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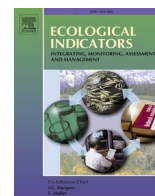
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The promising combination of a remote sensing approach and landscape connectivity modelling at a fine scale in urban planning

Elie Morin ^{a,*}, Pierre-Alexis Herrault ^b, Yvonnick Guinard ^c, Frédéric Grandjean ^a, Nicolas Bech ^a

^a Université de Poitiers, Laboratoire Ecologie et Biologie des Interactions (UMR CNRS 7267), 5 Rue Albert Turpin, 86022 Poitiers, France

^b Université de Strasbourg, Laboratoire Image, Ville, Environnement (UMR CNRS 7362), 3 Rue de l'Argonne, 67000 Strasbourg, France

^c Grand Poitiers Communauté Urbaine, 86000 Poitiers, France

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ABSTRACT

Urban landscapes are rapid changing ecosystems with diverse urban forms that impede the movement of organisms. Therefore, designing and modelling ecological networks to identify biodiversity reservoirs and their corridors are crucial aspects of land management in terms of population persistence and survival. However, the land cover/use maps used for landscape connectivity modelling can lack information in such a highly complex environment. In this context, remote sensing approaches are gaining interest for the development of accurate land cover/use maps. We tested the efficiency of an object-based classification using open-source projects and free images to identify vegetation strata at a very fine scale and evaluated its contribution to landscape connectivity modelling. We compared different spatial and thematic resolutions from existing databases and object-based image analyses in three French cities. Our results suggested that this remote sensing approach produced reliable land cover maps to differentiate artificial areas, tree vegetation and herbaceous vegetation. Land cover maps enhanced with the remote sensing products substantially changed the structural connectivity indices, showing an improvement up to four times the proportion of herbaceous and tree vegetation. In addition, functional connectivity indices evaluated for several forest species were mainly impacted for medium dispersers in quantitative (metrics) and qualitative (corridors) estimations. Thus, the combination of this reproducible remote sensing approach and landscape connectivity modelling at a very fine scale provides new insights into the characterisation of ecological networks for conservation planning.

1. Introduction

Land use changes originating from anthropic activities significantly disturb ecosystem dynamics worldwide. They therefore represent one of the main threats to biodiversity and associated ecosystem services (Benítez-López et al., 2010; McKinney, 2006). These land use changes deeply perturb the structure of the landscape and the associated habitats, thus modifying both the landscape composition (i.e., land cover) and configuration (i.e., spatial arrangement of land cover) (Fahrig et al., 2011; Taylor et al., 1993). Specifically, this manifests through the loss, degradation and fragmentation of habitats, which are reshaped into small isolated patches surrounded by unsuitable habitats (i.e., biogeographic islands) (Fahrig, 2003; Wilcove et al., 1986). Playing the role of refuge, these remaining patches shelter wildlife populations whose connectivity across the landscape is crucial to ensure both their maintenance and resilience. Indeed, geographical isolation can notably lead

to an inbreeding mating system and eventually to an extinction vortex (Frankham, 2015; Keyghobadi, 2007).

Resulting in drastic and sustainable habitat modifications, urbanization illustrates the perforation of habitats worldwide and its impact on the connectivity of global landscapes (Ramalho & Hobbs, 2012; Sanderson & Huron, 2011). In response to human population growth and the expansion of human-dominated landscapes, governments have adopted environmental measures to promote the reconnection of isolated patches with significant biodiversity and thus slow down the collapse of populations. These management practices aim to identify and localize biodiversity reservoirs and hotspots sheltering significant biodiversity and then design and preserve ecological corridors to reconnect these areas to each other through an ecological network. Biological populations within these fragmented habitats located in urban landscapes, for example, adopt specific dynamics (e.g., meta-populations) to cope with their changing environment (Hanski & Ovaskainen, 2000). In this

* Corresponding author.

E-mail addresses: elie.morin2.0@gmail.com, elie.morin2.0@gmail.com (E. Morin).

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case, the persistence of the population is modulated by the balance of colonisation and extinction within the available habitat patches. Thus, maintaining functional connections among habitats across landscapes is crucial for the survival and resilience of populations. As biodiversity is increasingly integrated into land use policies, landscape ecologists and land managers must make rapid diagnoses and analyses to take ecological networks into account.

Ecological networks implicitly involve ecological processes (e.g., foraging, territorial defence, dispersal, migrations) related to resource availability and movements for organisms, including several spatial and temporal scales (Abrahms et al., 2017; LaPoint et al., 2015). Thus, ecological modelling aims to integrate these ecological processes in order to estimate and quantify the functional connectivity shaped by the landscapes. For two decades, resistance-based models were widely used and showed a good correlation with real or measured connectivity (i.e., telemetry, gene flows) (Zeller et al., 2018). Pixel resistance values represent an organism's difficulty to move, or more precisely, the willingness, energetic cost and/or survival rate of organisms to cross each landscape element (Zeller et al., 2012). The higher the resistance value, the more difficult it is to move, thus representing the permeability or impedance to move. Many connectivity models exist such as least cost modelling (Adriaensen et al., 2003), circuit theory (McRae, 2006; McRae et al., 2008) or landscape graphs (Bunn et al., 2000; Urban & Keitt, 2001). Among these methods, landscape graphs (combining resistance maps and least cost modelling) provide an interesting compromise between the data requirements and the capacity to represent ecological processes (Fagan & Calabrese, 2006).

Graphs build ecological networks from nodes (i.e., habitat patches) and edges (i.e., functional connexions) through Euclidean distances or least cost paths (LCPs). These edges can be pruned using a cost or distance value that reflects, for example, the dispersal distance of a target organism (Foltête et al., 2012). Moreover, connectivity metrics are usually computed from these graphs at different scales (i.e., patch or edge, component and/or global level) to quantify functional connectivity and create simulations for landscape management (Foltête et al., 2014; Pascual-Hortal & Saura, 2006; Rayfield et al., 2011; Saura & Pascual-Hortal, 2007). Even though LCPs connecting habitat patches do not encompass all possible corridors, they provide reliable functional connectivity assessments for terrestrial organisms and thus for conservation (Balbi et al., 2021; Zeller et al., 2018). However, all these cartography-based approaches strongly depend on the precision and quality of the input spatial information, particularly land cover databases that include and delineate habitat patches and ecological corridors and barriers. To this end, satellite and aerial images are analysed using geographic information science (GIScience) methods and tools (e.g., geographic information system [GIS] tools and remote sensing analyses) to determine the characteristics of the landscape and extract natural elements such as trees, waterways and gardens. Most studies combine existing data from national geographic institutes, although fine-scale elements are often under-represented, as they require time-consuming manual processing (i.e., manual digitization). In urban landscapes, for example, trees and grass, often reduced to small isolated patches, are frequently underestimated, thus resulting in a lack of information that biases both landscape knowledge and ecological modelling (i.e., connectivity and ecosystem services). However, urban vegetation, and especially its different strata, are crucial for fine-scale modelling, as these structures are fundamental for studying the movements of organisms. Indeed, herbaceous vegetation does not play the same ecological role as tree vegetation with regard to a wooded species or an herbaceous species. Thus, integrating vegetation strata is crucial to model biological flows and identify landscape structures (Choi et al., 2021; Grafius et al., 2017; Tattoni & Ciolli, 2019).

Remote sensing approaches with very high-resolution (VHR) images thus become essential, and among the high-resolution data, airborne light detection and ranging (LiDAR) and hyperspectral data provide very useful information for land cover/use classification (Casalegno et al.,

2017; Neyns & Canters, 2022; Shahtahmassebi et al., 2021). For instance, airborne LiDAR has been used in urban and forest areas to provide digital elevation models and digital surface models from a point cloud characterizing height of land cover elements. Such information helps detect and distinguish the different vegetation strata (i.e., herbaceous, shrubby and wooded) specifically within landscapes showing high complexity and heterogeneity such as cityscapes (Casalegno et al., 2017). Even though these spatial data are well known and should be more affordable in the future, they are still rare, because they need specific materials to be acquired (e.g., drones or airborne platforms) and analysed. An alternative approach consists of analysing available VHR images using remote sensing tools that combine learning-based and geographic object-based image analysis (GEOBIA) methods. GEOBIA is a subdiscipline of GIScience that uses remote sensing analyses on satellite or aerial images (i.e., raster) to obtain semantic objects (i.e., vector) (Blaschke, 2010; Blaschke et al., 2014; Chen et al., 2018; Hay & Castilla, 2008). The first step (i.e., segmentation) aims to identify and extract objects and features (i.e., segments), while the second step (i.e., classification) consists of assigning each segment to a specific land cover category. Many advances have been made to successfully identify and distinguish land cover categories from VHR images such as vegetation strata (De Luca et al., 2019; Dupuy et al., 2020; Li & Shao, 2013; PUISANT et al., 2014; Zhang et al., 2010; Zhou & Troy, 2008). Such methods are based on images with common spectral bands (i.e., red, green, blue and near infrared [NIR] bands), thus making this method useful and affordable in analysing numerous existing spatial data. Beyond the extraction of tree and grass vegetation, this methodology applied to a VHR image allows for the detection of isolated trees that could profoundly change the landscape description and ecological modelling (App et al., 2022; Tiang et al., 2021). However, to our knowledge, no empirical study has estimated the improvement of a remote sensing (i.e., learning-based and GEOBIA) approach at a fine scale in urban landscape connectivity modelling (Wellmann et al., 2020).

Indeed, based on the VHR images of three French cities, the first objective of this study is to develop a remote sensing methodology to identify and extract vegetation strata. Then, to consider the significance of the results (i.e., feasibility and reliability), we compare the obtained vegetation with that found on maps downloaded from existing databases. Nevertheless, we add the vegetation obtained from the remote sensing approach (firstly without strata distinction and then with strata distinction) to the maps from the existing databases to assess the influence of data quality (i.e., by adding the remotely sensed vegetation) on landscape connectivity modelling. To this end, we analyse and compare the landscape structure indices (i.e., landscape composition and configuration) of these different maps. Finally, we computed and compared the functional ecological indicators (i.e., functional connectivity metrics and models) for several biological and ecological behaviours and capabilities.

By comparing these three levels of resolution data, this study highlights that ecological modelling depends on the quality of the land cover on which it is based, while a good description of the vegetation is crucial to estimate the ecological networks. Furthermore, by relying on open-source tools and methodology, this paper draws attention to the benefits of combining two different and complementary disciplines (i.e., GIS and landscape ecology) in the design of ecological networks.

2. Material and methods

2.1. Study area and global land cover

The study was conducted in three cities located in the west of France: Poitiers (46.58° N, 0.34° E), Niort (46.32° N, 0.46° W) and Châtelleraut (46.81° N, 0.54° E). The cities are separated by around 100 km and exhibit a similar oceanic climate.

Poitiers has a population of 131,499 inhabitants (2017 census), the altitude varies from 65 to 144 m, the average annual temperature is

11.5 °C, and the average annual precipitation is 687 mm. This city is an important historical metropolis in the west of France that is crossed by a motorway and a high-speed line (train). The long-established historic centre of Poitiers features a high density of housing and buildings, while the peripheral areas have experienced rapid urbanization since the 1950 s. The broader landscape also includes semi-natural areas such as forests, wetlands, open fields, and an urban natural park (along the river Le Clain) that spans Poitiers and aims to preserve and promote natural areas in the urban landscape (e.g., grasslands, wetlands).

Niort has a population of 72,894 inhabitants (2017 census), the altitude varies from 2 to 77 m, the average annual temperature is 12.5 °C, and the average annual precipitation is 867 mm. Niort, an important historical city in the region, has experienced serious urban sprawl since 1950 and currently features both old and recent urban

areas. The city is crossed by a green corridor alongside the river Sèvre Niortaise, composed of forest areas, permanent meadows and wetlands.

Châtellerault has a population of 40,721 inhabitants (2017 census), the altitude varies from 42 to 134 m, the average temperature is 12.5 °C, and the average annual precipitation is 734 mm. This smaller city, crossed by a motorway, is composed of a less dense urban area compared to the other two cities. It has industrial and suburban areas as well as semi-natural habitats such as forest areas, wetlands and open fields.

2.2. Production of the raw map

An initial description of the land cover in the study areas was obtained at a high resolution (1:5000) by combining existing databases using QGis v.3.10 (Quantum GIS Development Team, 2019) (Fig. 1b). As

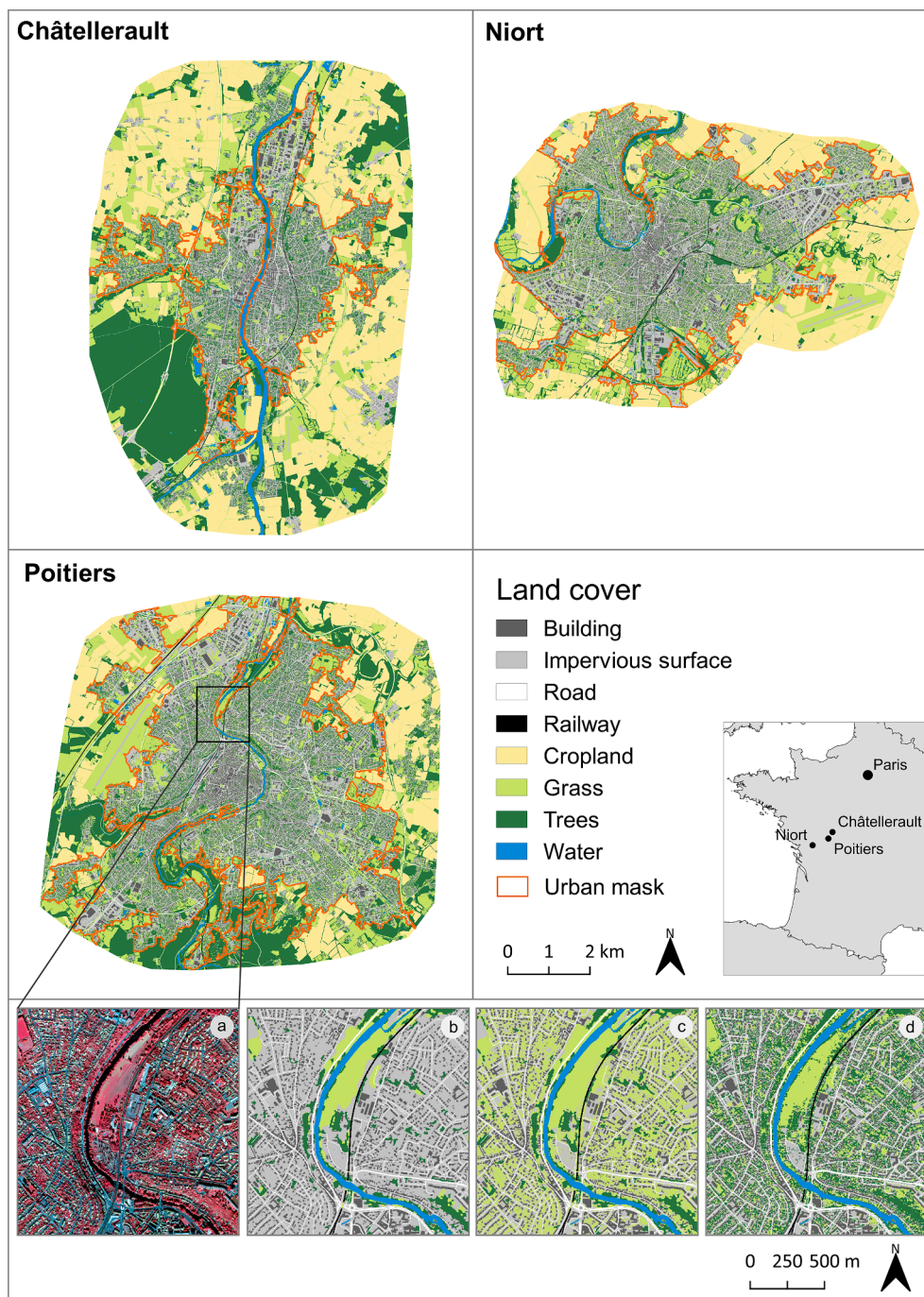


Fig. 1. Study area showing the locations and land cover/use classifications of Poitiers, Niort and Châtellerault.

numerous studies are based on similar maps (i.e., resolution and description), we use this raw map as a reference map for comparisons with the enhanced maps obtained using the remote sensing approach.

This raw map was obtained using the BD TOPO vector database of the French National Geographic Institute (IGN) to acquire the tree vegetation (scattered and rare patches in cities), buildings, water bodies and transport infrastructure. Furthermore, the agricultural plot boundaries were obtained by downloading the vector data Registre Parcellaire Graphique (RPG) from 2017. In parallel, we used the French land cover maps (OSO) from 2016, 2017, 2018 and 2019 based on the Sentinel-2 image time series (Inglada et al., 2017) to identify, for each agricultural plot, annual croplands (at least 3 out of 4 years of annual cropland), temporary grasslands (2 or 3 years of grassland), permanent grasslands (4 years of grassland) and vineyards. Finally, the urban areas (i.e., continuous urban fabric, discontinuous urban fabric, industrial and commercial units, road surfaces) were obtained from the French land cover map (OSO) from 2017.

2.3. Multispectral data

The French IGN provided the orthophotos for the three cities. The images were acquired using a digital camera between 2017/10/11 and 2017/10/15 for Poitiers and Châtelleraut and on 2018/05/19 for Niort. The on-board sensors provided multispectral data including three spectral bands with a spatial resolution of 0.5 m: a green channel, a red channel and a NIR channel. They were projected into the Lambert-93 (EPSG: 2154) projection based on the RGF93 geoid (IAG GRS 1980 ellipsoid). These false colour composites (RGB = NIR/Red/Green) were used for object-based classifications.

2.4. Land cover classification

We analysed these multispectral data using an object-based classification with a learning step to detect and extract grass and tree patches within the study areas. For this purpose, we used the open-source Orfeo

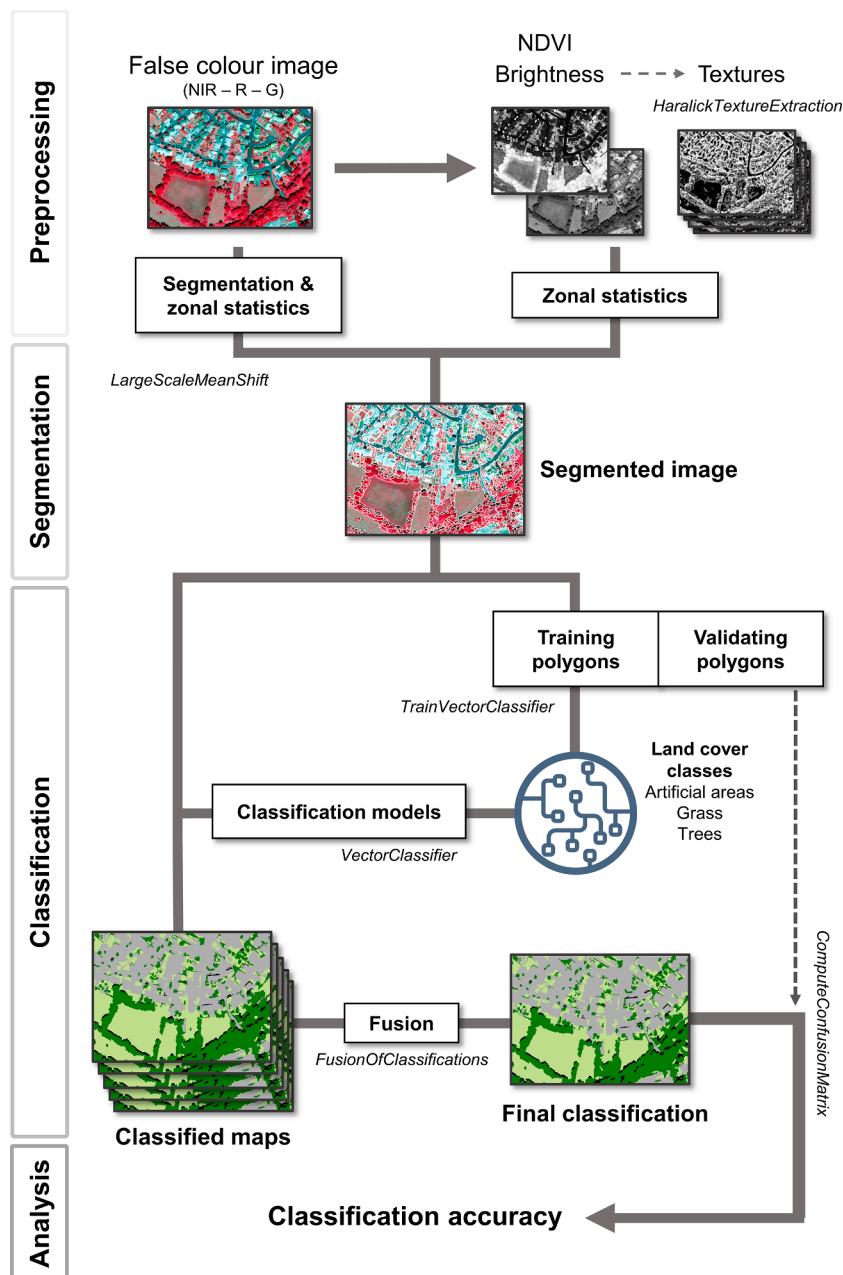


Fig. 2. Workflow of the main steps of the object-based classification process from the false colour composite.

Toolbox library (Grizonnet et al., 2017). The workflow used for the object-based image analysis is summarised in Fig. 2. The main steps are pre-processing (including feature extraction), segmentation, classification (including the learning step) and accuracy assessments. This remote sensing approach only considers artificial areas (including buildings, impervious surfaces and bare soil) and vegetation strata, which are mainly lacking from existing databases.

2.4.1. Segmentation

The first step of the object-based analysis was to identify and extract objects or segments. Segments are groups of adjacent pixels that show similar radiometric information corresponding to a semantic meaning (Blaschke et al., 2014). We used the *LargeScaleMeanShift* function, which uses a smoothing step to facilitate the segmentation procedure. This application executes four steps: i) the *MeanShiftSmoothing* algorithm facilitates the segmentation by smoothing the image; ii) the *LSMSegmentation* algorithm is the segmentation step; iii) the *LSMSSmallRegionsMerging* algorithm removes all segments smaller than a given size (in pixels) by merging them into a similar neighbouring object; and iv) the *LSMSVectorization* algorithm converts the segmentation into a vector file and calculates the mean and standard deviation of each raster band inside segments (Grizonnet et al., 2017). Based on the empirical tests used to obtain the best segmentation and avoid over- or under-segmentation, we chose a spatial radius of 5 pixels, a range radius of 28 pixels, and a minimum segment size of 60 pixels for the *LargeScaleMeanShift* algorithm. The high range radius value provided strong smoothing, particularly to avoid over-segmentation at the grass/shadow interface. Finally, the 60-pixel threshold corresponded to the crown of smaller isolated trees.

2.4.2. Feature extraction

To assign the target categories to each segment, spectral and texture features were added. We computed the normalized difference vegetation index (NDVI) (Rouse et al., 1973) that is commonly used in remote sensing applications to detect vegetation. Brightness was also calculated as the mean of the three bands (NIR, Red and Green). To improve the classification accuracy, we identified and removed shadow segments showing a mean value of brightness below 65 for Poitiers and Châtellerault and 70 for Niort according to the histogram of brightness (Zhou et al., 2009).

Nevertheless, textures were calculated from the brightness band. They have been used to enhance the classification accuracy by distinguishing vegetation strata or urban objects (Dorigo et al., 2012; Feng et al., 2015; Marceau et al., 1990; Murray et al., 2010; Neyns & Canters, 2022; Shahtahmassebi et al., 2021; Wood et al., 2012). For example, whereas grass showed a smoother or more regular aspect, trees had a more irregular aspect (Appendix A). According to Gonzalez and Woods (2002), textures describe the smoothness, coarseness and regularity of an image. They are characterized by a grey-level co-occurrence matrix (Haralick et al., 1973; Nixon & Aguado, 2002), which represents the spatial homogeneity around each pixel based on a given size of moving window. Variations in grey levels are quantified in the matrix and used to compute the textures. Haralick textures are categorized into three types of measures in which the textures are highly correlated: statistics measures, contrast measures and orderliness measures. Moreover, Hall-Beyer (2017) showed that two measures from the same group can highlight different information: visual edges or patch interiors (Appendix A). Thus, using the *HaralickTextureExtraction* algorithm, we computed four textures with a window size of 7×7 pixels: *Energy* (orderliness measure – patch interior information), *Correlation* (statistics measure – patch interior information), *Contrast* (contrast measure – visual edge information) and *Entropy* (orderliness measure – visual edge information).

The average value within segments was extracted for all spectral bands and textures. The standard deviation was used for the green band and textures, because grass segments show less variability than tree segments (Table 1).

Table 1

Information type calculated within each segment and used for the learning step.

Raster	Information type	Mean	SD
Near infrared	Spectral	X	
Red	Spectral	X	
Green	Spectral	X	X
NDVI	Spectral	X	
Energy	Texture	X	X
Entropy	Texture	X	X
Correlation	Texture	X	X
Contrast	Texture	X	X

2.4.3. Random forest classification

Random forests, introduced by Breiman (2001), are frequently used in remote sensing because of their accuracy, robustness, capacity to manage large input variables and few parameters to tune (Feng et al., 2015; Ma et al., 2017; Puissant et al., 2014). This learning method combines classification and regression trees (CART; (Breiman et al., 1984) as well as a bagging-based method. As a set of decision rules, a classification score is calculated from the classification results of several randomized decision trees. After the empirical tests, for the three cities, we chose a value of 250 trees for each forest and a value of 4 for the depth of the trees corresponding to a third of the number of the predictor variables (Rodriguez-Galiano et al., 2012).

To improve the classification accuracy, we used a stratified subsample followed by a cross-validation process as suggested by Dupuy et al. (2020). We divided the training data into five equal subsets to produce five different classifications: four subsets are used as the training dataset and one subset as the validating dataset, and then each subset was used as a validating vector. Finally, the five classifications were merged by majority voting.

To estimate the performance of the classifications, we computed the overall accuracy and Cohen's kappa for the global performance of the classification. The precision, recall and F-score (which is the harmonic mean of precision and recall) were computed for each class. These metrics, calculated for each of the five validated subsets, were averaged, while the standard deviation was calculated.

2.4.4. Training and validating vectors

Choosing the training and validating polygon is an important step as classification models rely on it. The selected segments must represent statistical variations for each category across the entire study area. Based on the photointerpretation, polygons were sampled from the segmentation for the three target categories: artificial areas, grass and trees (Table 2). Artificial areas contained buildings, roads, bare soils and other impervious surfaces; grass contained meadows, lawns, herbaceous wastelands and herbaceous fallows; trees contained tall trees, shrubs, wooded wastelands and wooded fallows. They were selected across all

Table 2

Number of polygons per class for the learning step in each study area.

City	Category	Number of polygons
Poitiers	Artificial areas	1134
	Grass	350
	Trees	376
	Total	1860
Niort	Artificial areas	1370
	Grass	626
	Trees	698
	Total	2964
Châtellerault	Artificial areas	1260
	Grass	480
	Trees	700
	Total	2440

the study areas (Appendix B) to avoid spatial autocorrelation, which can bias the evaluation of classification performance (Mannel et al., 2011).

2.5. Comparison of the three vegetation maps

To test the contribution of the data quality to the modelling, we constructed three maps for each city (Fig. 1). The first is the previously described map that compiles the available data from different databases and is known as the raw map (RM) (Fig. 1b). To construct the second map, known as the Very High-Resolution vegetation map (VHRvm), grass and tree segments identified using the object-based image analysis were merged into the same category as the global vegetation. This global vegetation map was added to the RM, which conserves the vegetation patches of the first map (Fig. 1c). The third map, known as the Very High-Resolution stratified vegetation map (VHRsvm), was constructed from the RM elements, although grass and tree segments were distinguished and described from the object-based classification (Fig. 1d) for which we accessed the accuracy. To facilitate the landscape analyses with efficient computing, all land cover maps were converted into a spatial resolution of 3 m.

2.6. Landscape connectivity analysis

2.6.1. Structural connectivity analysis

As the structural connectivity analysis was only carried out on the vegetation patches within the urban context, we used an urban mask corresponding to the urban fabric of the OSO map (Fig. 1). We calculated and compared the proportion of grass and trees as well as the number and mean size of the grass and tree patches for the three maps of each city. The Hanski index, implemented in Chloé v.4.0 (Boussard & Baudry, 2017), was calculated for grass and trees using following the formula:

$$\sum_{p1} \sum_{p2} e^{-d} a_{p2} / nb(p)$$

where d is the inter-patch distance (km) and a is the area (ha) of the second patch.

This index increases when the size of the patches increases and the distance between them decreases, thus reflecting the quality of the structural connectivity.

Moreover, choropleth maps were built to quantify the spatial gain of the tree vegetation surface (ha) and the loss of impervious surfaces (ha) from RM to VHRsvm using a 500×500 m grid with QGis v.3.10 (Appendix C) (Quantum GIS Development Team, 2019). Applied to the three cities, these choropleth maps allow the visualization of spatial variations in land use, resulting from the different mapping approaches used to construct the VHRsvm and RM.

2.6.2. Functional connectivity analysis

We used graph theory to investigate the contribution of the land cover description/resolution resulting from the different mapping approaches in the computations of the functional connectivity parameters (Urban & Keitt, 2001) using Graphab 2.6 (Foltête et al., 2012). Combining the concept of landscape resistance (i.e., resistance maps) and LCPs (Adriaensen et al., 2003; Spear et al., 2010), this approach identifies functionally connected habitats according to the dispersal distance of a target organism. To implement this approach, we simulated virtual forest species with ecological requirements consistent with tree habitats. We focussed on forest habitats using habitat patches larger than 1 ha. To create resistance maps, we identified five categories of cost values: 1 = habitat or very suitable surfaces, 10 = suitable surfaces, 100 = neutral surfaces, 1,000 = unsuitable surfaces and 10,000 = very unsuitable surfaces (Sahraoui et al., 2017) (Appendix D). In parallel, we created seven different species with seven maximum dispersal distances: 50, 100, 200, 500, 1,000, 1,500 and 2,000 m. Even though these resistance values can correspond to real species, the term virtual species is used here, because the models were not validated using biological data.

In practice, these distances make it possible to test a wide range of behaviour and dispersal capacities of forest organisms. The seven maximum dispersal distances were converted into a cost distance (Conversion distance function) from each VHRsvm (Appendix E). For each of the three maps and three cities, seven landscape graphs (i.e., planar graphs) were constructed using the seven cost distances. These cost distances were used to prune the edges of the planar graphs and thus test how the landscape shapes the movement of forest species with low dispersal capabilities (e.g., 50 m) such as forest ground-dwelling arthropods and those with medium dispersal capabilities (e.g., 2,000 m) such as forest songbirds. From the resulting graphs, we obtained the number of components (i.e., a subunit of the global graph in which patches are connected) indicating the degree of connectivity, or conversely, the degree of fragmentation of habitat patches (i.e., the more isolated the patches are, the more components there are). To investigate the contribution of the map resolution at this fragmentation level, the number of habitat patches was divided by the number of components. Moreover, the probability of connectivity (PC) metric was computed at the global (i.e., whole graph level) and local scale (i.e., edge level) (Saura & Pascual-Hortal, 2007). This index reflects the probability that two individuals taken at random within the study area can reach each other. It is calculated using the following formula:

$$\sum_{i=1}^n \sum_{j=1}^n a_i a_j p_{ij}^* A_L^2$$

where a_i and a_j are the area of patches i and j , A_L is the total landscape area and p_{ij}^* is the maximum of probability movement between these patches calculated using the function:

$$p_{ij} = e^{(-\alpha d_{ij})}$$

where α describes the intensity of decreasing the probability of dispersion, d is the distance and p describes the dispersion using a value of 0.05 for the maximum dispersal distance (used in this study for all graphs).

Finally, to illustrate differences between the ecological corridors from different maps, the network of corridors was constructed with the *corridor* function using a maximum dispersal distance fixed at 2,000 m as an example. All the functional paths or areas that can be crossed between patches were modelled by a cumulative cost function. LCPs were also compared between maps by showing the cumulative resistance of each path and their dPC value (Appendix F). The cumulative resistance describes the difficulty to move using the corridor. The dPC identifies the contribution of an element k to the overall habitat availability and connectivity within the landscape using a removal method to calculate the percentage of variation in PC (dPC_k) (see also Duflo et al., 2018; Saura & Pascual-Hortal, 2007) from the formula:

$$dPC_k = \frac{PC - PC_{remove.k}}{PC} \times 100$$

3. Results

3.1. Segmentation

The segmentation step provided semantic objects from the false colour composite (Fig. 3). Tests showed that the smoothing step was important to limit over-segmentation and, for example, to avoid the creation of small segments at the grass/shadow interface that had similar spectral and texture characteristics to the tree segments. Due to the acquisition date of the images of Poitiers and Châtelleraut, shadows were larger than in the images of Niort. For Poitiers, Niort and Châtelleraut, segmentation provided about 940,000, 570,000 and 500,000 segments, respectively, from which 167,000, 43,000 and 52,000 shadow segments were filtered and removed for the classification step.

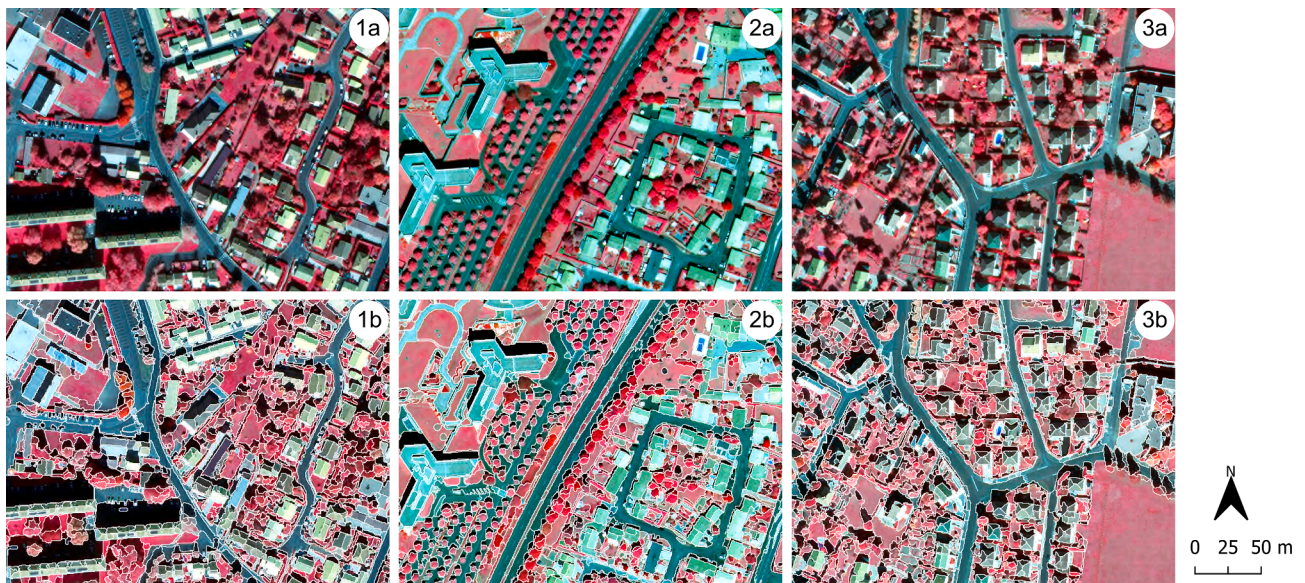


Fig. 3. False colour composite (RGB = NIR/Red/Green) (a) for Poitiers (1), Niort (2) and Châtellerault (3) and segmentation results (b).

3.2. Analysis of accuracy assessments

The classifications showed good global results with an overall accuracy of 95.20% (± 0.86), 96.72% (± 4.61) and 98.10% (± 1.26) and a Cohen's kappa of 0.90 (± 0.04), 0.94 (± 0.08) and 0.95 (± 0.01) for Poitiers, Niort and Châtellerault, respectively.

At the class level, Fig. 4 showed accuracy assessments for each category (mean \pm SD). Classifications showed similar trends in the three cities regardless of the categories involved.

Artificial areas and grass were well detected with F-scores of 94.6%, 97.24% and 99.8% for the urban segments and F-scores of 95.8%, 96.54% and 95.64% for the herbaceous segments for Poitiers, Niort and Châtellerault, respectively. Despite the good results for trees, more contrasting performances were obtained with slightly lower F-scores: 85.52%, 86.58% and 83.46% for Poitiers, Niort and Châtellerault, respectively. Artificial areas were the best-detected category; more variation was found for the classification of Poitiers in which these areas are slightly over-detected (i.e., precision of 94%). Grass had high metric values for each city, showing less variability in its performance between cities (i.e., average values) and within cities (i.e., standard deviation). However, grass was possibly over-detected and under-detected, because trees and grass can be mistaken for each other. Indeed, trees had lower

values of precision and recall, meaning that trees were over-detected (containing true grass segments) and under-detected (true tree segments were classified as grass segments). In addition, the three classes revealed stronger differences for the classification of Niort in which grass and trees showed more spectral differences compared to those of Châtellerault and Poitiers (showing very close image characteristics) (Appendix G).

3.3. Landscape connectivity analysis

3.3.1. Structural connectivity

Due to the lower resolution of the RM, urban vegetation at the very fine scale was not well detected and identified in the studied areas that measured 4136.66 ha for Poitiers, 3199.86 ha for Niort and 1918.57 ha for Châtellerault (Fig. 1b). As previously stated, this results from the high heterogeneity and complexity of urban landscapes as well as the small area occupied by features such as small isolated trees. The structural connectivity varied among maps and cities but showed similar patterns for the three cities in terms of RM, VHRvm and VHRsvm (Fig. 5). Overall, the object-based classification of VHR images improved the characterization of the total vegetation surface. Compared to RMs, VHRsvm increased the vegetation areas by about four times (Fig. 5a).

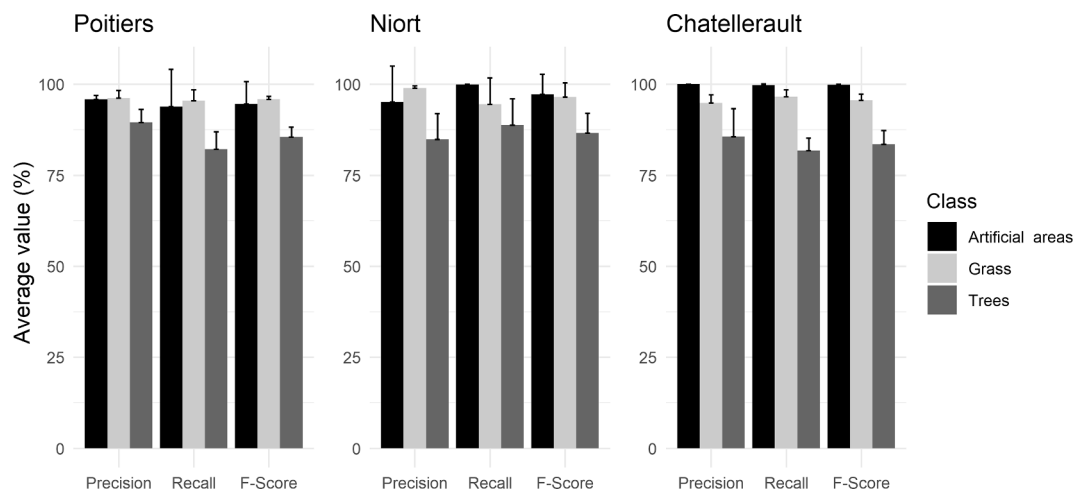


Fig. 4. Accuracy assessment of the final classification (average value \pm SD) for each study area.

For example, while grass proportions varied from 4.28% to 6.04% for RMs, they ranged from 14.03% to 14.44% for VHRsvm. This trend was also found with the tree proportions. Only large patches such as parks were detected in RMs, while VHRvm and VHRsvm identified lawns, shrubs and other small vegetation elements. Indeed, our remote sensing approach allowed us to detect fragmented and small isolated patches resulting in an exponential increase in the number of patches (Fig. 5b, c). As expected, Poitiers, which has the largest urban area, showed the highest gains in terms of the number of patches, followed by Niort and then Châtellerault. Moreover, newly detected vegetation patches in VHRvm and VHRsvm were smaller, as evidenced by the mean patch size decreasing by three to five times for Niort and Châtellerault (Fig. 5c), and to a lesser extent, for Poitiers. Agricultural plots (i.e., meadows) explain the high mean patch size in Niort and Châtellerault.

The Hanski connectivity index, which increases as the patches become larger and geographically closer, increased within VHRsvm for grass and tree patches and showed a strong increase for grass patches within VHRvm (Fig. 5d). Despite the decrease in the mean patch size, these results showed that the inter-patch distance strongly decreased in the grass patches within both VHRvm and VHRsvm as well as for tree patches within VHRsvm. Regarding the spatial variations of trees and urban areas between RMs and VHRsvm, the greatest changes in choropleth maps were mainly observed around the urban core of each city within residential areas, for example (Appendix C).

3.3.2. Functional connectivity

The VHRsvm detected new habitat patches (i.e., greater than 1 ha) in each study area compared to RMs (and VHRvm): 24 new habitat patches for Poitiers, 15 for Niort and 35 for Châtellerault (Table 3).

Fig. 6a indicates variations in the PC metric at the global scale for the seven maximum dispersal distances for each map. Based on the surface

of the habitat patches and their reachability across the landscape, the connectivity index increases with the maximum dispersal distance for all the landscape graphs, as expected. VHRsvm showed the highest functional connectivity for each city. Lower PC values were found for the VHRvm- and RM-based landscape graphs, which had more similar PC values. The functional connectivity of VHRvm-based graphs was slightly better than that of RM-based graphs for distances greater than 500 m for Poitiers and Niort but not for Châtellerault in which PC values were very similar for all distances. Regarding the functional connectivity among cities, Châtellerault showed the highest values of PC ranging from 2.07×10^{-3} to 3.69×10^{-3} , followed by Poitiers with values from 3.45×10^{-4} to 1.18×10^{-4} and Niort with values from 4.53×10^{-5} to 1.29×10^{-4} . When focussing on the degree of fragmentation, the ecological networks were more fragmented for RMs, VHRvm showed more connections between habitat patches, and VHRsvm were the least fragmented networks (Fig. 6b).

Table 3

Number of forest patches larger than 1 ha for raw maps (Raw), very high-resolution vegetation maps (VHRvm) and very high-resolution stratified vegetation maps (VHRsvm).

Zone	Map	No. patches
Poitiers	Raw	156
Poitiers	VHRvm	156
Poitiers	VHRsvm	180
Niort	Raw	85
Niort	VHRvm	85
Niort	VHRsvm	100
Châtellerault	Raw	135
Châtellerault	VHRvm	135
Châtellerault	VHRsvm	170

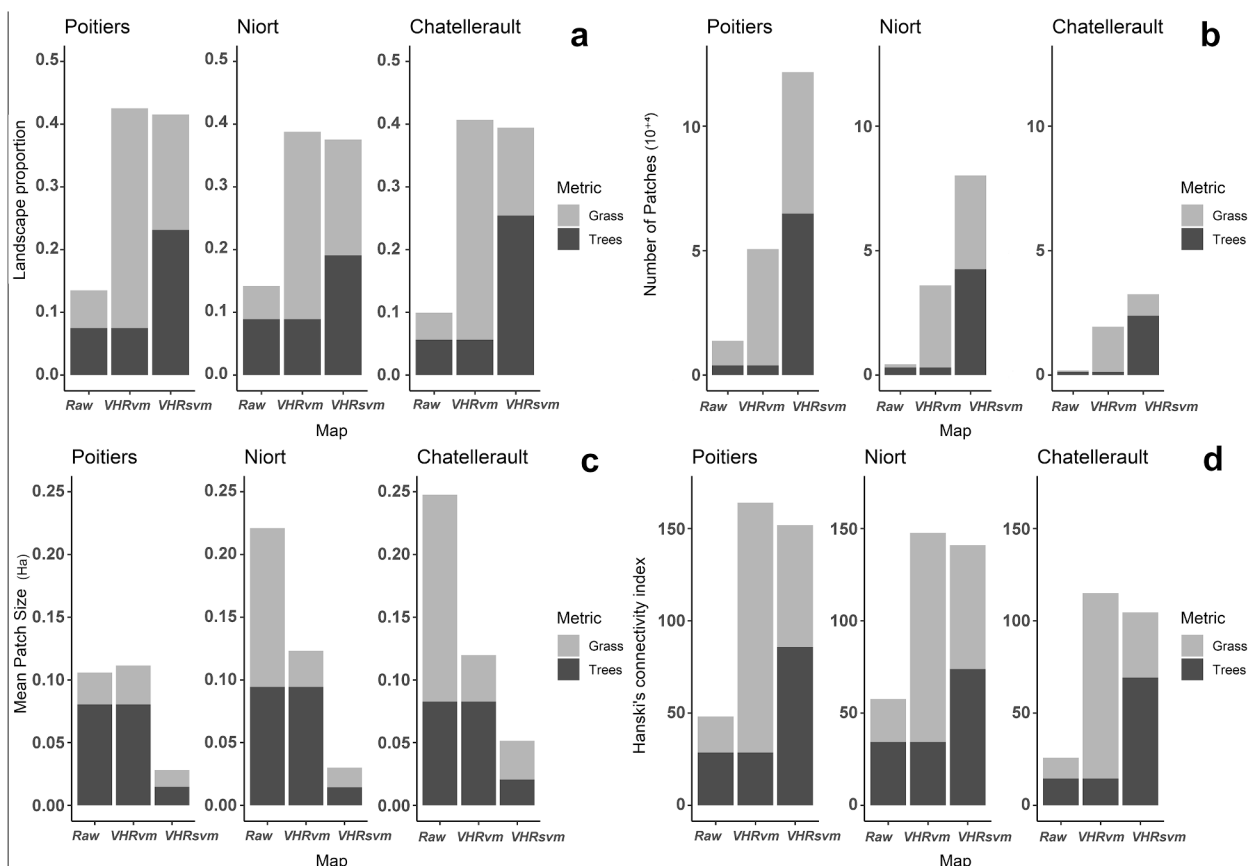


Fig. 5. Structural connectivity indices focussed on grass and tree vegetation from the three land cover/use maps for each of the three cities: landscape proportion of grass and tree areas (a), number of grass and tree patches (b), mean size of grass and tree patches (c) and Hanski connectivity index for grass and trees (d).

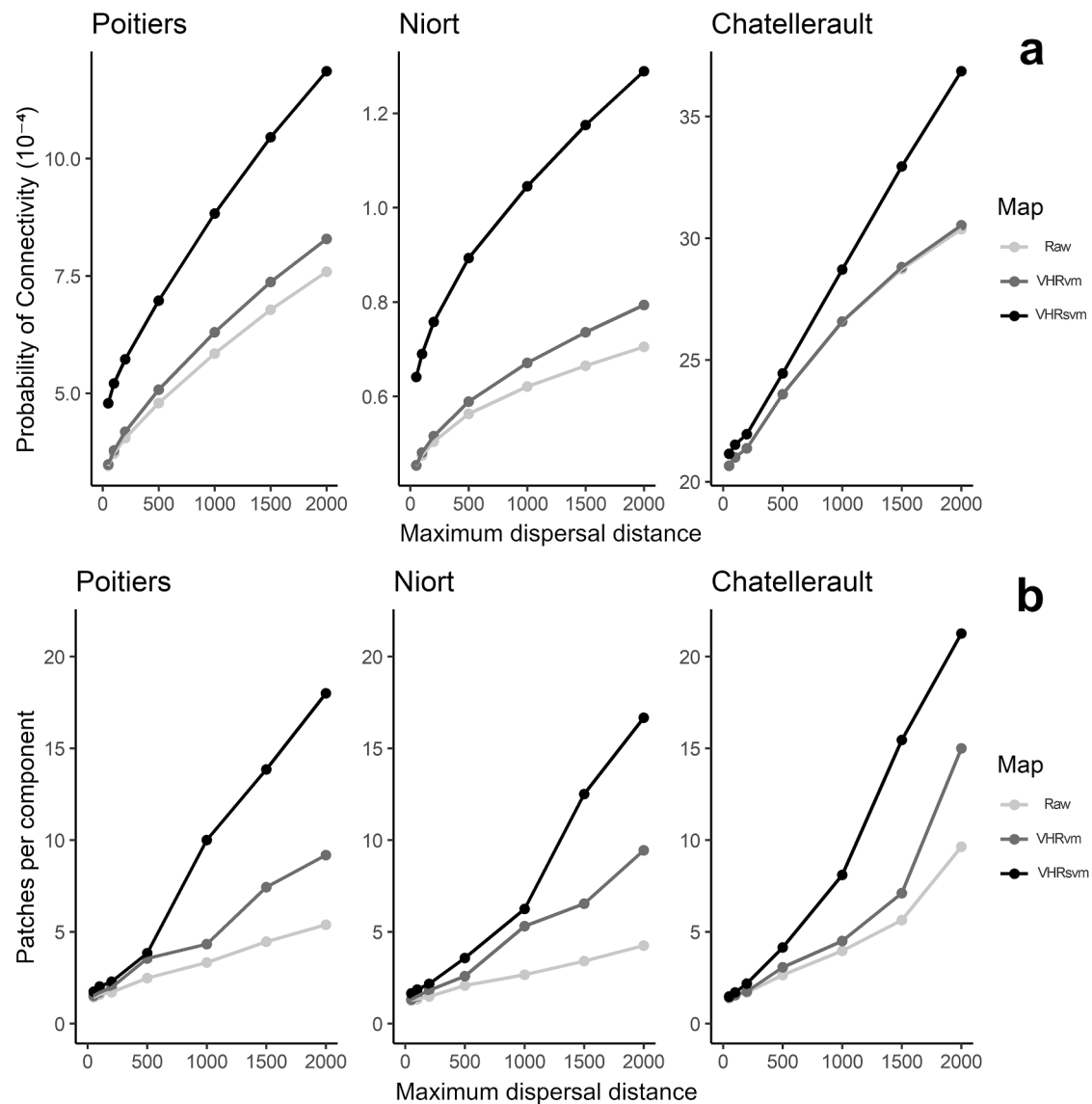


Fig. 6. Functional connectivity indices focussed on urban woodland habitats (larger than 1 ha) for the raw maps (light grey), very high-resolution vegetation maps (dark grey) and very high-resolution stratified vegetation maps (black). Evolution of the probability of connectivity according to several maximum dispersal distances (a). Number of patches divided by the number of components (b).

However, there were fewer differences between the maps for short distances (i.e., < 500 m). Regarding the corridor modelling, these degrees of fragmentation were also observed (Fig. 7). VHRvm showed more extended corridors with a higher quality compared to those of RMs. VHRsvm revealed even more widely distributed corridors of a higher quality, especially within the urban cores. In addition, modelled LCPs showed strong differences between maps for an identical maximum dispersal distance (i.e., 2,000 m). An identified corridor within RMs had lower cumulated resistance values within VHRvm and VHRsvm, and new corridors were identified by enhancing the description of vegetation for these two maps (Appendix E). Furthermore, the contribution of LCPs in the landscape graphs also changed with the map quality (Appendix F).

4. Discussion

This study shows that the remote sensing methods used in this study are a reliable approach to detect isolated and scattered patches of vegetation and distinguish vegetation strata from VHR images. We also

show that the quality of the land cover description influences the ecological process modelling (such as ecological corridors) and that the combination of the vegetation strata obtained from our remote sensing approach with maps from existing databases greatly improved the quality and representation of land covers.

4.1. The Object-based classification from VHR images : an effective approach for mapping very fine scale elements in urban contexts

Our study showed the importance of considering the GEOBIA approach in landscape connectivity modelling. Classifications showed good results with high kappa values and F-scores, which were expected based on a small number of land cover classes (i.e., 3) as well as the use of texture analyses (Dorigo et al., 2012; Feng et al., 2015; Neyns & Canters, 2022). The NIR channel (included in the NDVI) was crucial in order to reliably distinguish vegetation from non-vegetation areas (Puissant et al., 2014), although the true-colour aerial imagery (i.e., RGB channel) may also be used in urban areas to conduct object-based classification (Baker et al., 2018). Relatively low F-score values for

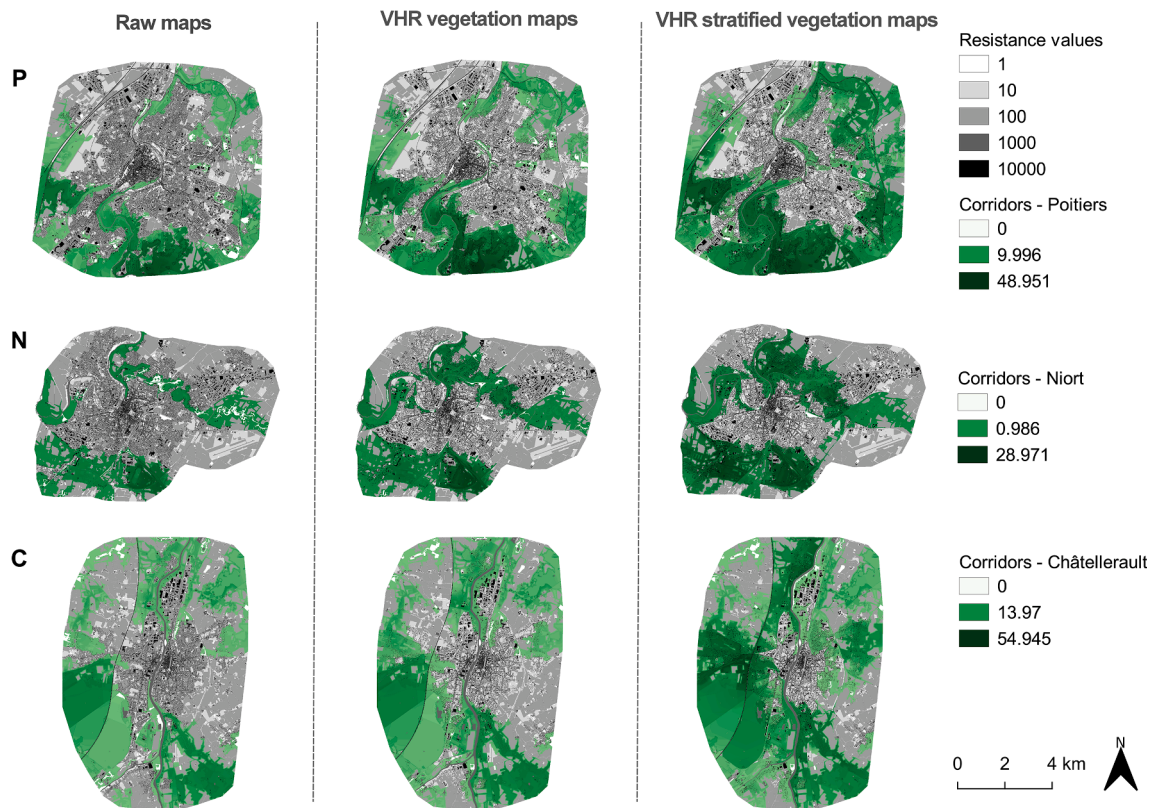


Fig. 7. Network of corridors (functional paths/areas between habitat patches) modelled for a maximum dispersal distance of 2,000 m for each map within Poitiers (P), Niort (N) and Châtellerault (C).

trees mainly stem from the confusion between complex structures such as gardens with isolated small bushes, which correspond to the transition between grass and trees categories (Puissant et al., 2014).

Regarding the methodology and notably the object-based classification that is widely used in remote sensing urban green spaces studies (Neyns & Canters, 2022; Shahtahmassebi et al., 2021), we carefully considered several crucial steps to achieve good results when LiDAR data are not available. First, the smoothing step of the segmentation was important in terms of the mean shift segmentation. While the smoothing step did not improve segmentation in the study of DeLuca et al. (2019), our tests showed that the absence of the smoothing step generates an over-segmentation, thus creating small segments with low compactness. In this case, these small segments at the grass/shadow interface could lead to the detection of false tree segments. In our case, the segments obtained were quite compact and corresponded to more meaningful objects. However, attention must be paid to the segmentation and over-segmentation should be preferable than under-segmentation to achieve a good classification accuracy (Gao et al., 2011; Jian Yang et al., 2015; Smith, 2010; Stumpf & Kerle, 2011). As the parameters depend on the characteristics and proximity of pixels, the values of the *Large-Scale Mean Shift* algorithm could be different for another image resolution (Chen et al., 2018). In addition, the date (day and hour) of the image strongly influences the results (De Luca et al., 2019; Wulder et al., 2008). Images taken in autumn (i.e., Poitiers and Châtellerault) showed larger shadows than those taken in spring (i.e., Niort). Moreover, due to the phenology of the herbaceous vegetation, grass and trees had more similar spectral values in the images of Poitiers and Châtellerault compared to Niort. The best classification accuracy is obtained when the intra-class variation of the categories is low, and the inter-class variation is high. Thus, the identification of vegetation strata was easier for the classification of Niort compared to Poitiers and Châtellerault.

4.2. Implications of urban green space detection on landscape connectivity

While some landscape ecology studies use high-quality maps with LiDAR (an expensive and time-consuming method) (Grafius et al., 2017; Jensen et al., 2009), none focusses on object-based image analysis and its considerable ability to yield a land cover map able to model a high-quality landscape connectivity at a small scale (App et al., 2022; Balbi et al., 2021; Casalegno et al., 2017; Choi et al., 2021; Grafius et al., 2017; Zhou & Troy, 2008). Our study showed that existing databases are useful but can suffer from a lack of information at a very fine scale or in the urban landscape when considering vegetation (Puissant et al., 2014). In comparison, VHRvm revealed complex landscapes by multiplying the detected vegetation (regardless strata) by about four times and identifying smaller and fragmented vegetation patches. Moreover, VHRvm showed a slightly higher proportion of total vegetation compared to VHRsvm. As in Puissant et al. (2014), this excess vegetation is due to tree vegetation vectors provided in the official French database (IGN BD Topo) for which the details and precision (due to the detection threshold used) did not accurately match the processed orthophoto. However, VHRvm do not distinguish vegetation strata and can bias the assessment of landscape indices (Casalegno et al., 2017). For example, the Hanski connectivity index for grass showed very high values in VHRvm compared to VHRsvm due to the overestimated grass areas and their proximity. Thus, ecological studies analysing landscapes that do not distinguish vegetation strata should consider these potential impacts on the assessments of ecosystem services or landscape connectivity. Therefore, the object-based classification involved in VHRsvm improved the detection of urban vegetation and notably small and isolated trees, thus revealing additional scattered habitat patches. Tree alignments, which are characteristic of the urban environment, were mapped, as were trees or shrubs within gardens. Indeed, choropleth maps showed that the information gap mainly occurred in residential areas where

gardens contain trees and lawns. Coarse cartographies do not describe such areas, although these patches strongly enhance structural connectivity (App et al., 2022; Shahtahmassebi et al., 2021). We identified more wooded habitat patches (>1 ha), which consequently influence functional connectivity modelling. The identification of new habitat patches and effective corridors enhanced habitat quantity and availability by improving the ecological connectivity estimations (i.e., PC values). Thus, compared to RMs, VHRvm (including global vegetation) induced a slightly higher PC value for Poitiers and Niort, and to a lesser extent, for Châtelleraut. Overall, greater differences in PC values between the maps for Poitiers and Niort were likely due to their high urban density and diversity, whereas Châtelleraut is a smaller city with a much higher proportion of habitat areas that are less sensitive to urban fragmentation. It can be difficult to see global patterns in the connectivity modelling, because the urban entities (e.g., terraced houses, detached houses, major road verges) have complex forms that lead to a very high diversity of permeability influencing the movements of organisms (Grafius et al., 2017). Interestingly, greater differences in PC values and the degree of fragmentation were found for medium dispersal distances (i.e., >500 m). Hence, the resolution of the input data used in the connectivity modelling within the urban landscape changed the results, mainly for medium dispersers (e.g., songbirds). The remotely sensed vegetation strata incorporated in VHRsvm added habitat patches, thus reducing the distance between them. Moreover, the global average distance of the surrounding patches around each patch was probably about 500 m, which could explain these results. Above all, the landscape resistance strongly decreased by identifying tree alignments or shrubs (App et al., 2022; Balbi et al., 2019, 2021; Choi et al., 2021; Grafius et al., 2017). For example, VHRvm that only change the landscape permeability by identifying the global vegetation concomitantly showed a decrease in habitat fragmentation.

Undoubtedly, the results obtained for functional connectivity are strongly influenced by the methods and parameters involved when constructing both the land cover and resistance maps. Among these parameters, a relevant spatial resolution is crucial to describe continuous elements such as roads when building resistance maps. Such a high spatial resolution plays an important role in landscape connectivity and biodiversity assessments in urban and rural landscapes (App et al., 2022; Barr et al., 2021; Tiang et al., 2021). Indeed, the movement of organisms depends on their perception of the landscape, which affects their dispersal behaviour (App et al., 2022; Baguette & Van Dyck, 2007; Balbi et al., 2021; Bélisle, 2005), therefore small elements such as isolated trees can trigger the organisms' willingness to move. Thus, the detection of fine-scale elements in the landscape and a better estimation of the quality of the landscape matrix through remote sensing methods could lead to better modelling of landscape connectivity in urban landscapes. It will be interesting to test how much estimation of real connectivity (i.e., telemetry, gene flow) is correlated to ecological networks produced from different map resolutions in urban landscapes.

4.3. Implications and suggestions for conservation in land planning

Biodiversity conservation in urban land planning aims to conciliate anthropic and biodiversity distribution by incorporating natural spaces that allow cities to be more permeable to biodiversity and thus more sustainable. To meet the current urban challenges, it is crucial to integrate and combine remote sensing, urban ecology and urban planning approaches to design more sustainable and functional cities (Wellmann et al., 2020). As a consequence, landscape modelling is a useful tool to estimate ecological networks and test the impact of different scenarios on ecological connectivity in land planning (Drielsma et al., 2022; Sahraoui et al., 2021). As highlighted in this study, this type of ecological modelling depends on the resolution, quality and description of land cover, which can sometimes suffer from a lack of information, notably in terms of urban vegetation. Thus, the combination of a remote sensing approach at a very fine scale and landscape connectivity

modelling provides efficient land cover map leading to more realistic ecological networks. Landscape modelling of suitable habitat patches combined with their LCPs is relevant and useful for land managers, as it provides them with a prioritisation of areas to conserve or rehabilitate (Balbi et al., 2021; Sahraoui et al., 2021). For instance, stakeholders should focus their conservation efforts on corridors with higher resistance values (difficult paths to cross) or those that are more important in the modelled ecological networks (i.e., high dPC value) (Duflot et al., 2018). Furthermore, landscape graphs can provide an understanding of functionally connected habitats by identifying both connected and isolated geographic areas. As our results showed that map quality and resolution strongly impacted the connectivity indices, attention should be paid to the ecological networks based on low-quality land cover maps, which may lead to inaccurate conclusions regarding conservation planning.

Combining these affordable methods of remote sensing and urban ecology based on open-source projects and data is a powerful approach for conservation planning. Therefore, as each city is unique, land planners should integrate such methodology to analyse complex social-ecological-technological issues and challenges (Wellmann et al., 2020).

5. Conclusion and perspectives

Working at a small scale can be problematic, because the digitalization of landscape elements is time-consuming and needs human resources. In this study, the objective was to test the influence of remote sensing products as **supporting information** to detect urban vegetation in landscape modelling. This study supports the fact that free existing imagery and open-source projects represent powerful data and tools for landscape connectivity modelling at a very fine scale. Remote sensing methods such as object-based classifications or even simple methods (e.g., NDVI to detect global vegetation) are useful to improve knowledge about urban areas. Therefore, as supported by our results, the quality of land cover can strongly impact the connectivity indices, which quantify the landscape structure and functional connectivity and thus determine the importance of each corridor in terms of land management. The identification of small elements by remote sensing is crucial for landscape management in rapidly changing areas (e.g., cities) in order to consider spatial and temporal dynamics in landscape analysis. Thus, based on such remote sensing methods, future works should focus on aerial photographs archives to reconstruct the past landscape and to understand ecological processes such as the changes in landscape connectivity over time.

CRedit authorship contribution statement

Elie Morin: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Validation. **Pierre-Alexis Herrault:** Writing – review & editing, Validation. **Yvonnick Guinard:** Supervision, Project administration, Funding acquisition. **Frederic Grandjean:** Writing – review & editing, Project administration, Supervision, Funding acquisition. **Nicolas Bech:** Conceptualization, Methodology, Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2022.108930>.

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