to be identified to the genus level the classification by types was treated case by case (see also Appendix Table A2) and following the rules outlined in Table 4.

Table 4 – Criteria used for species identified to the genus level.

Conditions	Criteria
Only species present in the region according to bibliography	Use of that species
Only species found in the region according to the surveys	Use of that species
If there are more species of the genus found in the region	Use of the most abundant species of the genus in Portugal
If there are equal values of abundance for several species of the same genus	Mean values of the various species with the higher equal value of abundance

2.5. Satellite remote sensing data processing

Satellite platform and data description

Currently, there are a few satellite-based scientific missions that consist on collecting open and readily available Earth Observation data which have optical sensors on-board. These include satellite platforms such as: Landsat, MODIS and Sentinel-2. Of these, Landsat missions are the most appropriate for long-term biodiversity and ecological monitoring taking in account the fact that they have a resolution similar to Sentinel-2 but a much longer active time and data archive dating back from the 1970’s. More precisely, Landsat includes a total of eight missions, covering over 45 years (NASA, 2013, 2014; European Space Agency, 2016). MODIS also has a long time series, nearing now 20-years, but it presents a lower spatial resolution and therefore a mismatch with the fine-scale passerine sample data and its diversity patterns collected from the field. As such, Landsat archive offered the best compromise for analysis given the objectives in the thesis.

One key aspect regarding sensor design of Landsat missions is continuity. As such, the main features and resolution of the bands is compatible after Landsat 5 (launched in 1984), when the sensor TM was incorporated, having a 30m resolution. Landsat 7 Enhanced Thematic Mapper Plus (TM+) and Landsat 8 Operational Land Imager (OLI) also have the 30m resolution, making it possible to analyse 35 years with Landsat 5, 7 and 8 (NASA, 2013). Further detailed information on Landsat program can be consulted on Appendix Table A3 and Table A4.

Input data

For analysing landscape pattern and its change, we used EVI which can be evaluated over the course of a time series. To get this time series, Google LLC provides a service called Google Earth Engine (GEE, https://earthengine.google.com), which can be described as a platform for scientific analysis and visualization of geospatial datasets. This cloud-based service possesses several types of satellite data, namely Landsat data, already pre-processed in the form of spectral vegetation and water indices (e.g., NDVI, EVI). From GEE, collections of EVI images forming a dense time series from Landsat missions 5, 7 and 8, spanning from 1984 to 2019, can be accessed, analysed and downloaded.

All these satellites have a temporal resolution of 16 days, but with the pre-processing made by the service we get a 32-day composite of all images collected during that period (Google LLC, n.d.) nearing one image per month.

Time series gap filling and smoothing

The methodology and subsequent algorithm used for this section was developed by João F. Gonçalves (2017). In order to have a complete time series we filled data gaps in Landsat time series by using a moving average data-imputation algorithm (with k= 4 images). This works by removing the seasonal component from the time series, performing the imputation on the deseasonalized series and afterwards adding the seasonal component back again (Moritz and Bartz-Beielstein, 2017).

For improving the retrieval of meaningful information from the EVI time-series, and increase the signal-to-noise ratio, two procedures were used in tandem, combining robust outlier detection/removal and time-series smoothing:

(i) the Hampel filter (Hampel, 1974; Davies and Gather, 1993) with k=3 (number of observations) and t=3.5 (factor to consider a point an outlier) and

(ii) Whittaker-Henderson smoother [attributed to Whittaker (1922)] with upper envelope fitting meaning that larger annual values receive more weight in the smoothing with lambda (defining the smoothing amount) equal to 5.

Calculation of Ecosystem Functioning Attributes

It is possible to use EVI time-series to calculate annual indices that are representative (i.e., a surrogate) of the ecological systems dynamics (Cabello et al., 2012) more specifically of ecosystem carbon gains. Using these indices, it is possible to characterize: productivity (amount of biomass, vegetation cover, 'greenness' levels), seasonality (the intra-annual range or variation), and phenology (timing of certain events in the annual vegetative cycle; e.g., day of growing-season peak).

To capture productivity, we considered the annual average, with x_i equal to an EVI value in a given 32-day period i={1,…,12}; in total, a year y has a maximum of 12 values. To evaluate seasonality, we first calculated annual extrema (maximum and minimum) and then annual amplitude. Annual standard-deviation was also used to assess seasonality (e.g. a forest with deciduous trees would have higher values of the standard-deviation compared to a forest of evergreen species). For analysing phenology, and taking into account the cyclical properties of this variable, we calculated the season of the day of maximum EVI recorded annually, ranging between 1 and 4, with 1 corresponding to winter and 4 to autumn (representing when the peak of the growing season occurs) (see Table 5).

All indices were calculated using the smoothed EVI time-series to avoid spurious values and to minimize errors.

Table 6 – EFAs indices used and their respective formulas

Index	Meaning	Formula
Annual average	The mean value of the year represents a surrogate of the system productivity	$AVG_y = \frac{\sum_{i=1}^{n} x_i}{n}$
Annual std-deviation	Represents seasonality	$SD_y = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})}{n-1}}$
Annual extrema: minimum and maximum value	Minimum and maximum values of EVI represent seasonality	$MAX_y = maximum(x_i)$ $MIN_y = minimum(x_i)$
Annual amplitude	Represents seasonality	$AMP_y = maximum(x_i) - minimum(x_i)$
Season of maximum	Attributes a value ranging from 1 to 4 for each season to indicate on which the max value of EVI occurred, corresponding to the peak of the growing season	$Smax = season(maximum(x_i))$ $season(x)$ → season on which the maximum value occurs

Calculation of Ecosystem Functioning Types

Ecosystem Functional Types are defined as “*groups of ecosystems or patches of the land surface that share similar dynamics of matter and energy exchanges between the biota and the physical environment*” (Paruelo et al., 2001). The calculation of EFTs was made based on the combination of EFAs for the average (represents productivity), amplitude (represents annual variability) and season of the maximum (phenology, growing season) similarly to the approach of (Alcaraz-Segura et al., 2006). In order to divide by types, the average and the amplitude were split up into 4 classes by the distribution quartiles. Then each class was based on the combination of the quartiles and the season maximum. For example, EFT type ‘111’ represents: low productivity and low annual variability with a maximum in winter. The total number of different EFTs generated is 64 (Table 5). EFT’s are calculated independently by year and thus are relative to the distribution of EFA values in each annual interval.

Table 7 – EFTs classification scheme following the combination of the annual mean, amplitude and season of the year where the maximum EVI value occurs.

			Annual variability						
			Low			High			
			1	2	3	4			
Productivity	Low	1	111	121	131	141	1	Winter	**Season of maximum**
			112	122	132	142	2	Spring	
			113	123	133	143	3	Summer	
			114	124	134	144	4	Autumn	
		2	211	221	231	241	1	Winter	
			212	222	232	242	2	Spring	
			213	223	233	243	3	Summer	
			214	224	234	244	4	Autumn	
		3	311	321	331	341	1	Winter	
			312	322	332	342	2	Spring	
			313	323	333	343	3	Summer	
			314	324	334	344	4	Autumn	
	High	4	411	421	431	441	1	Winter	
			412	422	432	442	2	Spring	
			413	423	433	443	3	Summer	
			414	424	434	444	4	Autumn	

Spatial metrics of heterogeneity based on EFAs and EFTs

To analyse the relation between passerine diversity and diversity/heterogeneity in ecosystem functioning (EFD) attributes and types another step was needed. Because birds generally have a high mobility and generally high dispersion ability and to minimize sampling bias we quantified species richness (total and by group) for the whole 1km^2 PSU grid. This analysis unit also allowed to quantify the existing diversity/heterogeneity in EFA/EFTs using the mean value (centrality) and especially the standard-deviation (dispersion) for EFAs since these are continuous values.

Because EFTs are discrete entities, a different approach must be used. As such, the following diversity metrics Shannon and EFT richness as well as evenness (E_{var}) were calculated (preliminary tests discarded other diversity/evenness metrics due to poor correlation – not shown). Diversity and evenness are two aspects that allow us to characterize a landscape. While diversity refers to the measurement of different categories or types present in an area (e.g., land use/cover types; with heterogeneous landscapes having higher values of diversity richness), while evenness refers to the relative percentage of the distribution of the types (Nagendra, 2002).

The Shannon index (Shannon and Weaver, 1964) is one of the most commonly used indices to measure alpha-diversity and is defined by:

$$H = \sum_{i=1}^{n} pi \ln(pi)$$

(Eq. 1)

In this formula (Eq. 1) $\boldsymbol{n}$ equals to the number of types (e.g., species, land cover categories) and pi to the proportional abundance of each type, and the result ranges between 0 and infinity. This index estimates the average uncertainty in predicting which type a randomly selected sub-unit of the landscape will belong to (Whittaker, 1972; Magurran, 1988; Nagendra, 2002; Spellerberg and Fedor, 2003).

EFT richness was calculated by counting the number of different types of EFT present in 1km^2 unit. This was done using a vector, in which its length indicated the richness of a pixel (e.g. if the length was four, then there would be four types of EFTs in that particular pixel).

Another index used was evenness E_{var} , proposed by Smith and Wilson (1996). This index is based in Camargo (1993) evenness index and is defined as:

$$E_{var} = 1 - \frac{2}{\pi} arctan\left\{\sum_{s=1}^{S}\left(\ln(x_S) - \sum_{t=1}^{S}\ln(x_t)\Big/S\right)^2 \Big/S\right\}$$

S = total number of land cover types in the sample
x_S = abundance of the s land cover type
x_t = abundance of the t land cover type

(Eq. 2)

In this equation (Eq. 2) log variance of abundance of types is used to measure evenness and to examine proportional differences, making it independent of the units used. Later, a transformation with $arctan$ limits it to a scale that ranges from 0 (minimum evenness) to 1 (maximum evenness). Landscapes with lower evenness suggest that the elements present have asymmetrical frequencies of distribution, whereas landscapes with higher evenness suggest that different types of elements are more similarly and evenly distributed.

In total, there are 15 index to be analysed, as Table 8 shows.

Table 8 – Summary of Ecosystem Functioning Diversity indices used in the analyses.

Index		**Metrics**	**Abreviation in graphs**
Ecosystem Functioning Attributes	Annual maximum	Standard deviation	EFAmax_std
		Average	EFAmax_avg
	Annual amplitude	Standard deviation	EFAamp_std
		Average	EFAamp_avg
	Season of maximum	Standard deviation	EFAsemax_std
		Average	EFAsemax_avg
	Annual average	Standard deviation	EFAAverage_std
		Average	EFAAverage_avg
	Annual minimum	Standard deviation	EFAmin_std
		Average	EFAmin_avg
	Annual standard deviation	Standard deviation	EFAstd_std
		Average	EFAstd_avg
Ecosystem Functioning Types	Shannon	shannon	
	E_{var}	evar	
	EFT richness	eft_count	

2.6. Passerine diversity analysis and modelling

To relate the response variables (overall species richness and species richness by group) and Ecosystem Functioning Diversity predictive variables (EFD; Table 6) we used elastic net regression (Friedman et al., 2010) which selects the most suitable variables incorporating multiple collinear explanatory factors and is based both on lasso regression and ridge regression thus being more resistant to overfitting (De Mol et al., 2009; El-Gabbas and Dormann, 2018). The formula is as follows:

$$C = SSE + \alpha\rho||L1|| + \alpha(1-\rho)||L2||$$

SSE = sum of squared errors

ρ = relative weighting term

α = penalty weighting term

$L1 = \sum||\beta||$ → Absolute value of all parameter coefficients

$L2 = \sum||\beta^2||$ → Sum of all parameter coefficients squared

(Eq. 3)

Generalized Linear Models (GLM) with Elastic net is an algorithm which uses two penalties, lasso regression penalty and ridge regression penalty, controlled by a weighting factor α. In our case $\alpha\rho$ = 0,5 to give the same weight to both penalties (if: $\alpha = 0 \rightarrow Ridge$; $\alpha = 1 \rightarrow Lasso$). The merged regression analysis penalizes model complexity and forces the coefficients of trivial parameters to zero, identical to a lasso regression (Tibshirani, 2011; Park and Mazer, 2018). But it also “groups” them in a way that the weights of the coefficients are distributed across all collinear parameters, stabilizing it and avoiding problems with variance inflation commonly found in other based regressions that use highly collinear datasets (De Mol et al., 2009; Raschka and Mirjalili, 2017; Park and Mazer, 2018).

After the variable selection done by elastic net algorithm (i.e., retaining only variables with non-zero coefficients) we used “simple” Generalized Linear Models with Poisson family-type errors (also used in GLM Elastic net), on which the excepted values y_i are the counts of the number of occurrences of a certain event under different conditions (Boyce and McDonald, 1999). This step allowed to quantify the goodness-of-fit of the models based on pseudo-R^2 measures (which is not trivial to calculate with GLM elastic net), calculate variance inflation for checking potential multicollinearity issues and check for over-dispersion in the data (which limits the use of Poisson models).

$$y_i = \exp\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)$$

x_i = independent habitat variables

β_i = selection coefficients

(Eq. 4)

In GLM, β_0 and β_i (Eq. 4) are usually obtained using the principle of maximum likelihood and iterative calculation (Manly et al., 2002).

The next steps were to quantify the pseudo R^2 to assess the overall fitness of the models and to observe how much a variable (or combination of) is able to explain the variation of the model. The pseudo R^2 is an unitless measure that ranges from 0 to 1 (1 being perfect fit), being useful to compare models that have different units (Quinlan, 2006; Nakagawa and Cuthill, 2007). We used two types of pseudo R^2: Efron (1978) and Nagelkerke (1991).

In 1978 Efron proposed an index (Eq. 5) where $\hat{\pi}_i$ is the model predicted probabilities, y_i the observed binary outcomes and $\bar{y}$ the mean outcome (Smith and Mckenna, 2013).

$$R^2_{\text{Efron}} = 1 - \frac{[\sum_i (y_i - \hat{\pi}_i)^2]}{[\sum_i (y_i - \bar{y})^2]}$$

(Eq. 5)

In 1991 Nagelkerke developed a rescaled pseudo R^2 index based on the formulated by Cox and Snell (1989) (this last one could potentially exceed 1.0).

$$R^2_{Nagelkerke} = \frac{1 - \left(\frac{L_0}{L_\beta}\right)^{2/n}}{1 - L_0^{2/n}}$$

(Eq. 6)

In this index (Eq. 6) L_β is the likelihood of the full model and L_0 is the likelihood of the functions for the intercept-only model; n is the total size (Nagelkerke, 1991; Nakagawa and Schielzeth, 2013; Smith and Mckenna, 2013).

The next phase was to determine the variance inflation factors (VIF) in order to check the multicollinearity of the variables selected. Multicollinearity is the dependence among predictors in a regression model (Belsley et al., 1980; Thompson et al., 2017) and can be measured through VIF (Fox et al., 2010).

$$\text{VIF}_j = \frac{1}{1 - R_j^2}$$

(Eq. 7)

VIF_j (Eq. 7) is the variance inflation factor for the jth predictor and can take on values from unity to infinity; R^2 is the multiple correlation coefficient. For VIF values to be acceptable they should be <10 (Hair et al., 1995).

When applying a Poisson distribution model a verification of overdispersion is also needed due to the possibility of the variance being higher than the mean, which means that data is overdispersed (in that case an alternative model to Poisson must be applied, usually negative binomial) (Dean, 1992).

To check for overdispersion one can apply a variety of tests that includes Likelihood Ratio Test (LRT), Dean's P_B and P'_B tests (Gómez-Rubio et al., 2005). LRT test compares the goodness-of-fit of two models, a nested Poisson model against a nested Negative Binomial model to assess ρ value (Brown and Zhao, 2002). Dean's P_B and P'_B are both score tests. On all tests values closer to 1 mean that overdispersion is not occurring and Poisson model is indeed a correct choice model for the data (Dean, 1992; Yang et al., 2009).

2.7. Trend analysis of EFAs and EFTs heterogeneity indicators

Trend analysis based on Ecosystem Functioning Diversity (EFD) indices allows assessing which areas of the landscape potentially reveal most changes and explore potential modifications in passerine communities' composition and diversity.

For this purpose, we first performed a selection of the best spatial metrics of diversity/heterogeneity based EFAs (continuous approach) and EFTs (discrete approach) supported by the GLM Elasticnet models. The trend analysis of these two selected indicators was then implemented for three nested periods: complete period of 35 years (1984-2018), last 20 years (1999-2018) and last 10 years (2009-2018).

The Theil-Sen slope was used for this analysis, which allows calculating a robust non-parametric measure of the magnitude, sign and significance of the trend. This method minimizes the effects of noisy pixels in the time-series, being less sensitive to outliers (Olthof and Fraser, 2014). For this purpose the function "sens.slope" of the R package "trend" can be used (Pohlert, 2018) (Eq. 8), where d is the slope, x denotes the variable, n is the number of data, i and j are indices (note that $1 \leq i < j \leq n$):

$$d(k) = \frac{(x_j - x_i)}{j - i}$$

(Eq. 8)

After that first step the median of all slopes is calculated (Eq. 9), generating the Sen slope (b):

$$b = median\ d(k)$$

(Eq. 9)

3. Results

3.1. The local passerine community

Number or relative frequency of families, genera and species

Field surveys found a total of 61 passerine species of 35 genus and 22 families on the study area, the most common family being Muscicapidae (a family that includes robins, stonechats and rock thrushes) (Figure 9). Of those 61 species, 11 were only identified to the genus level.

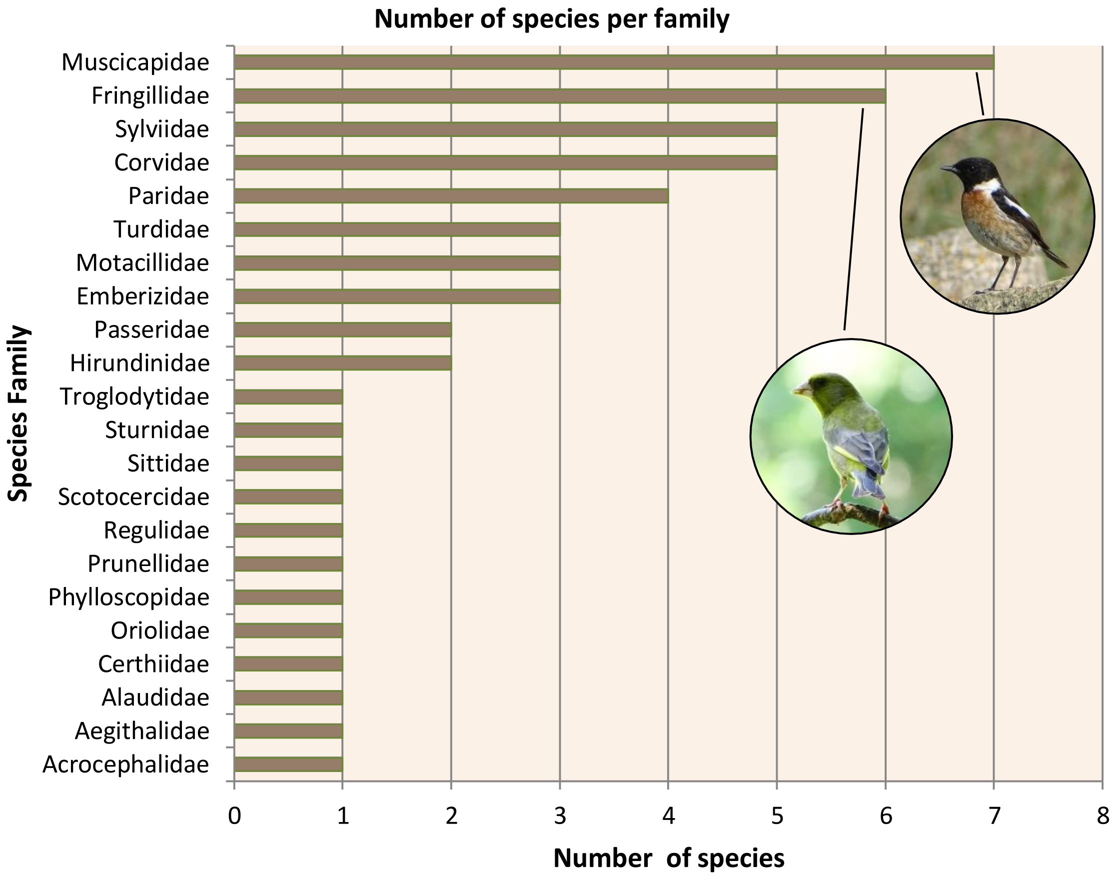


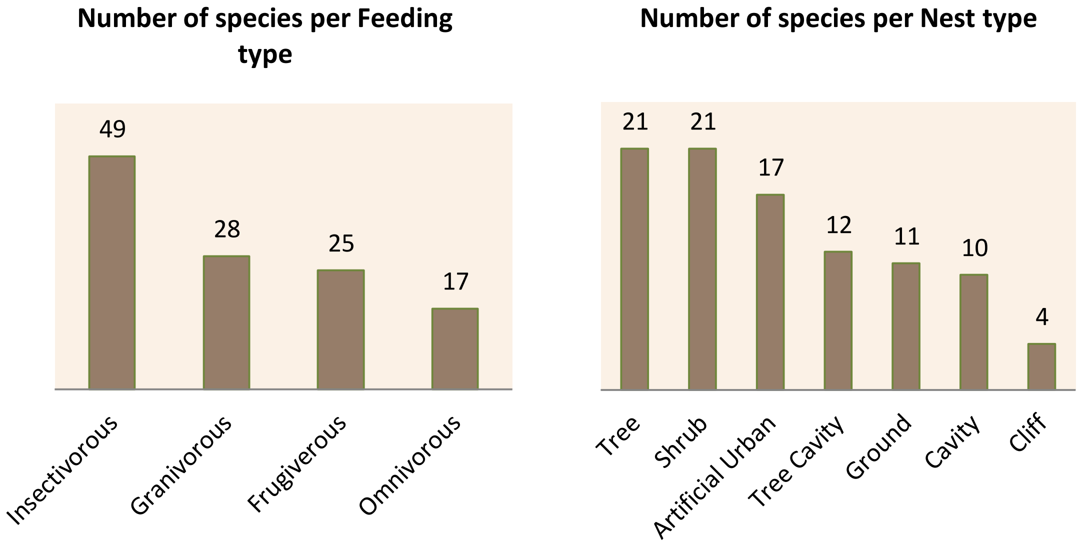
Figure 9 - Number of passerine species per family and examples of species of the 2 most numerous families (from top down: *Saxicola rubicola, Chloris chloris*)

Species traits distribution

With the support of the bibliography previously mentioned, species were classified according to feeding, habitat, nest and size type. The classification is not mutually exclusive which means that the sum of species by each category is bigger than the real species total (with the exception of size type). Regarding size type the classification was done by dividing the distribution of size values in quartiles, each class frequency regular. When it comes to feeding type (Figure 10A), the most common type was insectivorous totalling 49 species. And the less common was omnivorous birds with 17 species.

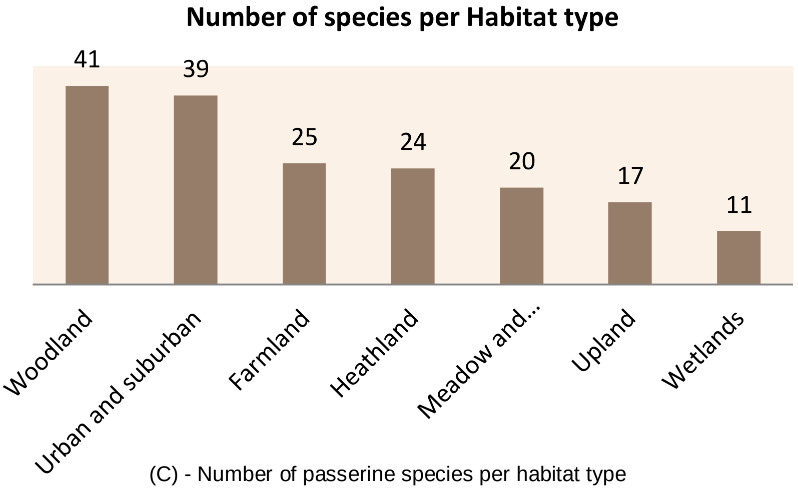
Respecting nest type (Figure 10B) there was a high variability of types, with the most common being trees, shrubs and artificial urban locations. Cliffs seem to be the chosen nest site of only a few select passerine species.

Concerning habitat type (Figure 10C), woodland and urban/suburban types of habitat were the most frequent habitats but the distribution was much diversified, with interesting values for other locations too, having wetlands the lowest value.



(A) - Number of passerine species per feeding type

(B) - Number of passerine species per nest type



(C) - Number of passerine species per habitat type

Figure 10 – Species richness per functional group: (A) – Feeding type; (B) – Nest type; (C) – Habitat type.

3.2. Ecosystem Functioning Attributes (EFA) and Types (EFT)

Plots of raw vs. smoothed series by land cover/use type

With the help of tools such as the Portuguese Land Use Map (COS – *"Carta de Uso e Ocupação do Solo de Portugal")* and street view from Google we were able to identify certain types of land cover/use types and pin them geographically, later plotting them with raw and smoothed data of a time series ranging from 1984 to 2019 (Figure 11 Figure 13). Note that the scale of EVI (y-axis) changes between figures.

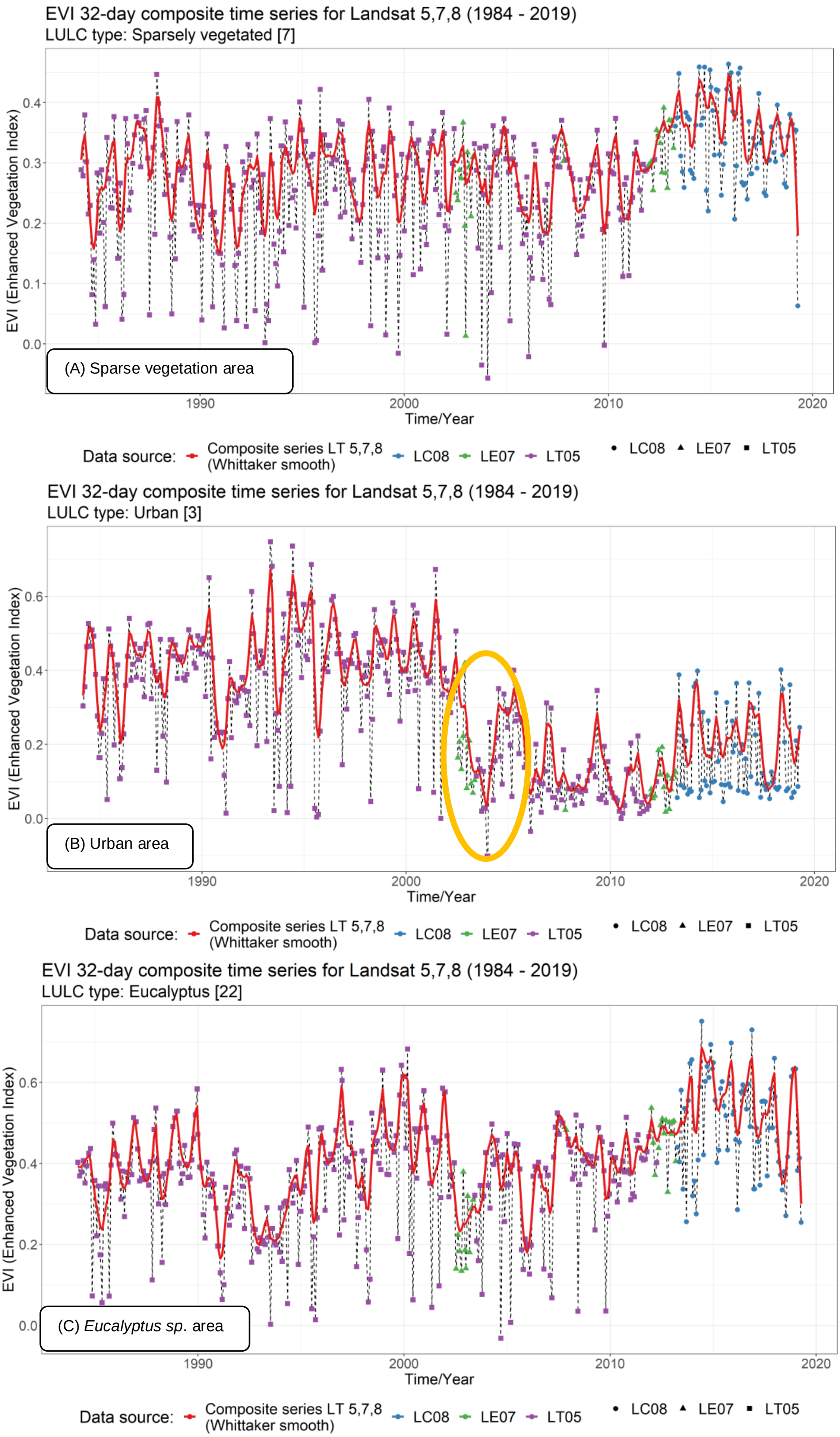


Figure 11 - EVI 32-day composite time series of sparse vegetation (A), urban area (B) and *Eucalyptus sp.* area (C)

EVI levels for sparse vegetation (Figure 11A) are the lowest, meaning that the productivity of this type of land cover is also generally low. In general, this type of vegetation also shows low seasonality. On our study area it covers around 8,11km^2 (3,08%).

The illustrative pixel used for Figure 11B corresponds to an area of what is now an industrial zone known as "Parque Industrial de Mogueiras", occupying 0,2km^2. Prior to 2003 this was an area occupied by maritime pine (*Pinus pinaster*), shrubs and cultivated land (based on 1995 COS). That fact can be observed on the plot, indicated with the orange circle, when it occurred an enormous drop on EVI levels, from 0,6 to around 0, showing the complete removal of vegetation and its conversion into an artificial surface.

Searching for images from previous years and comparing them with present ones, we can also observe the construction of that industrial zone (Figure 12). This area highly altered with man-made structures shows very low levels of EVI such is the absence of vegetation in the area (EVI being a measurement of vegetation greenness it is very low on deeply urbanized areas like this), with only a few remnants of its previous condition. Urban areas occupy an area of 13,45 km^2 (5,11%) of the landscape.

Figure 12 – Satellite image of pre and post urbanization (07/09/2003 vs 21/02/2004)

Eucalyptus spp. plantations on the study area represent about 7,62% with 20,03km^2 occupied. When analysing the EVI time series for this type (Figure 11C) we can see clearly what could be cyclical cuts with roughly seven to ten years of frequency. The vegetation reaches high levels of EVI of about 0,6 showing good productivity levels, and values as low as 0,2 corresponding to the post-harvest situation.

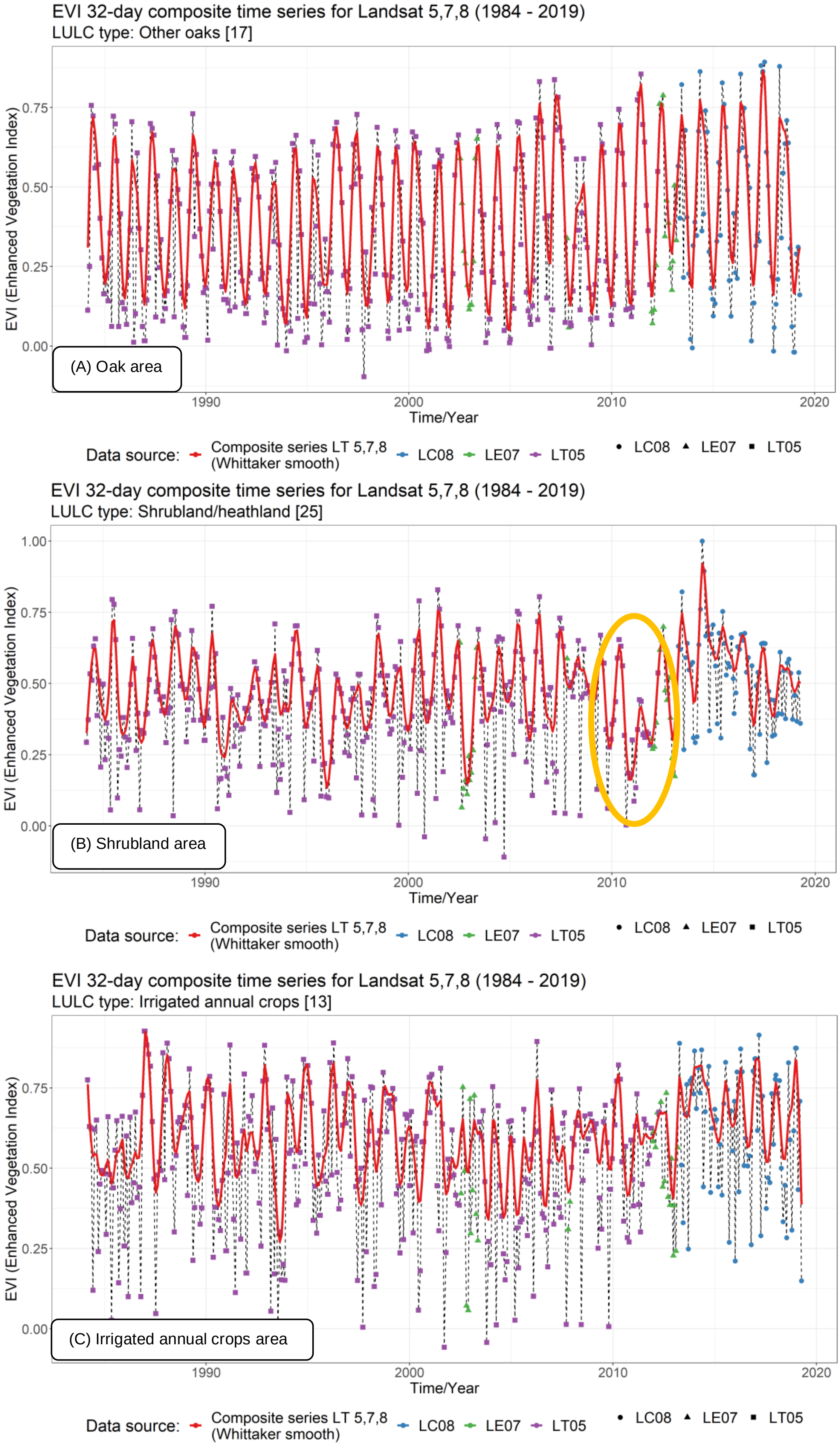


Figure 13 - EVI 32-day composite time series of an oak area (A), a shrubland area (B) and irrigated cropland area (C)

The next figure is a contrast to the preceding one, representing a more stable pixel dominated by species of oaks, namely *Quercus robur* (pedunculated oak, Figure 13A). The seasonality of these trees and deciduous formations can be observed with the regular maximum reaching values as high as 0,8 (peak of the growing season) and minimums of little more than 0 (dormant season). We can also see a slight trend of increase in vegetation greenness over the 35 years' period potentially showing a steady increase in biomass. On the study area this type of land cover represents 12,91%, covering 33,93km^2.

Shrubland areas are very widespread on the territory being the major class of land cover (101,22km^2) making up around 38,52% of the area. The occurrence of fire in this type of fire-prone formations can be observed with the accentuated drop of EVI in 2010 (pointed out with the orange circle in Figure 13B).

Using satellite imagery it is also possible to see the effects of that fire (Figure 14), being clearly visible the new dark spot on September when compared to March of the same year.

Figure 14 - Pre and post fire (13/03/2010 vs 11/09/2010) (burnt area highlighted)

Irrigated annual crops (Figure 13C) have an expression of 7,96% on the area (20,92km^2). EVI values generally found in these areas are as high as in deciduous forest areas (in reaching 0,8), but with higher minimums, showing that it is a very productive and strongly seasonal type of land cover.

This 35 year-long smoothed time series show that different types of land cover present different types of response behaviour to indices that translate net primary production such as EVI. Urban land cover type exhibits the lowest values of EVI as does sparse vegetation (the presence of rock surface has similar behaviour that of artificial structures). By contrast, deciduous forest and temporary crops have the highest values for EVI.

Ecosystem Functioning Attributes (EFAs)

The maps on this section refer to the year of 2014, the same year as the birds' field surveys in an attempt to display the values for that year.

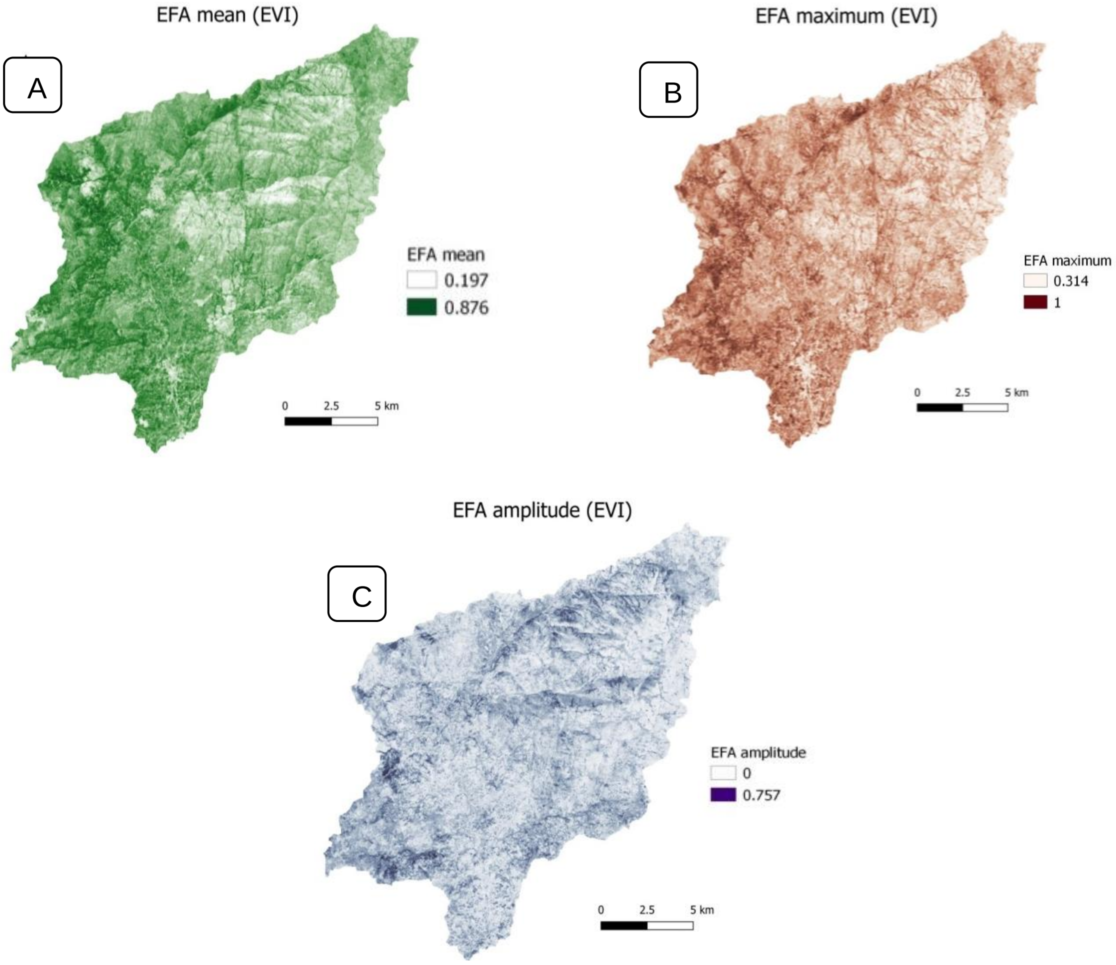


Figure 15 - Maps of EVI mean (A), of EVI maximum (B), EVI amplitude (C) in the Vez watershed.

Observing the mean values of EVI (Figure 15A) it is possible to check that high altitude areas on the eastern part of the territory generally have lower values, while the areas in the bottom of the river valley have higher EVI values. It is also possible to see that regions in the western part of the territory have even higher values. The centre of Arcos de Valdevez and the industrial zone are also visible in the southern part of the territory, with whiter spots (low EVI values).

The same patterns can be viewed in the annual maximum map (Figure 15B). The lack of vegetation in the town centre/industrial zone has the lowest maximum values, and oak areas on the western region have high levels of maximum (more productive).

On the amplitude map (Figure 15C) we can see small patches of *Quercus pyrenaica* that are present on the high altitude valleys on the eastern region, and *Q. robur* patches on the western area (on the other maps the first one is not so visible because they have lower productivity when compared to *Q. robur*, but due to their evergrenness they still have significant amplitude, which we can observe on this projection).

Ecosystem Functioning Types

The EFT classification shows a highly diversified landscape with various ecosystem functioning types (Figure 16) forming complex and diversified mosaics. All possible 64 EFT combinations were present in the study area, which indicates that this is a very heterogeneous region in terms of ecosystem functioning. It is possible to observe areas with generally low productivity levels on elevated mountainous regions, with productivity progressively increasing on the bottom of the valleys and in areas with woodlands typically dominated by oaks.

As observed on EVI time series, shrublands have a very strong presence in the area. Such type of land cover shows lower productivity levels (blue tones of the scale) corresponding to the higher altitude areas (along with sparse vegetation). The red tones of the scale correspond to maximum productivity of the vegetation and matches with the forested areas of oak. In general, there seems to be a trend of higher productivity areas following the path of the Vez river This pattern links not only to the agricultural land uses of valley areas but also to soil fertility and the occurrence of riparian galleries some of which in good conservation state.

Considering the timing of the maximum value, the vast majority occurred in the summer (64,60%) as it typically happens in temperate ecosystems, followed by spring (15,16%) and autumn (14,92%), and last in winter (with only 5,31%). It should be noted that some pixels with low seasonal variation (e.g., low shrubs, rock outcrops with sparse vegetation) the determination of the season peak is limited and with higher uncertainty. To see in further detail relative frequencies for each functioning type please check Appendix

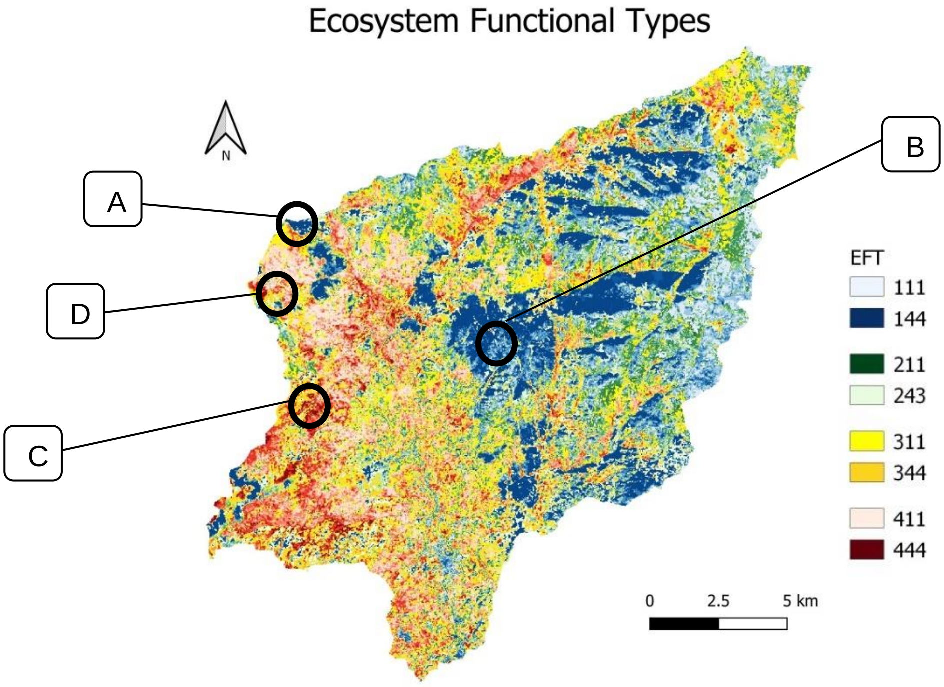


Figure 16 – Map of ecosystem functioning types in the Vez watershed.

Figure 17A shows an area dominated by shrubs, having low productivity (with blue colours dominating the EFT mapping); Figure 17B shows a region of shrubs and rock, having also low productivity (the map is dominated by low productivity EFTs being very homogeneous). Figure 17C shows the contrast between a forested area and a stream (lower part of the valley, more fertile) and a shrubby area (upper part, less fertile) (it is visible the red strip – that represents the forested/stream area - in the middle of yellow areas); Figure 17D shows a typical landscape mosaic. Around small villages it is typical to have a very heterogeneous landscape mosaic with artificial structures, farmland, patch edges and the surroundings often punctuated by some type of forest, more commonly *Eucalyptus sp*, maritime pine or/and oaks (such fact can be viewed on the EFT mapping where all the main categories occur, having more colours present than the rest).

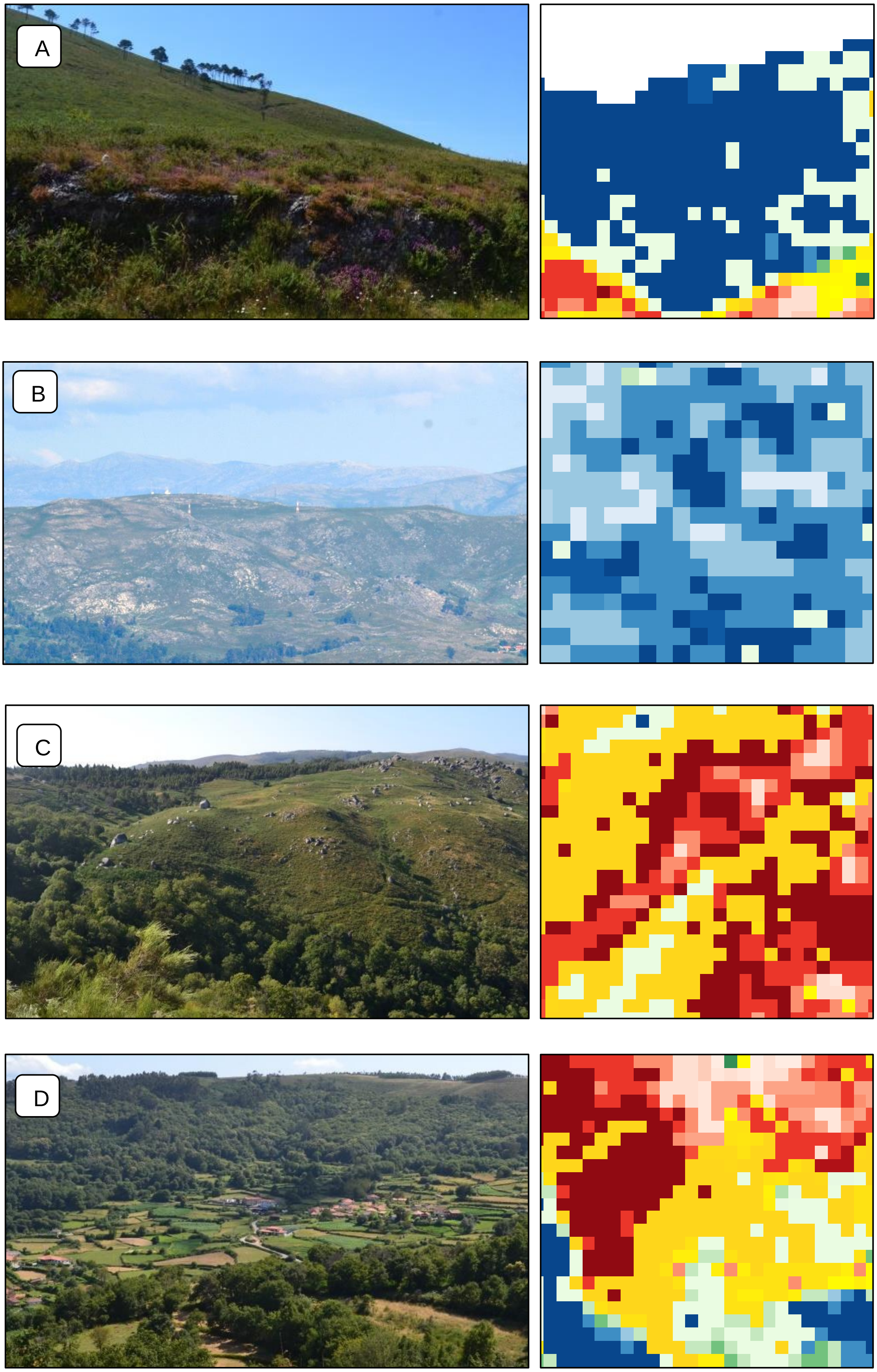


Figure 17 – Field photography compared with EFT map (with progressive increase of landscape diversity from A to D)

3.3. Patterns of EFA/EFT diversity

To evaluate more clearly the patterns of the landscape we upscaled the EFA/EFT data to 1km^2 grid thus portraying the variability, heterogeneity and diversity in ecosystem functioning (Figure 18 - note on all these maps the more saturated the colour the higher the value).

Regarding EFAs (average, maximum, amplitude of EVI) (Figure 18), these represent the heterogeneity of landscape mosaics occurring throughout the study area. Darker values on the maps represent greater heterogeneity which means a more diversified combination of land cover types with different primary production values in the annual EVI average, maximum or amplitude value (higher standard-deviation).

One thing that becomes clear is the greater homogeneity of the eastern region, a higher altitude region dominated by sparse vegetation and shrublands. The city centre and the industrial zone (*Parque Industrial de Mogueiras*, with very contrasting vegetated/artificial features) in the south become more obvious on the EVI maximum map too (more saturated colours).

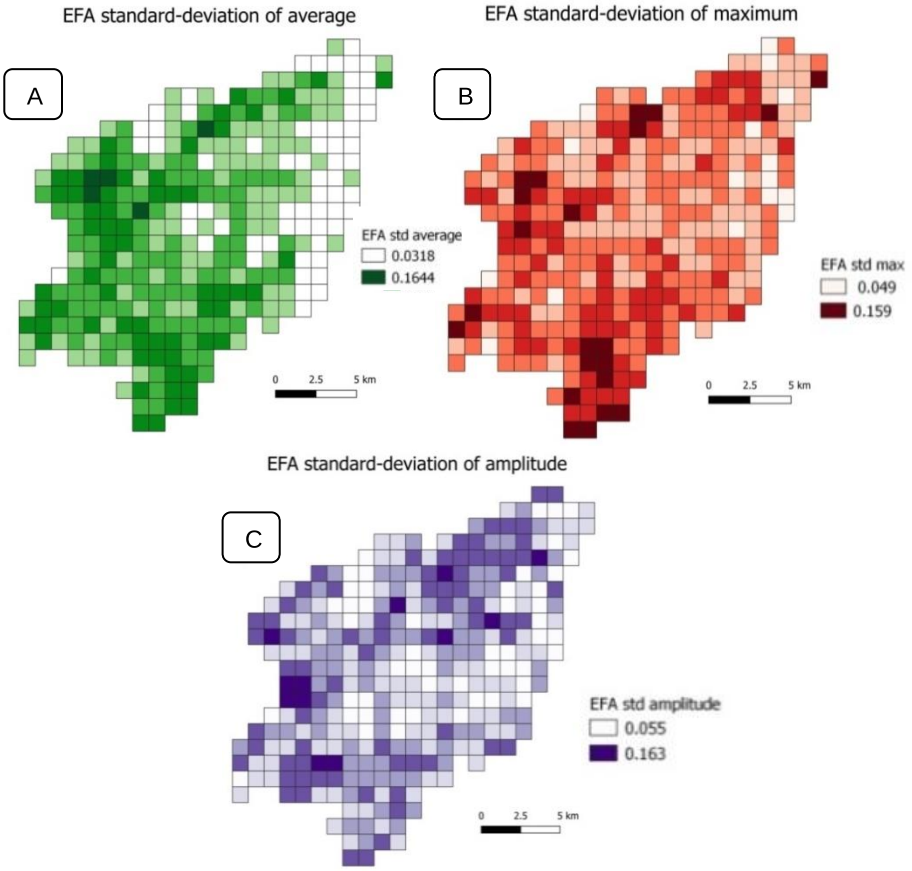


Figure 18 -- Map of 1km grid with EFA standard-deviation of the annual average (A), maximum (B) and amplitude (C) of EVI

.

EFT based maps (Figure 19) have similar characteristics but the underlying discrete data, these maps reveal different patterns of ecosystem functioning diversity. That could explain why the river main course is a bit more obvious, being clearly visible darker colours flowing through the centre of the map from south to northeast. The rest of the patterns previously observed on EFAs can still be noticed: lower richness values of land cover types present on the eastern region, and the diversified area of the city centre and industrial zone with strong contrasting land-cover types. Another interesting fact is the northwest region where small villages punctuate the area (having croplands, trees, and shrubs as in viewed on Figure 17B) appears on these maps as highly diversified, which indeed is.

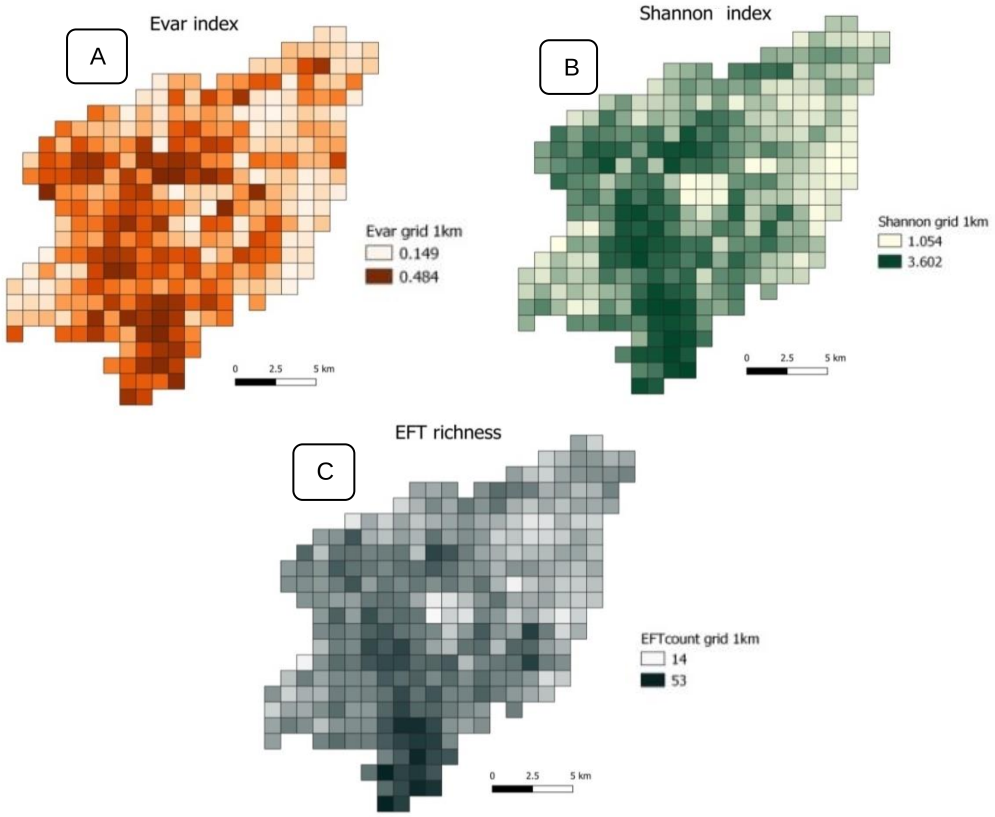


Figure 19 - Map of 1km grid for Evar (A), Shannon (B) and EFT richness (C) indices

3.4. Relation between passerine diversity and EFA/EFT diversity

Model preliminary testing

Over-dispersion test for Poisson count models

We tested the models for over dispersion with Poisson count models tests. Results for all tests (Likelihood-ratio, DeanB and DeanB2), reveal that over-dipersion is absent and therefore Poisson regression can ‘safely’ be applied to model the data. Results can be seen in further detail on Table A10 of the Appendix section.

Variance Inflation Factor

To test multicollinearity effects we used VIF. Results in most cases were <10 (considered the limit acceptable value for VIF results), which means they weren’t redundant with each other. Only for response variables *Nest type = Artificial Urban* and *Nest type = Tree Cavity* was found a high collinearity value which means that one of these variables: EFAstd_avg or EFAamp_avg - could be supressed from these models. Results can be seen in further detail on Table A11 of the Appendix section.

Best models and predictors of passerine diversity

Model performance

After checking for overdispersion and multicollinearity we modelled passerine diversity and selected the best indices. Using pseudo-R^2 measures (Effron and Nagelkerke) we obtained the results of Figure 20 which show the overall performance of GLM models of species richness by passerine functional groups vs. EFD indicators. These plots show that some response variables exhibit generally worse results than others and also that strong differences exist between groups in terms of predictive performance of EFD variables. Namely for Insectivorous (feeding type), Meadow and grassland, Upland and Heathland (habitat type), Shrub and Ground (nest type) and Small (size type) showed generally low performance. The remaining groups generally had

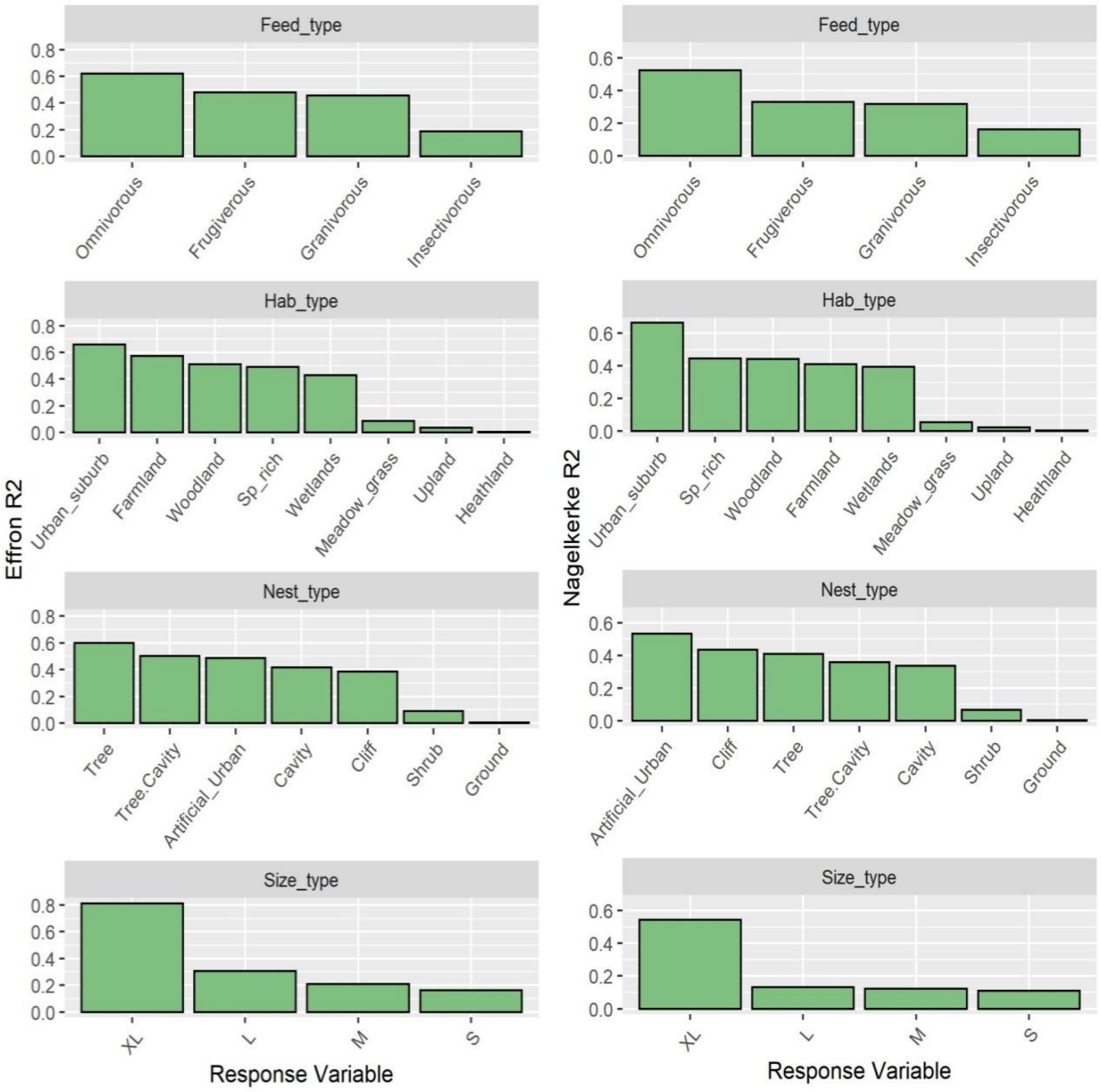


Figure 20 - Pseudo R2 tests to quantify the overall fitness of the models (Effron and Nagelkerke)

satisfactory to good results in terms of modelling performance. In particular, Omnivorous (feed type), Urban/suburban, Farmland and Woodland (habitat type), Tree, Artificial Urban (nest type) and XL (the largest size type) showed overall the best performance results (with all these models including k=4 predictors and solely linear terms with no interactions, and n=24 observations).

Best predictors

In respect to predicitive variables, the ones that had better results were: “EFAmax_std” (standard deviation of the annual EVI maximum), “eft_count” (EFT richness) and

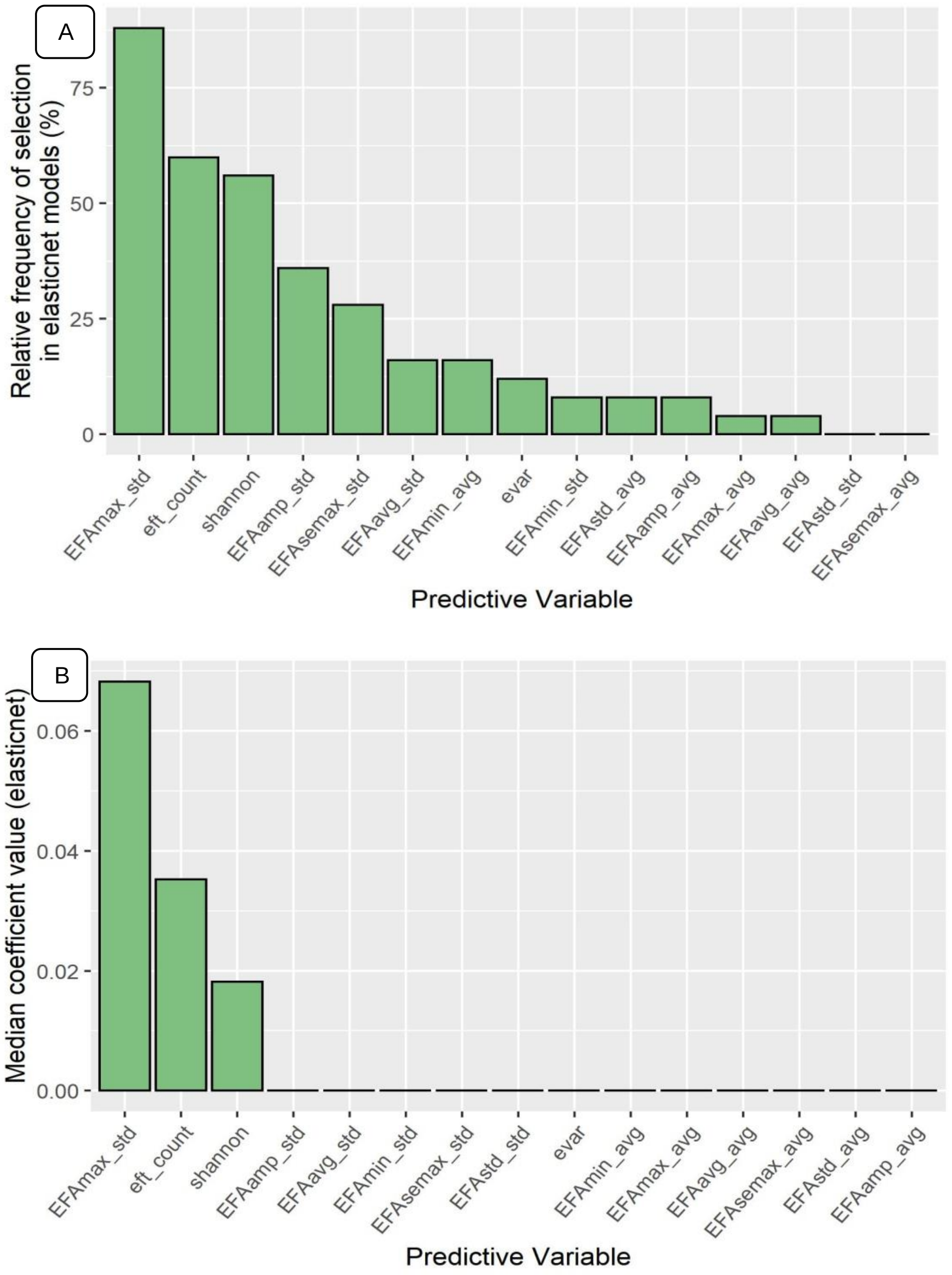


Figure 21 – (A) Relative frequency of selection in elasticnet models for each predictive variable
(B) Median coefficient values of GLM Elasticnet for each predictive variable

“shannon” (Shannon index of EFTs). Both relative frequency of selection (Figure 21A) and median coefficient values (Figure 21B) for GLM Elasticnet models had higher scores, having better perfomance (the relative frequence of selection of EVImax_std and eft_count was of ~90% and ~60%). All predictive variables showed a positive linear relation. Figure 21B also shows (as expected) median positive coefficients (across all passerine groups) for the best variables and, thus a general positive association between EFD and species richness.

Trends of EFA/EFT diversity

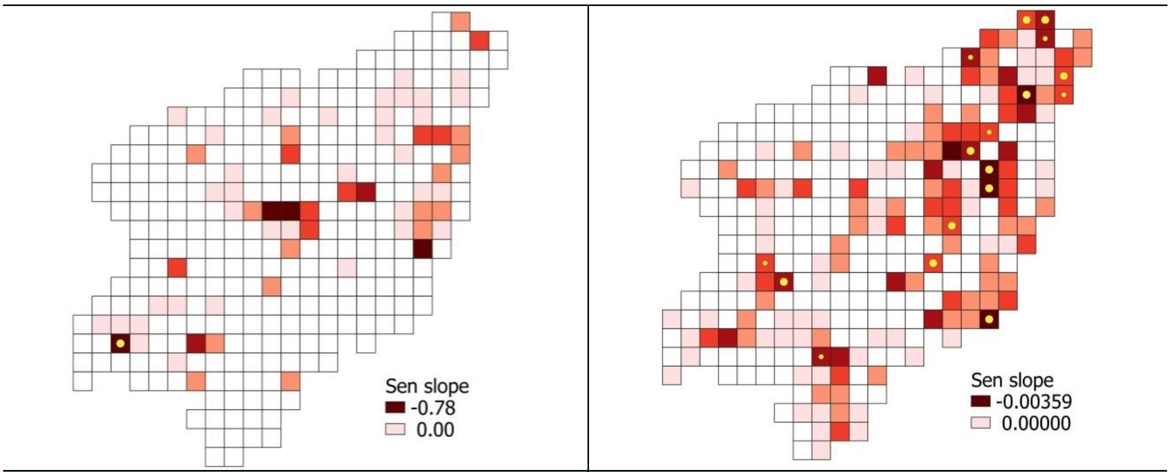
To explore how landscape changed we analysed trends for 1km^2 sample plot units using the Theil-Sen slope. For that we chose the best spatial metrics of EFD/heterogeneity from GLM elasticnet models (EFT richness and EFA max standard-deviation) for three different and nested periods: complete period 35-year (1984-2018), 20 last years (1999-2018) and 10 last years (2009-2018). Because we observed a general positive relation in GLM’s between selected EFD indicators and species richness (total and by passerine group), we can infer that negative trends in these variables are likely associated to a spatial homogenization process and a concomitant potential loss in passerine species diversity (and potentially other taxa). Based on this assumption we focused our analyses only on negative trends.

Considering the 10-year period trends (Figure 22 A and B) were a bit different between EFT richness and EVI max std-dev, with a greater number of spatially coherent areas, often forming clusters, with a negative trend on the second one indicating a loss of landscape diversity. If we consider the 20-year period (Figure 22 C and D) and the complete 35-year time period (Figure 22 E and F) more than half of the landscape shows negative trends for EFT richness (EVI max is slightly different).

To evaluate the significance of the trend results we used p-values. Values of this measurement reveal that statistically significant areas are associated with locations where the magnitude of the trend is more negative (higher displacement from a non-zero trend) thus potentially more homogenised through time. We also found that the 20-year period recorded the highest amount of areas with statistically significant negative trends (Table 7) reaching up to 14% ($p<0.1$) and 6% ($p<0.05$). These sites also tend to cluster in certain areas, generally in uplands, meaning that this process of homogenization has a high degree of spatial autocorrelation.

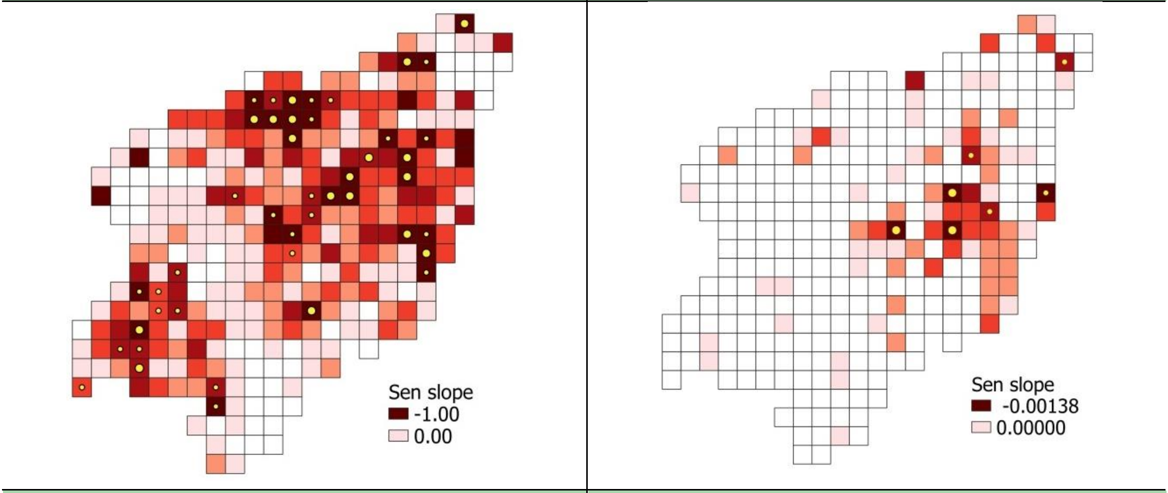
EFT trends (EFT richness) | **EFA trends (EVI max std-dev)**

● $p<0.05$ ● $p<0.1$



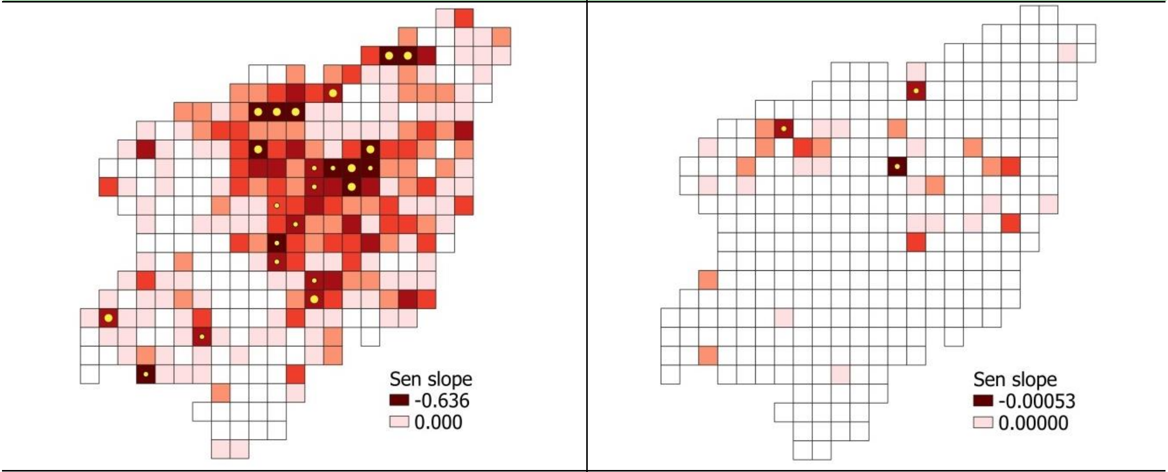
(A) - EFT trend for 10 years (2009-2018)

(B) - EFA trend for 10 years (2009-2018)



(C) – EFT trend for 20 years (1999-2018)

D) – EFA trend for 20 years (1999-2018)



(E) – EFT trend for complete period (1984-2018)

(F) - EFA trend for complete period (1984-2018)

Figure 22 - Comparison of trends between EFT/EFA for three periods (10, 20 and complete period of 35 years)

Table 9 - Percentage of 1km2 units with negative trends for sen slope with p values <0,05 or <0,1

Scenario → sen slope < 0	**Percentage of 1km^2 units**	
	EFT count	EVI max
10 years $p < 0.05$	0,32%	3,53%
10 years $p < 0.1$	0,32%	5,45%
20 years $p < 0.05$	5,77%	0,96%
20 years $p < 0.1$	14,10%	2,24%
Complete 35-year period $p < 0.05$	3,85%	0,0%
Complete 35-year period $p < 0.1$	7,37%	0,96%

4. Discussion

4.1. The local passerine community and its relation with ecosystem functioning diversity

Life cycle dynamics of passerine birds is known to affect local species richness, both total richness and by functional groups. Feeding resources also condition species distribution (Karr, 1976). One example is the higher species richness we found for the insectivorous class (feeding type). This feeding behaviour is exhibited by many species, especially on juvenile stages and is synchronised with the period of greatest abundance of insects during the year (Wilson et al., 1999). Passerine that are not insectivorous may also ocasionaly feed on insects, to suplement their diet for specific nutrient requirements (Geiger et al., 2014).

We found that nesting resources impact bird communities as well. The greater availability of nesting sites implies that species that use these locations to nest are more common (Butler et al., 2010). In our case, the most common were species that nest on trees, shrubs and man-made structures.

Habitat diversity also plays a fundamental role shaping diversity patterns. The distribution of species per habitat type is very diversified in our analysis, meaning that most species require more than one habitat type in order to have optimum development (Julliard et al., 2006). This also means that remotely-sensed indicators capable of capturing habitat diversity are crucial to understand and monitor species diversity in space and time.

Results on habitat type distribution also show the importance of disturbance refuge habitats. The foremost example we see is the high species richness associated with forested spaces. Many species depend on this type of habitat to take refuge, and in reality forest edges around farmlands generally increases the overall diversity of birds (Reino et al., 2009) which is also consistent with higher levels of ecosystem functioning diversity (EFD). Highly stable habitats (in mosaic with other habitat types) also act as disturbance refuges or “buffers” for species which may also have an important role in maintaining population processes (Devictor and Jiguet, 2007)

Our results also show a high frequency of species associated with man-made landscapes. The built-up structures along with the active management of these landscapes creates opportunities for numerous species adapted to these environments. Previous studies have found a positive relation between humanized landscapes and bird diversity in a European context, with tendencies having a hump-shaped relationship (areas with no human development or with too much of it will have a low bird species diversity) (Tratalos et al., 2007).

These results suggest that several passerine life cycle dynamics depend on ecosystem functioning diversity. As such, we hypothesize that integrative EFD measures are capable of tracking several aspects key to explain the distribution, diversity and community assemblage of passerine species which mainly includes feeding resources (mainly linked to primary productivity and its spatial variation) and the diversity of habitats (EFD heterogeneity) but also disturbance refuge (stability and seasonal variation), nesting resources and life cycle synchronism (phenology), which in turn are deeply connected to landscape pattern and processes (Figure 23).

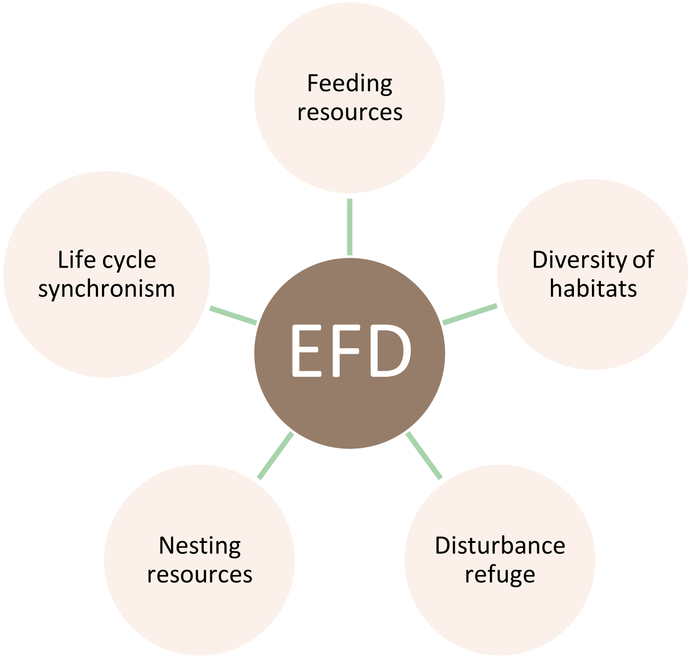


Figure 23 – A graphical synthesis connecting birds life cycle dynamics and ecological requirements with ecosystem functioning diversity (EFD).

Ecosystem functional diversity is measured through EFAs and EFTs which in turn are deeply connected to phenology, seasonality and primary productivity and can describe ecosystem processes that may closely affect species distributions (Arenas-Castro et al., 2018).

Mapping both of them allowed us to visualize the different dynamics of the landscape. Higher values of productivity were associated with woodland (of oak and maritime pine dominance and with presence of eucalyptus as well) and cropland, on bottom valley regions. Differently, high altitude areas of shrubland and sparse vegetation were less productive. EFD indicators also showed a very diversified landscape, with many functioning types present but with landscape mosaics clearly more heterogeneous than others. If we take in consideration that different types of land cover may display a similar behaviour of functioning traits, but be compositionally and structurally different, landscape diversity may be even greater (Paruelo et al., 2001).

By using measures of heterogeneity such as the standard-deviation of EFAs we were able to measure landscape heterogeneity on a finer scale. These analyses further testified the greater landscape diversity of bottom valleys, with utter landscape heterogeneity nearby river Vez course. High heterogeneity was also found on the city centre mosaic. Different landscape components like man-made structures, green areas or the river have different EVI values and therefore different productivity levels. Those different levels of productivity mean that the landscape is as much heterogeneous as the different types of structures present on it. This shows that landscape heterogeneity can be explained by multiple factors with distinct often contrasting effects on biodiversity, including: land use for different types of agriculture/livestock farming and their different regimes; presence of human settlements throughout the landscape; disturbances created by fires; exploitation of forest resources, and many more (Blondel and Aronson, 1995; Geri et al., 2010).

Overall we found that ecosystem functioning heterogeneity (measured by remotely-sensed variables) and passerine diversity have a positive relation. An increase in the local functioning diversity will support a more diverse passerine community, as we further describe in the next section when analysing predictive variables.

4.2. Determining the best predictors and response variables

Passerine bird species with more diverse behaviour and of larger size obtained better models (e.g., omnivorous, in habitats associated with man-made structures where they can also nest, and also on trees/tree cavities). In the previous section we observed that the study area is quite heterogeneous and species have proved to benefit from landscape heterogeneity (Devictor et al., 2008).

Results also showed that open areas (meadows, uplands, ground nesting) and shrubland (heathland, shrub nesting) along with small size species attained models with generally lower performance. That may be the result of lower abundance of species in those classes or due to conspicuous behaviour of species associated with those groups, making them arduous to detect.

Insectivorous species also shown lower performance of the models, which may be a consequence of seasonality. Insects are more easily available as a feeding resource on summer, coinciding with the breeding season. For example species that are granivorous in the rest of the year do eat insects on warmer months complementing their diet, and so represent a moment in the life cycle and not the whole year (Martin, 1987) making it harder to model such species. Nonetheless EFD trends can potentially predict resource abundance, such as insects, by associating trends of the landscape to requirements for resources availability. Later that can be potentially used to assess trends on feeding behaviours of passerine species

Overall functional groups (feeding, nest, size, and habitat) show different modelling performances. Models for size type can account up to 0,8 of the variation, while other groups account up to a maximum of around 0,6 of the variation of the model. This could be related to the amount of landscape heterogeneity in the study area and how it scales up with species richness for each different group.

The relative frequency of selection in models for each predictive variable pointed that the best results were obtained especially for two predictors, both with a positive linear relation with passerine species richness: the standard-deviation of maximum EVI (based on a continuous assessment of EFD) and EFT richness (based on a discrete assessment of EFD).

For better understanding EFD indicators such as the standard-deviation of maximum EVI we can divide it into two elements: the temporal component (maximum EVI) and the spatial heterogeneity component (standard-deviation).

Maximum EVI is an ecosystem functioning attribute that captures the peak of photosynthetic activity occurring in the annual cycle. Studies have already shown that greater maximum value relates directly to ecological systems with greater energetic resources for passerines (Phillips et al., 2008; Honkanen et al., 2010) and higher food and feeding opportunities available especially during periods of greater activity (e.g., breeding season). Also, higher ‘greenness’ and biomass availability potentially relates with more nesting and refuge opportunities for these animals.

This peak of productivity (i.e. annual maximum), which typically occurs in spring/summer in river Vez ecosystems may also coincide to the onset of other organisms such as insects that compose the diet of many passerines species, but especially during the early stages of their life cycle (as mentioned before). As such, the annual maximum may also relate to the ecological synchronization occurring between the life-cycles of different, but interacting, species.

The standard-deviation captures spatial heterogeneity, which has proved before to be associated with species richness. In fact, spatial heterogeneity caused by different functioning types increases the diversity of processes and habitats occurring at the landscape level, providing with more suitable areas for species occurrence (Stein et al., 2014).

Merging both components results in an integrative predictor (i.e., EFD) that combines ecosystems functioning with spatial and habitat heterogeneity. This supports a broader look into landscape heterogeneity analysis, relating intra-annual cycles of flows of matter and energy to spatial configuration and structure of ecosystems, when it usually only holds itself on the last ones.

EFT richness is based on EFAs and incorporates productivity, seasonal, and phenological aspects. It is a predictor that combines functioning and a temporal component (phenology) as well. Characterizing heterogeneity by counting the different EFTs presents a view into the complexity of the landscape with high EFT richness indicating a more heterogeneous landscape in terms of its functioning. That landscape will support more bird diversity, supplying resources to bird communities in the different land cover types, and also in different moments of peak productivity.

4.3. Spatiotemporal change of EFA/EFT patterns as a surrogate of passerine species richness.

Human presence has been a constant on the Mediterranean region for thousands of years, and that influence shaped the much diversified landscapes we see today (Blondel and Aronson, 1999). Passerine diversity is profoundly connected to landscape diversity and is affected by its change. Farina (1997) and Atauri and de Lucio (2001) relate landscape homogenization with bird diversity loss, particularly affecting farmlands and species associated with those areas. They show that the greater diversity of land cover types allows for various species to populate the numerous niches available. Yet, birds such as forest species may instead show positive trends to homogenization when afforestation takes place which allows their habitat to expand, creating corridors between patches of forest (Moreira et al., 2001; Gil-Tena et al., 2010).

It also depends on the context; either being disturbed for centuries (e.g. in European semi-natural traditional agricultural lands) where the trade-offs of afforestation may be negative; or by contrast in more recently disturbed areas (e.g. North America) with a growing landscape restoration movement that can bring benefits to regional biodiversity (Queiroz et al., 2014; Corlett, 2016; Leal Filho et al., 2017). Overall, a complex trade-off exists, mainly because when favouring one type of habitat there can be an increase of species related to particular that type but, in contrast, a decrease in other species that depended on more heterogeneous landscapes (Campagnaro et al., 2017).

Behind this landscape change in the Mediterranean basin, several driving factors are responsible (already introduced): frequent wildfires, habitat loss, degradation and fragmentation, farmland abandonment, agriculture intensification, spread of monoculture forest stands (e.g. *Eucalyptus spp*.) and afforestation.

The results we obtained for landscape dynamics show different trends. Ecosystem Functioning Attributes measured with EVI maximum predicts that there were no major decreases of diversity across the majority of the area, especially if we analyse the complete period of 35 years. With those trends we can potentially expect to take place maintenance or increase in passerine species diversity.

Distinctively, the trend in EFT richness (

Figure 22) showed a clear loss of diversity and therefore a homogenization of the landscape often forming clusters, especially in the 20 years period. This could be due to the fact that the 20 year period was influenced by changes in political policies (EU Common Agricultural Policy - CAP), continued rural abandonment potentially followed by encroachment and afforestation processes as well as modifications in fire regime with extreme years of 2003 and 2005. This means that in this case we can expect loss of habitats, with a localized decline on the passerine community diversity which deserves more research and monitoring effort. In a sense we expect the favouring of bigger patches of particular land cover types, which in turn favours only a few species associated with those conditions. This also strengthens that a multi-indicator approach is preferable due to the ability of portraying distinct patterns and trends.

However, the scale of the patches in the mosaic is also a factor to be taken in consideration. Isolation caused by pronounced fragmentation can prove to have negative impacts for bird communities and should be studied (Santos et al., 2002). A landscape can be very diverse but nonetheless dominated by one type of land cover. It is important to classify that diversity taking in consideration spatial scale. Weighing the different types of functioning observed may be a solution to check if there is some reasonable balance between landscape heterogeneity and “viable” functioning heterogeneity.

Understanding how the landscape functions is critical or else there is no way to perceive what processes and changes are occurring (Costanza et al., 1997).

On that note we analysed 6 different types of land cover to recognize dynamics associated with them in a 35 years long period. We were able to identify two main dynamics: stability and disturbance.

In opposite ends of the spectrum are sparse vegetation areas and oak forests. Both of them showed to be stable, but the first one is by far less productive. The complexity of sparse vegetation is not very high and the landscape is frequently punctuated by large rock areas, having low functioning diversity which means fewer resources. On the contrary, oak forests are productive and slowly accumulate biomass, accompanying the maturing of the trees. This stability may benefit more some bird species but it can also help increase the diversity of other ones on forest edges, for it can function as refuge or nesting location (Hovick et al., 2015).

Disturbance could be observed on all the other land cover types: Forest stands of *Eucalyptus spp* with growth and cut dynamics; conversion of vegetated areas into intensely urbanized zones; wildfires on shrubland; irrigated annual crop agriculture. Every single one implies different consequences for passerine diversity.

The most impressive and disruptive disturbance happens on the urbanization process. An area that previously provided natural resources to birds is no longer available, which can have a local negative impact on the diversity of the birds' species.

Wildfire occurrence on shrublands does not have a comparable impact to the urbanization process. This type of land cover is particularly fire-prone and very well adapted to that disturbance, being able to recover from it (Carmo et al., 2011). In fact, after a shrubland fire under most burning regimes, shrub species composition do not change substantially from one fire cycle to the next (Keeley, 1986). Being so, the effects of fire on bird communities may not be as marked as in other land covers, recovering quickly (one year after the fire levels of EVI were back up again).

One source of "disturbance" that goes in the opposite way of the previous is agricultural practice and land use. Usually present on fertile zones, these managed areas under extensive regime are used for growing different crops in spring/summer and throughout the rest of the year have green pastures for cattle. That means that temporal and spatial diversity of the landscape can potentially increase birds' species richness (Laiolo, 2005) in these. In fact, highly diversified agro-forestry mosaics in the study area tend to present high EFD and high levels of passerine diversity.

EVI worked as proxy to differentiate land cover types. Visualising trends for them for a relatively long period of time helped understanding how landscape dynamics affect bird communities and their diversity. Stability or disturbance, and their regime can be monitored through satellite time series, which allows identifying key moments and indicators that are able to support present conservation agendas.

5. Conclusions

This study provided information on how passerine diversity and their functional traits can be linked to ecosystem functioning diversity. By exploring the best predictive and response variables we were able to hindcast trends in EFA/EFT and use them as a proxy to detect potential effects on passerine species richness in a 35-year long time series.

Most works prior to this focused on the structural and compositional diversity and heterogeneity of landscapes, leaving aside functioning diversity. This work comes to show that functioning diversity holds the potential to predict trends in species richness as well thus complementing previous approaches. The methodology and assumptions used can be replicated with other taxa and in other study areas.

Remote sensing tools are crucial and proved to be capable of assessing ecosystem dynamics, detecting changes and providing knowledge of landscape diversity. That knowledge helps understanding underlying processes that occur on ecosystems which is essential to define conservation practices and to influence decision makers in creating policies that meet the best interest of biodiversity preservation.

5.1. Applications and future prospects

Next steps

The work developed on this study provided a view into landscape processes that are not only manifesting on the river Vez watershed, but on Iberian Peninsula and most of the Mediterranean basin. Some landscapes are becoming homogenized, losing its functions and species diversity and with it the crucial services provided by ecosystems to human livelihoods. To study what is behind this change is of upmost importance in order to understand the ecosystem dynamics and to create and apply policies that benefit conservation efforts. There are studies that already found main culprits of this loss of functioning diversity, drivers of change associated with political and social motives such as: rural exodus, frequent fires, farmland abandonment, agriculture intensification, and spread of monoculture forest stands (e.g. *Eucalyptus spp*.), urbanization, etc. We consider that evaluating which drivers have more expression on the area and to measure how they impact ecosystem functioning diversity and passerine communities is the next big step. For that, we would require additional field data of present communities to assess how they evolved since 2014, and link it to how the landscape itself evolved over the last few years.

Suggestions

The remote sensing tools used here have proven that it is possible to evaluate the ecosystem functioning modifications remotely. It reduces the effort invested on field surveys, but nonetheless it is still necessary to collect data from the terrain. Following that chain of thought we propose using citizen science for that. There is a growing use of mobile apps related to science (e.g. eBird, iNaturalist, etc.) that work on the basis of georeferenced and dated submissions of the sightings of organisms (Sullivan et al., 2014). On some apps those observations need to be submitted with photos or sounds, which are a fantastic way to confirm their truthfulness, enabling their use for species monitoring. One disadvantage we see is the bias of the observations which seem to be clustered around hotspots suggested by users (or sometimes associated with territories with better access or with more tourism – e.g. walkways, trails, etc.). We suggest the creation of an algorithm that allows informing users of places that are of scientific interest, to encourage incursions to those areas. The outputs of this thesis can help to define such locations were potential losses of diversity may be occurring. That should grant the scientific community with further data, decreasing the bias caused by hotspots and touristic sites. Nevertheless, the scientific community must be cautious with these types of data sets, filtering observations and using only validated data, mainly because there is the uncertainty associated with human errors, for we do not know how the data was obtained.

6. References

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7. Appendix

Table A1 - R packages used

Package name	Citation info
car	John Fox and Sanford Weisberg (2019). An {R} Companion to Applied Regression, Third Edition. Thousand Oaks CA: Sage. URL: https://socialsciences.mcmaster.ca/jfox/Books/Companion/
Dcluster	V. Gómez-Rubio; J. Ferrándiz-Ferragud; A. López-Quílez (2005). Detecting clusters of disease with R. Journal of Geographical Systems. 7, Number 2:189-206
DescTools	Andri Signorell et mult. al. (2019). DescTools: Tools for descriptive statistics. R package version 0.99.28.
dplyr	Hadley Wickham, Romain François, Lionel Henry and Kirill Müller (2019). dplyr: A Grammar of Data Manipulation. R package version 0.8.3. https://CRAN.R-project.org/package=dplyr
fasterize	Noam Ross (2018). fasterize: Fast Polygon to Raster Conversion. R package version 1.0.0. https://CRAN.R-project.org/package=fasterize
ggplot2	H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2016.
glmnet	Jerome Friedman, Trevor Hastie, Robert Tibshirani (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. Journal of Statistical Software, 33(1), 1-22. URL http://www.jstatsoft.org/v33/i01/.
magrittr	Stefan Milton Bache and Hadley Wickham (2014). magrittr: A Forward-Pipe Operator for R. R package version 1.5. https://CRAN.R-project.org/package=magrittr
MASS	Venables, W. N. & Ripley, B. D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN 0-387-95457-0
microbiome	Leo Lahti et al. microbiome R package. URL: http://microbiome.github.io
pracma	Hans W. Borchers (2019). pracma: Practical Numerical Math Functions. R package version 2.2.5. https://CRAN.R-project.org/package=pracma
psych	Revelle, W. (2018) psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA, https://CRAN.R-project.org/package=psych Version = 1.8.12.
ptw	Bloemberg, T. G. et al. (2010) "Improved Parametric Time Warping for Proteomics", Chemometrics and Intelligent Laboratory Systems, 104 (1), 65-74

raster	Robert J. Hijmans (2019). raster: Geographic Data Analysis and Modeling. R package version 3.0-2. https://CRAN.R-project.org/package=raster
Rcpp	Dirk Eddelbuettel and Romain Francois (2011). Rcpp: Seamless R and C++ Integration. Journal of Statistical Software, 40(8), 1-18. URL http://www.jstatsoft.org/v40/i08/.
readxl	Hadley Wickham and Jennifer Bryan (2019). readxl: Read Excel Files. R package version 1.3.1. https://CRAN.R-project.org/package=readxl
rgdal	Roger Bivand, Tim Keitt and Barry Rowlingson (2019). rgdal: Bindings for the 'Geospatial' Data Abstraction Library. R package version 1.4-4. https://CRAN.R-project.org/package=rgdal
Rstoolbox	Benjamin Leutner, Ned Horning and Jakob Schwalb-Willmann (2019). RStoolbox: Tools for Remote Sensing Data Analysis. R package version 0.2.6. https://CRAN.R-project.org/package=RStoolbox
sf	Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal 10 (1), 439-446, https://doi.org/10.32614/RJ-2018-009
sp	Pebesma, E.J., R.S. Bivand, 2005. Classes and methods for spatial data in R. R News 5 (2), https://cran.r-project.org/doc/Rnews/
SparseM	Roger Koenker and Pin Ng (2017). SparseM: Sparse Linear Algebra. R package version 1.77. https://CRAN.R-project.org/package=SparseM
tidyr	Hadley Wickham and Lionel Henry (2019). tidyr: Tidy Messy Data. R package version 1.0.0. https://CRAN.R-project.org/package=tidyr
tools	R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
trend	Thorsten Pohlert (2018). trend: Non-Parametric Trend Tests and Change-Point Detection. R package version 1.1.1. https://CRAN.R-project.org/package=trend
utils	R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
writexl	Jeroen Ooms (2018). writexl: Export Data Frames to Excel 'xlsx' Format. R package version 1.1. https://CRAN.R-project.org/package=writexl

Table A2 - Specific criteria used for each genus

Genus	**Criteria** **(species used)**	**Notes**
Anthus sp.	*Anthus trivialis*	The only species that was found in the area was *Anthus trivialis*
Carduelis sp.	*L. cannabina* *C. carduelis* *C. chloris*	Mean values of the three species, two of them formerly classified as *Carduelis* found in the study area
Corvus sp.	*Corvus corone*	The most common species in the country is *C. corone*[1]
Emberiza sp.	*E. cia,* *E.cirlus*	Mean values of the two most common species of *Emberiza*[1]
Hirundo sp.	*Hirundo rustica*	The only species that was found in the area was *H. rustica*
Monticola sp.	*M.saxatilis*	Distribution map of HBW indicated that the only species present in the area as *M. saxatilis*
Oenanthe sp.	*O. oenanthe*	The only species that was found in the area was *O. oenanthe*
Parus sp.	*C. caeruleus* *P. major*	Mean values of the two most common species of Paridae[1]
Phylloscopus sp.	*P. bonelli,* *P. ibericus*	The two species that breed in Portugal
Sylvia sp.	*S. melanocephala*	Of all *Sylvia* species found in the surveys, *S melanocephala* is the most abundant species in the country[1]
Turdus sp.	*T. viscivorus*	Of the two species of *Turdus* that are similar found in the area one is a winter visitor (*T. philomelos*), making *T. viscivorous* the only species present during the surveys

1 – Abundance values were based on an abundance classification that varies between 1 (highest abundance) and 5 (lowest abundance), present on Guia de Aves. *Assírio & Alvim, Porto Editora Lda: Porto*

Table A3 - Landsat missions (NASA, 2013).

Satellite	Launch date	Decommission date	Sensors
Landsat 1	23 July 1972	6 January 1978	MSS/RBV
Landsat 2	22 January 1975	27 July 1983	MSS/RBV
Landsat 3	5 March 1978	7 September 1983	MSS/RBV
Landsat 4	16 July 1982	15 June 2001	MSS/TM
Landsat 5	**1 March 1984**	**5 June 2013**	**MSS/TM**
Landsat 6	5 October 1993	Failed to reach orbit	ETM
Landsat 7	**15 April 1999**	**Operational**	**ETM+**
Landsat 8	**11 February 2013**	**Operational**	**OLI/TIRS**

Table A4 - Landsat 5, 7 and 8 specifications and their product codes in Google Earth Engine (Google LLC, n.d.; NASA, 2013).

Sensors	Band number	Band name	Resolution	Wavelenght (µm)
Landsat 5 (TM) Google earth engine product code: “LANDSAT/LT05/C01/T1_32DAY_EVI”	Band 1	Blue	30 m	0.45-0.52
	Band 2	Green	30 m	0.52-0.60
	Band 3	Red	30 m	0.63-0.69
	Band 4	NIR	30 m	0.76-0.90
	Band 5	SWIR	30 m	1.55-1.75
	Band 6	TIR	120x30 m	10.40-12.50
	Band 7	SWIR	30 m	2.08-2.35
Landsat 7 (ETM+) Google earth engine product code: “LANDSAT/LE07/C01/T1_32DAY_EVI”	Band 1	Blue	30 m	0.44-0.51
	Band 2	Green	30 m	0.52-0.60
	Band 3	Red	30 m	0.63-0.69
	Band 4	NIR	30 m	0.77-0.90
	Band 5	SWIR-1	30 m	1.55-1.75
	Band 6	TIR	60 m	10.31-12.36
	Band 7	SWIR-2	30 m	2.06-2.35
	Band 8	Pan	15 m	0.52-0.90
Landsat 8 (OLI/TIRS) Google earth engine product code:“LANDSAT/LC08/C01/T1_32DAY_EVI	Band 1	Coastal/Aerosol	30 m	0.44-0.45
	Band 2	Blue	30 m	0.45-0.51
	Band 3	Green	30 m	0.53-0.59
	Band 4	Red	30 m	0.64-0.67
	Band 5	NIR	30 m	0.85-0.88
	Band 6	SWIR-1	30 m	1.57-1.65
	Band 7	SWIR-2	30 m	2.11-2.29
	Band 8	Pan	15 m	0.50-0.68
	Band 9	Cirrus	30 m	1.36-1.38
	Band 10	TIR-1	100 m	10.60-11.19
	Band 11	TIR-2	100 m	11.50-12.51

Table A5 – Species habitat distribution

Species	**Woodland**	**Farmland**	**Meadow and grassland**	**Upland**	**Wetlands**	**Urban and suburban**	**Heathland**
Aegithalos caudatus	1	1	0	0	0	1	1
Alauda arvensis	0	1	1	1	0	0	1
Anthus sp.	1	0	1	0	0	0	1
Anthus trivialis	1	0	1	0	0	0	1
Carduelis carduelis	1	0	1	0	1	1	0
Carduelis sp.	1	1	1	1	1	1	1
Certhia brachydactyla	1	1	0	0	0	1	0
Cettia cetti	0	0	0	0	1	0	0
Chloris chloris	1	0	0	0	0	1	1
Corvus corax	1	0	1	1	0	0	1
Corvus corone	1	1	0	1	0	1	0
Corvus monedula	1	1	1	0	0	1	0
Corvus sp.	1	1	0	1	0	1	0
Cyanistes caeruleus	1	0	0	0	0	1	0
Delichon urbicum	0	1	0	0	0	1	0
Emberiza cia	0	0	0	1	0	0	0
Emberiza cirlus	1	1	0	0	0	0	1
Emberiza citrinella	1	1	1	0	0	0	1
Emberiza sp.	1	1	0	1	0	0	1
Erithacus rubecula	1	1	0	0	1	1	0
Fringilla coelebs	1	1	0	0	0	1	1
Garrulus glandarius	1	0	0	0	0	1	0
Hippolais polyglotta	1	0	0	0	0	1	1
Hirundo rustica	0	1	0	0	1	1	0
Hirundo sp.	0	1	0	0	1	1	0
Linaria cannabina	1	1	0	1	0	1	1
Lophophanes cristatus	1	0	0	0	0	0	0
Luscinia megarhynchos	1	0	0	0	0	1	1
Monticola sp.	0	0	0	1	0	0	0
Motacilla alba	0	1	1	0	1	1	0

Species	Woodland	Farmland	Meadow and grassland	Upland	Wetlands	Urban and suburban	Heathland
Motacilla cinerea	0	0	0	1	1	0	0
Oenanthe oenanthe	0	0	1	1	0	0	0
Oenanthe sp.	0	0	1	1	0	0	0
Oriolus oriolus	1	1	0	0	0	1	0
Parus major	1	0	0	0	0	1	0
Parus sp.	1	0	0	0	0	1	0
Passer domesticus	0	0	0	0	0	1	0
Passer montanus	1	0	0	0	0	1	0
Periparus ater	1	0	0	0	0	0	0
Phoenicurus ochruros	0	0	0	1	0	1	0
Phylloscopus sp.	1	0	0	0	0	0	0
Pica pica	0	1	1	0	0	1	0
Prunella modularis	1	0	0	0	0	1	1
Pyrrhula pyrrhula	1	0	0	0	0	1	1
Regulus ignicapillus	1	0	0	0	0	0	1
Saxicola rubetra	0	0	1	1	1	0	1
Saxicola rubicola	0	0	1	1	0	0	1
Serinus serinus	1	1	0	0	0	1	0
Sitta europaea	1	0	0	0	0	1	0
Sturnus unicolor	1	1	1	0	0	1	0
Sylvia atricapilla	1	0	0	0	1	1	0
Sylvia cantillans	1	0	0	0	1	0	1
Sylvia communis	0	0	1	0	0	0	1
Sylvia melanocephala	0	1	1	0	0	1	1
Sylvia sp.	0	1	1	0	0	1	1
Sylvia undata	0	0	0	0	0	0	1
Troglodytes troglodytes	1	0	0	1	0	1	0
Turdus merula	1	0	0	1	0	1	0
Turdus philomelos	1	0	0	0	0	1	0
Turdus sp.	1	1	1	0	0	1	0
Turdus viscivorus	1	1	1	0	0	1	0

Table A6 – Species feeding type distribution

Species	Frugiverous	Granivorous	Insectivorous	Omnivorous
Aegithalos caudatus	0	1	1	0
Alauda arvensis	0	1	1	0
Anthus sp.	0	1	1	0
Anthus trivialis	0	1	1	0
Carduelis carduelis	1	1	0	0
Carduelis sp.	1	1	0	0
Certhia brachydactyla	0	0	1	0
Cettia cetti	0	0	1	0
Chloris chloris	1	1	0	0
Corvus corax	0	0	0	1
Corvus corone	0	0	0	1
Corvus monedula	0	0	0	1
Corvus sp.	0	0	0	1
Cyanistes caeruleus	1	1	1	1
Delichon urbicum	0	0	1	0
Emberiza cia	0	1	1	0
Emberiza cirlus	0	1	1	0
Emberiza citrinella	0	1	1	0
Emberiza sp.	0	1	1	0
Erithacus rubecula	1	1	1	1
Fringilla coelebs	0	1	1	0
Garrulus glandarius	0	0	0	1
Hippolais polyglotta	1	0	1	0
Hirundo rustica	0	0	1	0
Hirundo sp.	0	0	1	0
Linaria cannabina	0	1	0	0
Lophphanes cristatus	0	1	1	0
Luscinia megarhynchos	1	0	1	0
Monticola sp.	1	0	1	0
Motacilla alba	0	0	1	0
Motacilla cinerea	0	0	1	0
Oenanthe oenanthe	0	0	1	0
Oenanthe sp.	0	0	1	0
Oriolus oriolus	1	1	1	1
Parus major	1	1	1	1
Parus sp.	1	1	1	1
Passer domesticus	1	1	1	1
Passer montanus	0	1	1	0
Periparus ater	0	1	1	0
Phoenicurus ochruros	1	0	1	0
Phylloscopus sp.	0	0	1	0
Pica pica	0	0	0	1
Prunella modularis	0	0	1	0
Pyrrhula pyrrhula	1	1	1	1
Regulus ignicapillus	0	0	1	0
Saxicola rubetra	0	0	1	0
Saxicola rubicola	0	0	1	0
Serinus serinus	0	1	0	0
Sitta europaea	0	1	1	0
Sturnus unicolor	0	0	0	1
Sylvia atricapilla	1	0	1	0
Sylvia cantillans	1	0	1	0
Sylvia communis	1	0	1	0
Sylvia melanocephala	1	0	1	0
Sylvia sp.	1	0	1	0
Sylvia undata	1	0	1	0
Troglodytes troglodytes	1	1	1	1
Turdus merula	1	0	1	0
Turdus philomelos	1	0	1	0
Turdus sp.	1	1	1	1
Turdus viscivorus	1	1	1	1

Table A7 – Species nest distribution

Species	Tree	Shrub	Ground	Artificial Urban	Tree Cavity	Cavity	Cliff
Aegithalos caudatus	0	1	0	0	0	0	0
Alauda arvensis	0	0	1	0	0	0	0
Anthus sp.	0	0	1	0	0	0	0
Anthus trivialis	0	0	1	0	0	0	0
Carduelis carduelis	1	1	0	0	0	0	0
Carduelis sp.	1	1	0	0	0	0	0
Certhia brachydactyla	0	0	0	0	1	1	0
Cettia cetti	0	1	0	0	0	0	0
Chloris chloris	1	1	0	0	0	0	0
Corvus corax	1	0	0	1	0	0	1
Corvus corone	1	0	0	0	0	0	0
Corvus monedula	0	0	0	1	1	1	1
Corvus sp.	1	0	0	0	0	0	0
Cyanistes caeruleus	0	0	0	1	1	0	0
Delichon urbicum	0	0	0	1	0	0	0
Emberiza cia	0	0	1	0	0	0	0
Emberiza cirlus	0	1	0	0	0	0	0
Emberiza citrinella	0	1	0	0	0	0	0
Emberiza sp.	0	1	1	0	0	0	0
Erithacus rubecula	0	0	1	1	1	0	0
Fringilla coelebs	1	0	0	0	0	0	0
Garrulus glandarius	1	0	0	0	0	0	0
Hippolais polyglotta	1	0	0	0	0	0	0
Hirundo rustica	0	0	0	1	0	0	0
Hirundo sp.	0	0	0	1	0	0	0
Linaria cannabina	0	1	0	0	0	0	0
Lophophanes cristatus	0	0	0	0	1	0	0
Luscinia megarhynchos	0	0	1	0	0	0	0
Monticola sp.	0	0	0	1	0	1	0
Motacilla alba	0	0	0	1	0	1	0
Motacilla cinerea	0	0	0	1	0	1	0
Oenanthe oenanthe	0	0	0	0	0	1	0
Oenanthe sp.	0	0	0	0	0	1	0
Oriolus oriolus	1	0	0	0	0	0	0
Parus major	0	0	0	1	1	0	0
Parus sp.	0	0	0	1	1	0	0
Passer domesticus	0	0	0	1	1	0	1
Passer montanus	0	0	0	1	1	1	1
Periparus ater	0	0	0	0	1	0	0
Phoenicurus ochruros	0	0	1	0	0	1	0
Phylloscopus sp.	0	0	1	0	0	0	0
Pica pica	1	0	0	0	0	0	0
Prunella modularis	1	1	0	0	0	0	0
Pyrrhula pyrrhula	1	1	0	0	0	0	0
Regulus ignicapillus	1	0	0	0	0	0	0
Saxicola rubetra	0	1	1	0	0	0	0
Saxicola rubicola	0	0	1	0	0	0	0
Serinus serinus	1	0	0	0	0	0	0
Sitta europaea	0	0	0	0	1	0	0
Sturnus unicolor	0	0	0	1	1	0	0
Sylvia atricapilla	1	1	0	0	0	0	0
Sylvia cantillans	1	1	0	0	0	0	0
Sylvia communis	0	1	0	0	0	0	0
Sylvia melanocephala	0	1	0	0	0	0	0
Sylvia sp.	0	1	0	0	0	0	0
Sylvia undata	0	1	0	0	0	0	0
Troglodytes troglodytes	0	1	0	1	0	1	0
Turdus merula	1	1	0	1	0	0	0
Turdus philomelos	1	1	0	0	0	0	0
Turdus sp.	1	0	0	0	0	0	0
Turdus viscivorus	1	0	0	0	0	0	0

Table A8 – Species size distribution

Species	S	M	L	XL
Aegithalos caudatus	0	1	0	0
Alauda arvensis	0	0	1	0
Anthus sp.	0	1	0	0
Anthus trivialis	0	1	0	0
Carduelis carduelis	1	0	0	0
Carduelis sp.	0	1	0	0
Certhia brachydactyla	1	0	0	0
Cettia cetti	0	1	0	0
Chloris chloris	0	0	1	0
Corvus corax	0	0	0	1
Corvus corone	0	0	0	1
Corvus monedula	0	0	0	1
Corvus sp.	0	0	0	1
Cyanistes caeruleus	1	0	0	0
Delichon urbicum	1	0	0	0
Emberiza cia	0	0	1	0
Emberiza cirlus	0	0	1	0
Emberiza citrinella	0	0	1	0
Emberiza sp.	0	0	1	0
Erithacus rubecula	0	1	0	0
Fringilla coelebs	0	0	1	0
Garrulus glandarius	0	0	0	1
Hippolais polyglotta	1	0	0	0
Hirundo rustica	0	0	0	1
Hirundo sp.	0	0	0	1
Linaria cannabina	0	1	0	0
Lophophanes cristatus	1	0	0	0
Luscinia megarhynchos	0	0	1	0
Monticola sp.	0	0	1	0
Motacilla alba	0	0	1	0
Motacilla cinerea	0	0	1	0
Oenanthe oenanthe	0	0	1	0
Oenanthe sp.	0	0	1	0
Oriolus oriolus	0	0	0	1
Parus major	0	1	0	0
Parus sp.	1	0	0	0
Passer domesticus	0	0	1	0
Passer montanus	0	1	0	0
Periparus ater	1	0	0	0
Phoenicurus ochruros	0	1	0	0
Phylloscopus sp.	1	0	0	0
Pica pica	0	0	0	1
Prunella modularis	0	1	0	0
Pyrrhula pyrrhula	0	0	1	0
Regulus ignicapillus	1	0	0	0
Saxicola rubetra	1	0	0	0
Saxicola rubicola	1	0	0	0
Serinus serinus	1	0	0	0
Sitta europaea	0	1	0	0
Sturnus unicolor	0	0	0	1
Sylvia atricapilla	0	1	0	0
Sylvia cantillans	1	0	0	0
Sylvia communis	0	1	0	0
Sylvia melanocephala	0	1	0	0
Sylvia sp.	0	1	0	0
Sylvia undata	1	0	0	0
Troglodytes troglodytes	1	0	0	0
Turdus merula	0	0	0	1
Turdus philomelos	0	0	0	1
Turdus sp.	0	0	0	1
Turdus viscivorus	0	0	0	1

Table A9 – EFT percentage cover (from highest to lowest)

EFT_class	EFT_Prod	EFT_Seas	EFT_Phen	PercCover
343	3	4	3	5.720269
143	1	4	3	5.578384
443	4	4	3	5.462204
243	2	4	3	5.150675
433	4	3	3	5.128056
333	3	3	3	4.994739
233	2	3	3	4.243164
133	1	3	3	4.0156
323	3	2	3	3.975845
223	2	2	3	3.707499
123	1	2	3	3.439495
423	4	2	3	3.412421
113	1	1	3	3.108089
213	2	1	3	2.878812
313	3	1	3	2.334237
112	1	1	2	2.287628
214	2	1	4	2.05698
424	4	2	4	1.893162
434	4	3	4	1.790347
122	1	2	2	1.764643
314	3	1	4	1.731057
114	1	1	4	1.57615
324	3	2	4	1.454143
413	4	1	3	1.4538
132	1	3	2	1.450373
212	2	1	2	1.221439
224	2	2	4	1.154267
222	2	2	2	0.978453
142	1	4	2	0.976054
414	4	1	4	0.969543
211	2	1	1	0.964059
312	3	1	2	0.904427
111	1	1	1	0.890376
444	4	4	4	0.871183
232	2	3	2	0.852677
322	3	2	2	0.803326
332	3	3	2	0.695713
422	4	2	2	0.680291
432	4	3	2	0.617574
311	3	1	1	0.577133
412	4	1	2	0.571993
421	4	2	1	0.571993

242	2	4	2	0.552801
334	3	3	4	0.503449
431	4	3	1	0.493168
124	1	2	4	0.472605
411	4	1	1	0.461295
342	3	4	2	0.457868
321	3	2	1	0.351284
442	4	4	2	0.344087
221	2	2	1	0.335519
234	2	3	4	0.269717
441	4	4	1	0.256351
121	1	2	1	0.161762
331	3	3	1	0.122692
344	3	4	4	0.080881
134	1	3	4	0.079853
231	2	3	1	0.074712
341	3	4	1	0.025361
131	1	3	1	0.022619
244	2	4	4	0.014737
144	1	4	4	0.006854
241	2	4	1	0.00377
141	1	4	1	0.000343

Table A10 - Overdispersion tests for Poisson models

Response variable		**Overdispersion test**		
		Likelihood-ratio test (p-value)	DeanB	DeanB2
Species richness		1	0.89	0.74
Habitat	Woodland	1	0.94	0.83
	Farmland	1	0.97	0.89
	Meadow grass	1	0.89	0.82
	Upland	1	0.83	0.75
	Wetlands	1	0.93	0.82
	Urban suburb	1	0.95	0.85
	Heathland	0.34	0.13	0.06
Feeding	Frugivorous	1	0.97	0.92
	Granivorous	1	0.97	0.91
	Insectivorous	1	0.8	0.65
	Omnivorous	1	0.96	0.86
Nest	Tree	1	0.99	0.95
	Shrub	1	0.85	0.72
	Ground	1	0.91	0.85
	Artificial Urban	1	0.87	0.71
	Tree Cavity	1	0.98	0.93
	Cavity	1	0.89	0.74
	Cliff	1	0.88	0.72
Size	S	1	0.91	0.8
	M	1	0.97	0.92
	L	1	0.99	0.98
	XL	1	0.99	0.97

Table A11 – Variance Influence Factors results

	EFAmax_std	EFAamp_std	EFAavg_std	EFAmin_std	EFAsemax_std	EFAstd_std	evar	shannon	eft_count	EFAmin_avg	EFAmax_avg	EFAavg_avg	EFAsemax_avg	EFAstd_avg	EFAamp_avg
Sp_rich	1.90	1.09	-	-	-	-	-	3.65	5.27	-	-	-	-	-	-
Hab_Woodland	2.08	-	-	-	2.68	-	-	4.29	5.96	-	-	-	-	-	-
Hab_Farmland	2.07	-	-	-	-	-	-	3.78	5.65	-	-	-	-	-	-
Hab_Meadow_grass	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hab_Upland	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hab_Wetlands	-	-	-	-	-	-	1.78	3.86	3.24	-	1.34	-	-	-	-
Hab_Urban_suburb	4.37	-	4.77	-	-	-	-	3.80	5.81	-	-	-	-	-	-
Hab_Heathland	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Feed_Frugiverous	-	1.81	-	2.47	-	-	-	3.11	3.96	-	-	-	-	-	-
Feed_Granivorous	1.88	-	-	-	-	-	-	3.75	5.30	-	-	-	-	-	-
Feed_Insectivorous	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Feed_Omnivorous	6.44	-	6.53	-	-	-	-	-	2.00	1.17	-	-	-	-	-
Nest_Tree	-	-	1.27	-	3.02	-	-	2.60	-	1.54	-	-	-	-	-
Nest_Shrub	1.10	1.08	-	-	1.03	-	-	-	-	-	-	-	-	-	-
Nest_Ground	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Nest_Artificial_Urban	-	-	-	-	-	-	-	3.37	3.06	-	-	-	-	85.69	87.59
Nest_Tree_Cavity	2.10	-	-	-	-	-	-	-	1.67	-	-	-	-	126.85	130.76
Nest_Cavity	-	1.07	-	-	-	-	-	2.89	2.97	-	-	-	-	-	-
Nest_Cliff	-	1.05	-	-	-	-	1.65	3.20	2.56	-	-	-	-	-	-
Size_S	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Size_M	1.16	1.10	-	-	2.56	-	-	2.71	-	-	-	-	-	-	-
Size_L	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Size_XL	2.08	-	-	-	-	-	-	3.71	5.59	1.12	-	-	-	-	-