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# Impact of spatial scale on the identification of critical habitat patches for the maintenance of landscape connectivity

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**Abstract**

An increasing awareness of the effects that the spatial scale of source maps may have on landscape analyses has lately prompted much research on this topic. Nevertheless, previous studies have just focused on describing the variations of different landscape metrics with scale, while the scale impact on the actual decision-making and landscape planning derived from connectivity analyses has not yet been tackled. We examined the influence of varying minimum mapping unit (MMU) and spatial extent on the prioritization of patches by their importance for the conservation of overall landscape connectivity, according to 10 different metrics as management support tools. We analyzed the forest patches distribution in three study zones within Spain with diverse spatial configuration from CORINE land cover data. Our results showed that the probability of connectivity, the area-weighted flux and the integral index of connectivity are the most robust metrics in terms of patches prioritization, while the results provided by the number of components, graph diameter and class coincidence probability are strongly scale-dependent. We found that scale sensitivity of the overall landscape metric value is not related to scale sensitivity in terms of patches prioritization. We provide guidelines for an appropriate selection of connectivity metrics and scale of analysis for landscape conservation planning and related applications.


*Keywords:* Landscape planning; Connectivity metrics; Ecological networks; Minimum mapping unit; Spatial extent; Dispersal distance

## 1. Introduction

Connectivity has become a key and priority issue in current biodiversity conservation policies (e.g. Pan-European Biological and Landscape Diversity Strategy – PEBLDS – (1995), Seventh Conference of Parties of the Convention on Biological Diversity (2004)) and research initiatives at all levels (Marull and Mallarach, 2005; Moilanen and Nieminen, 2002; Nikolakaki, 2004; Pascual-Hortal and Saura, 2006; Schumaker, 1996; Taylor et al., 1993; Tischendorf and Fahrig, 2000a; Van der Sluis et al., 2004). The need for maintaining ecological fluxes in the landscape and, particularly, the natural dispersal routes for wildlife species' movements, call for a more integrated management of ecosystems in which connectivity considerations should be necessarily incorporated. A proper mapping of the distribution and spatial configuration of the habitat and the landscape (e.g. Chust et al., 2004; Weiers et al., 2004) is first required in order to adequately deal with the structural pattern-dependent aspect of connectivity (see Tischendorf and Fahrig, 2000b). On the other hand, an estimation of the dispersal behavior and movement abilities of the focal species is necessary to measure functional connectivity, since the same landscape may have different connectivity as perceived by different species (Theobald, 2006; Tischendorf and Fahrig, 2000b).

Since spatial scale has a strong effect on the quantification of many landscape pattern metrics (e.g. Saura, 2004; Saura and Martínez-Millán, 2001; Wu, 2004), there is enough evidence to think that connectivity metrics may also be affected by the scale of the source spatial data. Scale comprises both spatial resolution (minimum mapping unit (MMU) or pixel size) and spatial extent (O'Neill et al., 1996; Saura, 2002). Land cover or habitat maps derived from remotely sensed data through either image interpretation or segmentation techniques are characterized by a minimum mapping unit which determines the degree of detail contained in the map. The MMU is defined as the smallest size

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areal entity to be mapped as a discrete entity (Lillesand and Kiefer, 1994) and it is selected to reduce the visual and spatial complexity of the information conveyed in the map (Davis and Peet, 1977; Saura, 2002). The extent of a map, as the total area being considered, is the other fundamental concept of spatial scale to be specified when approaching spatial analyses. Hence, the choice of the scale, both MMU and extent, might influence the results of the connectivity analysis itself (Knight and Lunetta, 2003; Mayer and Cameron, 2003; Saura and Martínez-Millán, 2001) and therefore it is necessary to quantify and consider those effects for an adequate analysis and interpretation of the results.

With the increasing recognition of the importance of scale on landscape pattern description and characterization, several studies have focused to date on the scaling behavior of many different landscape pattern metrics (e.g. Benson and Mackenzie, 1995; García-Gigorro and Saura, 2005; Ivits et al., 2005; Saura, 2002, 2004; Saura and Castro, 2007; Saura and Martínez-Millán, 2001; Turner et al., 1989; Wickham and Riitters, 1995; Wu et al., 2002; Wu, 2004). Nevertheless, the evaluation of these effects on particular spatial planning decisions, which are mostly taken on the basis of landscape pattern metrics, still remains untackled. On the other hand, identifying the most critical habitat patches for maintaining connectivity is necessary for effective implementation of conservation planning initiatives at the landscape scale. Hence, determining the appropriateness of different connectivity metrics for planning decisions concerning connectivity is a crucial issue that has been lately addressed, but the spatial scale issue has not yet been tackled (Jordan et al., 2003; Moilanen and Nieminen, 2002; Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007). While new powerful management support tools and improved connectivity metrics based on graph structures and algorithms have recently been developed with this purpose (Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007; Urban and Keitt, 2001), it remains unclear how conservation priorities based on those connectivity metrics (e.g. the identification of most critical habitat areas for maintaining landscape connectivity for a key species) are affected by the scale of the analyzed map.

Aware of the relevance that planning decisions have on the conservation and adequate management of natural resources, we approach the understanding of scale effects from a more practical perspective which goes beyond a simple analysis of its influence on the values of pattern-descriptive metrics. Focusing on connectivity as a key ecological issue, we examine the impact of scale on the determination of conservation priorities derived from connectivity analyses. We specifically intend to determine to what degree spatial scale (both MMU and spatial extent) affects the prioritization of patches by their contribution to overall landscape connectivity. We systematically explore these effects on the results provided by ten different graph-based connectivity metrics in three forested landscapes in Spain. By this we assess for the first time to our knowledge the impact of spatial scale on actual decision-making and real landscape planning situations based on these connectivity metrics. A comprehensive understanding of the response of connectivity metrics to changing scale will allow determining those that are most robust and suitable for comparison across scales. More importantly, the identification of such robust metrics will enable planners to use them for undertaking connectivity analysis with the confidence that the obtained results and subsequent planning decisions are not largely biased by the particular spatial scale of the analyzed dataset. In addition, this research may provide guidelines on the decision of choosing both an appropriate and cost efficient MMU and spatial extent of the input categorical coverage for undertaking connectivity analyses of this kind.

## 2. Materials and methods

### 2.1. Landscape data

CORINE Land Cover 2000 (CLC00) for Spain was the source map used in this study. CLC00 classifies the European land cover at a 1:100,000 scale into 44 categories, including urbanized areas, agricultural lands, forests, wetlands and water bodies. CLC00 has been derived from the visual interpretation of Landsat and SPOT satellite images, and has a minimum mapping unit of 25 ha (Bossard et al., 2000). Any connectivity analysis is generally focused towards the conservation of a particular endangered or key species and/or habitat, which may correspond to a particular land cover type (e.g. forest) or combinations of land cover types. We focus here our analysis on a specific cover type, *Forests and natural areas* (class 3.1), as mapped in CLC00.

The location of three squared zones with different forest spatial configuration within Spain was randomly selected for analysis (Fig. 1) in order to evaluate the robustness of the results across different study areas. The extent of the three squared zones was initially set to 10,000 km$^2$ (later varied for the spatial extent analysis) so that each zone contained a sufficiently large number of forest patches for subsequent analysis. A previous processing of the original CLC00 was carried out to remove those fragments of original patches that were crossed by a zone limit and consequently remained within the study zone with an area smaller than 25 ha. This resulted, for the 100 km × 100 km extent, in 693 forest patches (30.5% of forest cover) in zone 1, 478 patches (19.6% forest cover) in zone 2, and 552 forest patches (13.6% of forest cover) in zone 3.

From the original CLC00 forest data set, we constructed different maps in which either MMU or extent was varied. In this way, we generated different forest cover maps with varying scale characteristics. MMU in each zone was set to 25, 50, 100, 150 and 200 ha, with a fixed extent of 100 km × 100 km (Fig. 1). MMU increase was accomplished by removing all polygons smaller than the specified MMU. Therefore, the patches common to all MMU maps of a zone (those used for subsequent comparison) were the big ones still present for MMU = 200 ha. Other more sophisticated methods exist for increasing the MMU of a map (e.g. Saura, 2002), but they were not appropriate for this study since we need to preserve the whole areal entity of each large patch invariable for comparison of their importance for connectivity among the different MMU maps. The five maps for extent-comparison in each zone had an extent of 40 km × 40 km, 60 km × 60 km, 80 km × 80 km, 100 km × 100 km and 120 km × 120 km and a fixed MMU of 25 ha, all of them sharing the patches included

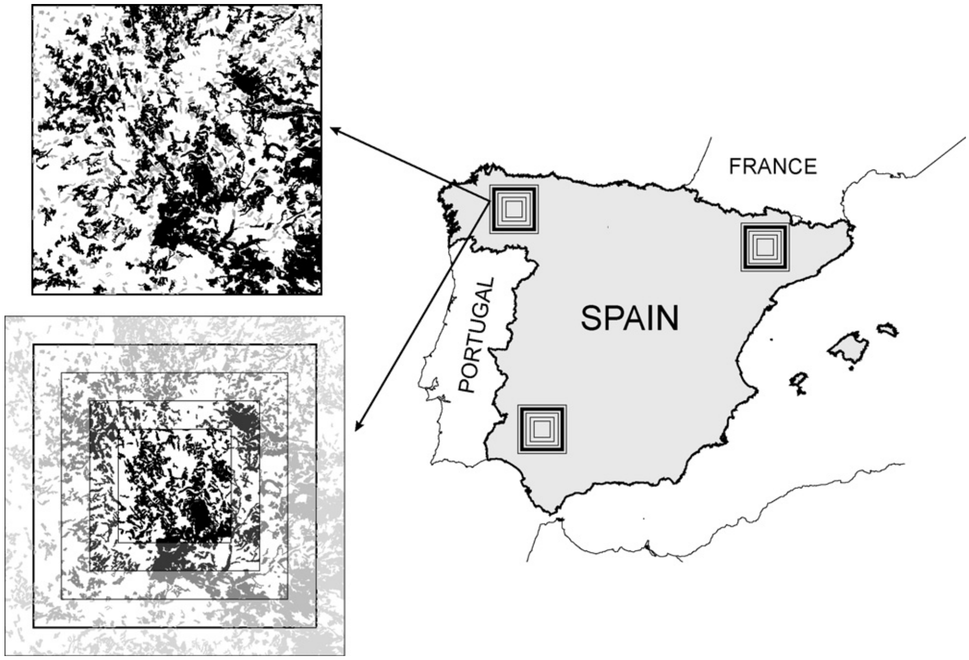


Fig. 1. Location of the three study zones within Spain (zone 1: North–West; zone 2: North–East; zone 3: South). Top left figure illustrates the different maps of the same zone 1 obtained for the MMU analysis (fixed 100 km × 100 km extent), with lighter grey patches belonging to finer MMU maps. Bottom left figure illustrates the different maps of the same zone obtained for the extent analysis (fixed 25 ha MMU), with lighter grey patches belonging to larger extent maps. Forest habitat patches in black belong to the base map in each case: the 200 ha MMU for the MMU analysis and the 40 km × 40 km extent for the extent analysis.

in the 40 km × 40 km common central part of that zone (Fig. 1). This resulted in a total of 30 maps (five for MMU analysis and five for extent analysis for each of the three zones) to be analyzed, each containing at least 100 forest patches.

To determine whether patches were equally prioritized by their importance in the maps with different MMU, only the big common patches present in all MMU (those patches bigger than 200 ha) were used for comparison, although their importance for connectivity was computed with respect to the entire set of patches in each map and MMU. Similarly for the extent, only the common patches in all map extents for the same zone (those patches contained in the 40 km × 40 km extent) were used for comparison, computing their importance with respect to all the patches present in each extent. Thereby, the common patches in each map with different scale characteristics were ranked by their importance for maintaining landscape connectivity (as described below). The importance rankings were then used (separately for the MMU and extent analysis, and separately within each zone) to examine how conservation priorities for those common patches were affected by changes in the spatial scale of the landscape data.

### 2.2. Connectivity metrics and patches prioritization

Measuring connectivity considering only landscape structure does not provide enough information for planning since the same landscape may be used by many species with different dispersal ranges. Thus, considering that a certain patch itself may be perceived as either isolated or connected to others depending on the organism under study, it is necessary to explicitly consider the species' movement abilities in addition to the particular spatial configuration of the landscape. This corresponds to the concept of functional connectivity (Theobald, 2006; Tischendorf and Fahrig, 2000b), which has been here adopted by considering different dispersal distances for each map. The connectivity metrics were computed, for each of the 30 maps, for the dispersal distances of 2, 4, 8 and 12 km, which are consistent with actual dispersal distances for different groups of wildlife animal species (e.g. Sutherland et al., 2000; Van Vuren, 1998). This resulted in 120 different cases (30 maps × 4 dispersal distances) where each metric was computed. In this way we could examine how the impact of spatial scale may depend on the dispersal distance considered in the connectivity analysis.

We focus on graph-based connectivity metrics as they have been shown to present considerable advantages regarding connectivity analysis and patches prioritization (Calabrese and Fagan, 2004; Jordan et al., 2003; Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007; Theobald, 2006; Urban and Keitt, 2001). Their convenience for landscape connectivity applications is also outstanding when it comes to calculating patch importance for large data; graph structures and algorithms present great computational power to solve this problem efficiently.

A graph is a set of nodes and links such that each link connects two nodes. Nodes represent habitat patches, while the existence of a link between a pair of patches implies the potential ability of an individual to directly disperse among them, which may be quantified through a binary or probabilistic connections model (Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007). In the binary model there is no modulation of the strength or feasibility of the connection among each pair of patches, which are just either connected (in which case a link exists connecting both patches) or not depending, for example, on a threshold dispersal distance (Keitt et al., 1997). In the probabilistic model, connections are characterized by a probability of dispersal ($p_{ij}$) between patches $i$ and $j$. We applied here a negative exponential as a function of interpatch edge-to-edge distance (see Bunn et al., 2000; Urban and Keitt, 2001). Depending on the type of information available for a particular planning problem, one or other connection model may be used (Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007). Since connectivity metrics corresponding to both models are here jointly analyzed (see below), we set to 0.5 the probability of dispersal corresponding to the threshold dispersal distances considered (2, 4, 8 and 12 km) in order to render both models equivalent. That is, for $p_{ij}$ above 0.5 in the probabilistic model (which corresponds to an interpatch distance below the fixed threshold) a link connecting two patches is assigned in the binary model.

We examined the following 10 graph-based connectivity metrics, 7 based on the binary connections model ($L$, NC, MSC, CCP, LCP, IIC, GD) and the other 3 ($F$, AWF and PC) based on the probabilistic connections model:

- *Total number of links* ($L$) or connections between the habitat patches in the landscape.
- *Number of components* (NC) in the landscape, where a component is a group of interconnected patches. Each component is functionally isolated from any other component in the graph (there are no links among different components).
- *Mean size of the components* (MSC), where the size of a component is the sum of the areas of all the patches belonging to that component.
- *Class coincidence probability* (CCP), and *landscape coincidence probability* (LCP), generalizations of the degree of coherence by Jaeger (2000) by considering components instead of individual habitat patches (Pascual-Hortal and Saura, 2006),

$$\mathrm{CCP} = \sum_{i=1}^{\mathrm{NC}} \left(\frac{c_i}{A_\mathrm{C}}\right)^2 \tag{1}$$

$$\mathrm{LCP} = \sum_{i=1}^{\mathrm{NC}} \left(\frac{c_i}{A_\mathrm{L}}\right)^2 \tag{2}$$

where $c_i$ is the total area of each component (sum of the areas of the patches belonging to that component), $A_\mathrm{C}$ the total habitat area (sum of all habitat patches) and $A_\mathrm{L}$ is the total landscape area (extent of the analyzed region, comprising both habitat and non-habitat patches). CCP is defined as the probability that two randomly chosen points within the habitat belong to the same component; or, alternatively, as the probability that two animals randomly placed within the habitat are able to find each other given the set of patches and links. LCP corresponds to the probability that two randomly points (or animals) located within the landscape (i.e. points can lie either in habitat or non-habitat areas) belong to the same habitat component.

- *Integral index of connectivity* (IIC) (Pascual-Hortal and Saura, 2006), given by:

$$\mathrm{IIC} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(a_i a_j/1+\mathrm{nl}_{ij})}{A_\mathrm{L}^2} \tag{3}$$

where $n$ is the total number of habitat patches in the landscape, $a_i$ and $a_j$ are the areas of the habitat patches and $\mathrm{nl}_{ij}$ is the number of links in the shortest path (topological distance) between patches $i$ and $j$. A path is a route along connected nodes in which no node is visited more than once.
- *Graph diameter* (GD), corresponding to the length of the longest stepping-stone path between two nodes in the largest component (Urban and Keitt, 2001).
- *Flux* ($F$) and *area-weighted flux* (AWF) (Saura and Pascual-Hortal, 2007; Urban and Keitt, 2001):

$$F = \sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} p_{ij} \tag{4}$$

$$\mathrm{AWF} = \sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} p_{ij} a_i a_j \tag{5}$$

where $p_{ij}$ is the direct interpatch probability of dispersal between patches $i$ and $j$.
- *Probability of connectivity* (PC) (Saura and Pascual-Hortal, 2007):

$$\mathrm{PC} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j p_{ij}^*}{A_\mathrm{L}^2} \tag{6}$$

where $p_{ij}^*$ is the maximum product probability of all possible paths between patches $i$ and $j$.

All these metrics increase with improved connectivity, with the exception of NC, which behaves in the opposite way. Only three of these metrics ($L$, NC, $F$) are computed without taking patch areas into account. CCP, LCP, IIC and PC have bounded ranges of variation from 0 to 1, while the rest of the metrics have a minimum value of 0 (NL, MSC, GD, $F$, AWF) or 1 (NC) but no theoretical upper limit.

The importance of a patch for maintaining landscape connectivity ($\mathrm{d}X_i$) according to a certain metric $X$ is defined as:

$$\mathrm{d}X_i = 100 \times \frac{X - X'}{X} \tag{7}$$

where $X$ corresponds to the overall metric value calculated for the landscape (considering all the habitat patches) and $X'$ corresponds to the value of the same metric calculated in the same way but after removing that patch $i$ from the landscape. In this way, patches can be ranked by their individual contribution to maintain landscape connectivity, in order to identify the most important patches for conservation. Typically, the highest importance will be assigned to key stepping-stone patches because their loss divides the remnant habitat into two or more isolated components (Pascual-Hortal and Saura, 2006). However, since each connectivity metric is based on different criteria, patch prioritizations (as well as its scale robustness) will be different for each analyzed metric.

Both overall metrics values and patch prioritizations (d$X$ for every patch) were computed within the new specific software for graph-based connectivity analysis "Conefor Sensinode 2.2", which includes all the metrics described here. Conefor Sensinode 2.2 has been developed at the University of Lleida by modifying, reprogramming, and including new metrics in the source codes developed by Dean Urban (Duke University) in the LandGraphs package (Sensinode 1.0). A free copy of Conefor Sensinode 2.2 can be obtained by contacting the authors or directly downloaded from http://www.udl.es/usuaris/saura/cs22.htm.

### 2.3. Scale impact analysis

To determine whether the prioritization of common patches, according to a particular metric, varied across different MMU and extent maps for each zone, Spearman rank correlations ($r_s$, theoretically ranging from 1 to −1) were calculated between the d$X$ values for the same common patches in the maps with different scale characteristics. For the MMU analysis, $r_s$ were computed, for each metric, between the d$X$ values for the common patches in the 25 ha MMU map (base map) and the corresponding d$X$ values for the same patches in each coarser-MMU map of the same zone. $r_s$ were computed equivalently for the common patches in the extent analysis, with the 40 km × 40 km as the base map in this case.

By the computation of a non-parametric rank-based coefficient ($r_s$) we measured the metrics robustness across scales. When the prioritization (ranking) of patches is identical at two different scales, $r_s = 1$; in this case both $X$ and d$X$ values may have changed but patch prioritization remains unvaried. When patch prioritization is increasingly altered by scale, lower ranking correlations ($r_s$) are obtained. $r_s$ can thus be interpreted as an indicator of the metric sensitivity to these scale effects. In practice, this leads to know if the patch prioritization (and the subsequent management, spatial planning and conservation decisions derived from it) is substantially affected or not by spatial scale characteristics. Lower $r_s$ values will indicate that conservation or planning decisions made on the basis of the connectivity analysis are more scale-dependent and less stable in this respect.

Now referring only to MMU effects, we quantified the contribution of those small patches that may be "lost" when selecting a coarser MMU. Specifically, we assessed whether omitting the small patches is relevant in terms of importance for the maintenance of landscape connectivity (as measured by their d$X$ values), in comparison with the importance of the big patches that are still present in the map for that MMU. For this, we calculated both the percentage of importance of omitted patches (PIOP) and the percentage of omitted critical patches (POCP) when selecting a MMU above 25 ha. PIOP is calculated as the sum of the d$X$ values in the base map (MMU = 25 ha) for those patches smaller than a certain MMU (bigger than 25 ha), divided by the sum of d$X$ values for all the patches in that base map. The loss of an isolated small patch may be interpreted by metrics like MSC as an improvement in connectivity as quantified by d$X$ for this metric (Pascual-Hortal and Saura, 2006), which would result in negative d$X$ and PIOP values. Negative d$X$ and PIOP values can also be obtained for NC, since lower values for this metric indicate improved connectivity. POCP is calculated as the number of small patches (smaller than a certain MMU above 25 ha) existing within the most important patches in the base map, divided by the total number of patches in that coarser-MMU map. The number of most important patches in the base map corresponds in each case to the total number of patches in the coarser-MMU map (MMU > 25 ha) that is being considered for calculating POCP.

## 3. Results and discussion

### 3.1. Impact of MMU on patches prioritization

PC and AWF resulted the most robust metrics against MMU variations, closely followed by IIC (Fig. 2), by maintaining quite the same prioritization of common patches across scales (high $r_s$). LCP and MSC also showed a relatively robust behavior, while the rest were highly sensitive to MMU changes (Fig. 2). Several of the metrics that did not take patch area into account were largely sensitive to MMU effects, as occurred for NC or GD. This seems logical since those metrics that considered patch area give more weight to larger patches in the overall landscape metric value and are expected to be less sensitive to the omission of small fragments caused by a larger MMU. However, patch area was not the only factor explaining the robustness of the different metrics in this respect; for example $F$ and NL (which just consider interpatch connections for its computation, and not any intrinsic patch attribute, Eq. (4)) were clearly more robust that CCP (which is calculated through patch and component areas, Eq. (1)) (Fig. 2). As expected, $r_s$ decreased as the MMU was increased further apart from the 25 ha; this tendency was very consistent for all the metrics but for CCP (Fig. 2), which presented a sharp drop on $r_s$ values for MMU = 100 ha and a dispersal distance of 12 km. This is due to the intrinsic limitations of CCP for discriminating the importance of different habitat patches in some circumstances (Pascual-Hortal and Saura, 2006). When the habitat is strongly interconnected so that all the patches belong to the same component (CCP = 1) and there are no key stepping-stone patches (but many alternative paths from any one patch to another), the overall index value remains unchanged by the loss of any of the habitat patches, which are therefore all assigned the same importance by CCP. This occurred for MMU = 100 ha and the large dispersal distance of 12 km for two of the analyzed zones.

Analyzing the importance of the small-omitted patches (Fig. 3), we found that it also increases (both in terms of PIOP and POCP) for bigger MMU, since this broader scale causes a larger set of patches to be omitted in the final map. However, the impact of omitted patches is minimal for some metrics like PC, AWF, IIC or MSC when the MMU is increased from 25 to 50 ha (PIOP and POCP about 5%, Fig. 3) and considerably low even when the MMU is as large as 200 ha (PIOP and POCP quite below 20%, Fig. 3). In these cases an analyst can be confident, when fixing a larger MMU, to omit patches that are too small for being considered on the landscape conserva-

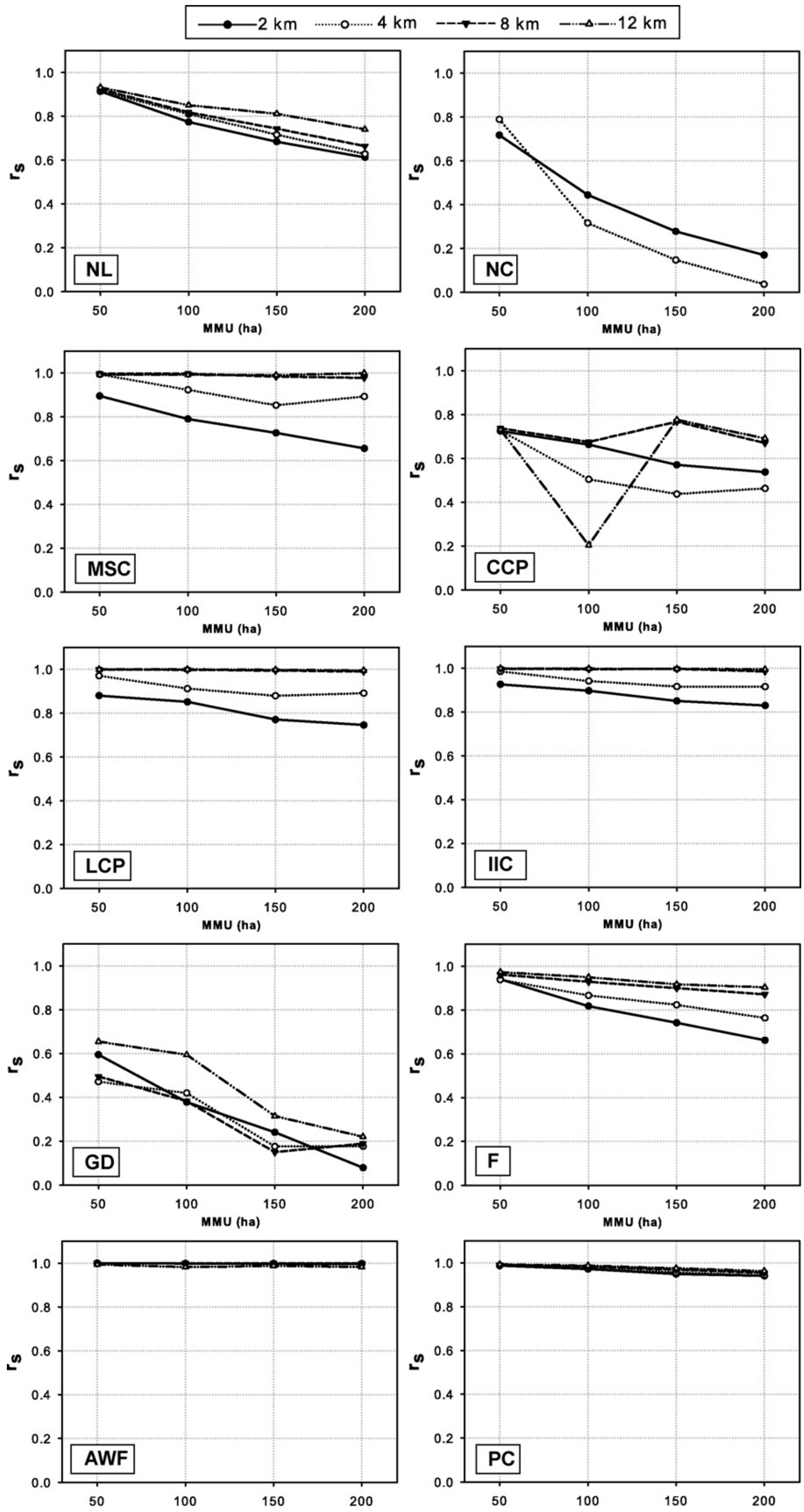


Fig. 2. Spearman rank correlations ($r_s$) between the d$X$ importance values in the base MMU map (25 ha) for the common patches (those bigger than 200 ha) and the d$X$ importance values for the same patches in the 50, 100, 150 and 200 ha MMU maps of the same zone. High $r_s$ values indicate that the metric is robust by maintaining the prioritization of common habitat patches (in terms of their importance for overall landscape connectivity) across different MMU. Values in the figures ($y$ axis) correspond to the average $r_s$ of the three study zones.

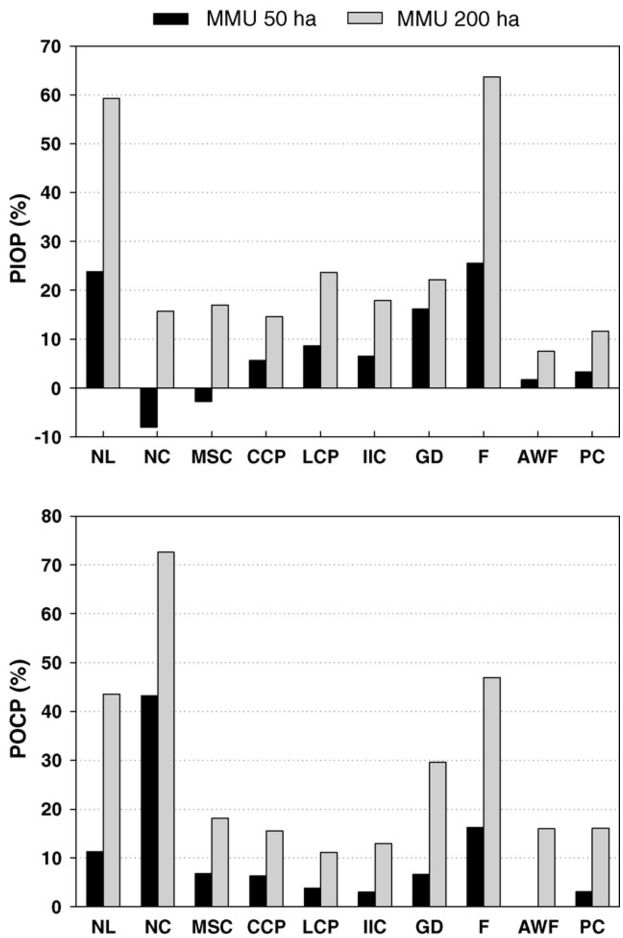


Fig. 3. Percentage contribution of the omitted patches (when fixing a larger MMU) as considered by PIOP and POCP (both theoretically ranging from 0 to 100) for each connectivity metric. The values refer to the average of the three study zones at their base maps (25 ha MMU and 100 km × 100 km extent) and with 2 km dispersal distance. For illustration, only results for MMU increased up to 50 and 200 ha are shown.

tion plan. On the contrary, higher values of PIOP and POCP would indicate that the omitted smaller patches held a high connectivity importance in the base map (MMU = 25 ha) and thus, they should be considered for planning in account of their significant role in the maintenance of overall landscape connectivity. GD, NL and *F* resulted the most sensitive metrics in this respect (Fig. 3). Although *F* showed a robust behavior to changing MMU in terms of maintaining the importance ranking of common (big) patches (Fig. 2), many of the most important patches in the base map (25 ha MMU) according to this metric are small (not present in the 50 or 200 ha MMU maps of same zone, Fig. 3). Although common patches may be similarly ranked across different MMU, the most important patches for this metric are not always the same ones when increasing the MMU. Thus, *F* cannot be generally recommended as a robust metric in terms of consistent identification of the same critical habitat patches.

Landscape analysts may have the flexibility to select from a range of appropriate MMU (in terms of the resultant decision making) in order to reduce the costs of creating or processing too detailed vector maps (Knight and Lunetta, 2003; Stohlgren et al., 1997) while maintaining the scientific rigor of the landscape connectivity analysis. However, even when a certain connectivity analysis may be performed through one of the most robust metrics to changing MMU, it is obvious that the MMU may not be indefinitely increased; those habitat patches big enough to be considered as candidate sites for conservation in management decisions should always be mapped and taken into account in the analysis. But our results show that as long as one of the most robust metrics is used, patches smaller than the ‘planning area threshold’ could be omitted in the input map in order to simplify the analysis and reduce mapping costs without largely affecting the prioritization of the remaining planning target patches.

### *3.2. Impact of spatial extent on patches prioritization*

AWF and PC turned out to be the most robust metrics to extent variations, closely followed by IIC, LCP and MSC (Fig. 4). The rest of the metrics showed high sensitivity to extent variation, with rank correlations ($r_s$) under 0.4 for the longer dispersal distances (Fig. 4); this indicates that the resultant prioritization of habitat patches by their contribution to overall landscape connectivity is not maintained across scales. Those metrics that are computed without considering habitat area (NL, NC, GD, *F*) tend to be largely affected by the spatial extent, but one of the area-dependent metrics (CCP) resulted the most sensitive of all metrics considered (Fig. 4). As expected, the more the scale is modified from the base map, the more the prioritization results for the same patches might diverge (lower $r_s$ values for larger extent maps, Fig. 4).

Since most habitat maps are only available (or are handled in that way by analysts) for specific administrative-defined boundaries, it is crucial to know whether the landscape elements (e.g. habitat patches) located outside the extent of interest are influencing the connectivity priorities allocated to the elements within the target extent (for example, for acting as a stepping-stone between two patches located within the extent). If extent-sensitive metrics (such as NL, CCP, GD or F) are used for the analysis, it would be necessary to enlarge the analyzed area to cover a larger extent than just the one where planning decisions regarding landscape-level connectivity are to be taken.

### *3.3. Scale impact for the different zones and dispersal distances*

For the top five robust metrics in both MMU and extent analysis (AWF, PC, IIC, LCP and MSC), rank correlations ($r_s$) were quite similar for the three different study zones (for a given scale and dispersal distance), with a low standard deviation (S.D. clearly below 0.1 in most cases); this indicates that these results are robust to the specific spatial pattern and configuration of each analyzed zone. The $r_s$ values for the most sensitive metrics (like GD and CCP) were, in contrast, much more variable (higher S.D.) across the different zones (e.g. S.D. = 0.7 for CCP in the MMU analysis and 12 km of dispersal distance). For GD and CCP, rank correlations ($r_s$) were in some cases negative, which mean inverse prioritization. This undesirable behavior of these

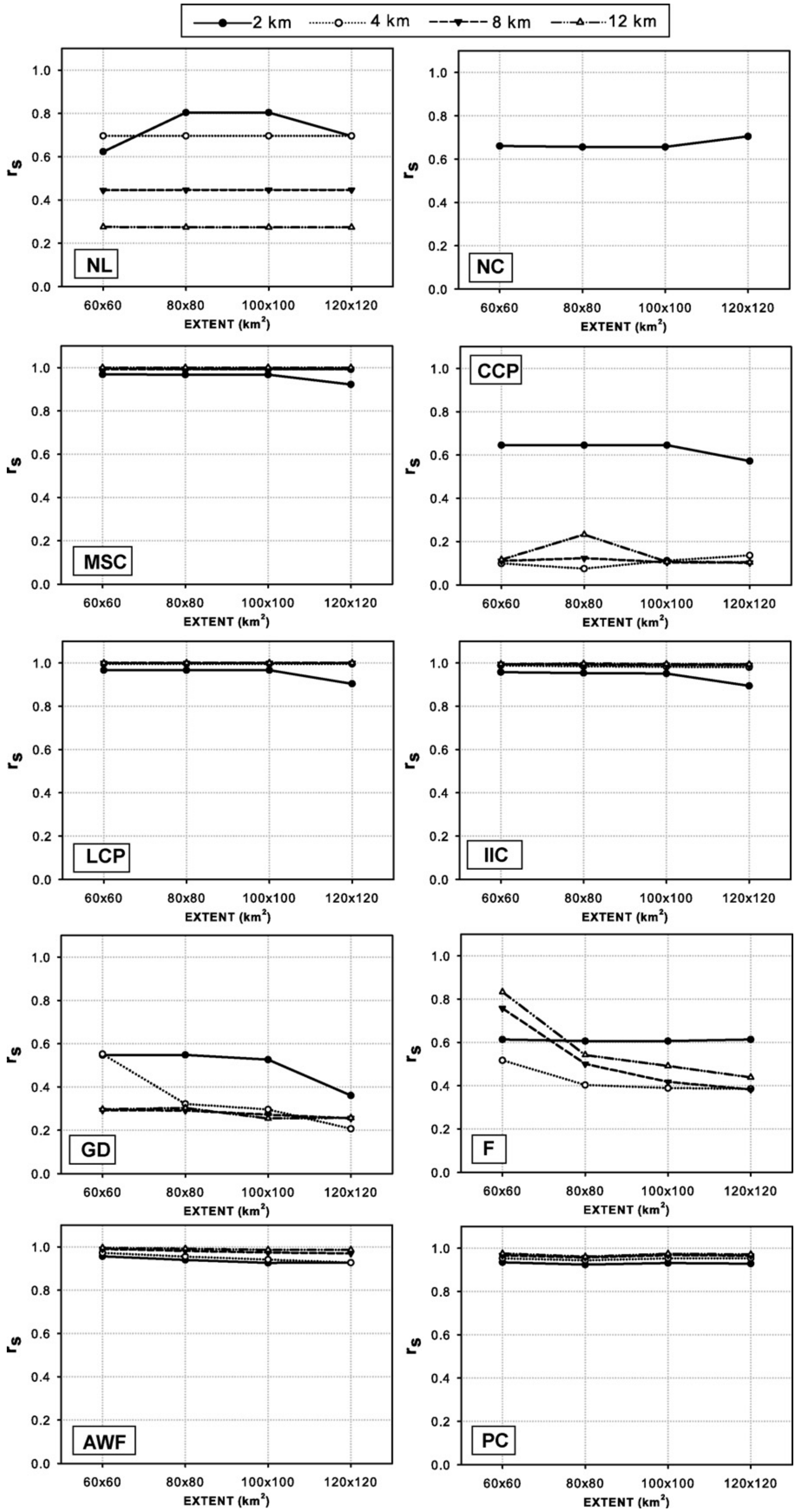


Fig. 4. Spearman rank correlations ($r_s$) between the d$X$ importance values in the base extent map (40 km × 40 km) for the common patches (those within the 40 km × 40 km extent) and the d$X$ importance values for the same patches in the 60 km × 60 km, 80 km × 80 km, 100 km × 100 km and 120 km × 120 km extent maps of the same zone. High $r_s$ values indicate that the metric is robust by maintaining the prioritization of habitat patches (in terms of their importance for overall landscape connectivity) across different spatial extents. Values in the figures ($y$ axis) correspond to the average $r_s$ of the three study zones.

Table 1
Variation of overall landscape metrics values with MMU for zone 1 at the 100 km × 100 km extent and a dispersal distance of 2 km

| Metric | Overall metric value | |
|---|---|---|
| | 25 ha MMU | 150 ha MMU |
| Number of links (NL) | 1801 | 508 |
| Number of components (NC) | 14 | 9 |
| Mean size of the components (MSC) | 21,758 | 30,601 |
| Class coincidence probability (CCP) | 0.9356 | 0.9301 |
| Landscape coincidence probability (LCP) | 0.0868 | 0.0705 |
| Integral index of connectivity (IIC) | 0.0176 | 0.0151 |
| Graph diameter (GD) | 17,223 | 12,566 |
| Flux (*F*) | 2995 | 709 |
| Area-weighted flux (AWF) | 254,497,204 | 122,378,352 |
| Probability of connectivity (PC) | 0.0434 | 0.0348 |

For illustration, only the metric values for two different MMU (25 and 150 ha) are shown.

metrics is due to their high sensitivity to the particular structure of the graph and to their inconsistent and inadequate reaction to many landscape changes (Pascual-Hortal and Saura, 2006). A minor modification in the landscape configuration caused by a slight scale variation would therefore entail a substantial variation in the resultant patches prioritization. This instability is an additional reason to discourage their use for landscape planning applications, apart from their already reported large-scale sensitivity (low average $r_s$).

Generally for the most robust metrics, which take patch areas into account, rank correlations ($r_s$) increase with increasing dispersal distance, both for MMU and extent analysis (Figs. 2 and 4). When dispersal abilities are high enough to perceive the entire habitat as wholly connected (extreme case), the area of each patch gains more relevance in the determination of its importance (Keitt et al., 1997). In that case, it would be possible to disperse directly among every pair of patches (no key stepping-stone patches would exist), and the importance of a patch would thus be determined just by its size (or the corresponding area-weighted habitat quality factor, see Pascual-Hortal and Saura, 2006). This is a scale-independent intrinsic patch characteristic not affected by whether other smaller or nearby patches are included or not in the analyzed map.

For some of the zones and dispersal distances NC was even unable to rank patches by their importance for overall connectivity, both for the MMU and extent analyses (no $r_s$ values in Figs. 2 and 4). This occurred when dispersal distance was so large that all the patches were interconnected and belonged to the same component; no patch loss caused the disconnection of the landscape in two isolated components and therefore all patches were considered equally unimportant.

### 3.4. Patches prioritization versus overall metric values

Apart from the impact on patches prioritization (ranks of d$X$ values of individual patches, Eq. (7)), the overall values of the connectivity metrics ($X$, Eq. (7)) were also clearly affected by scale variations (Table 1), although in a different way. Variations in the overall metric values were due to many different types of changes that occurred in the landscape network (habitat graph) when either the MMU or extent change. These included lost links, components split by the removal of key stepping-stone patches, longer distances and paths among the remnant patches, etc. In general, the most scale sensitive metrics in their overall values were NL, NC, MSC, GD, $F$ and AWF, the rest being considerably robust, especially CCP and IIC (Table 1).

Most of previous research on scale effects on landscape pattern metrics has focused on describing the variations of overall metrics values, and not on the planning decisions that may be derived from those metrics. However, it is important to note that a metric robustness in the patches prioritizations across scales does not necessarily imply robustness in the overall landscape metric values and vice versa. In fact, we found robust metrics in overall value but sensitive in terms of patches prioritization (CCP), robust metrics in both overall value and prioritizations (PC and IIC), sensitive metrics in overall value but robust in prioritizations (AWF) and sensitive metrics in both overall value and prioritization (GD) (Fig. 2 versus Table 1).

For the robust metrics (PC, IIC, LCP and AWF) we observed in general a decrease in the importance values (d$X$) for individual patches when the landscape map contained a larger number of patches (when decreasing MMU or increasing extent); in this case the percentage contribution of each patch to the maintenance of landscape connectivity (d$X$) decreases since it is shared out amongst greater number of patches. However, all the common patches seem to decrease their importance in a similar rate, therefore not altering largely the final patches prioritization for these metrics. For the rest of metrics, the behavior of d$X$ values to changing scale conditions was highly variable, without a consistent variation trend.

### 3.5. On the selection of an adequate scale and connectivity metric

The results we have provided are relevant for the practical decision of choosing both an appropriate and cost efficient MMU and spatial extent of the input categorical data for undertaking connectivity analyses of this kind. In addition, the evaluation of the degree of sensitivity of the different metrics to spatial scale may be valuable to guide an adequate selection of a reliable connectivity metric. Obviously, a robust metric will be preferable for undertaking landscape planning and conservation decisions concerning connectivity, in the sense of being sure that those decisions are not largely affected by the particular scale characteristics of the analyzed landscape map. However, we recognize that the primary criteria for selecting a connectivity metric is its appropriateness in terms of biological and landscape planning considerations, such as their ability to detect and prioritize those landscape elements (e.g. habitat patches) that most contribute to overall landscape connectivity; this has been specifically tackled and discussed in other studies (e.g. Calabrese and Fagan, 2004; Jordan et al., 2003; Moilanen and Nieminen, 2002; Pascual-Hortal and Saura, 2006; Ricotta et al., 2000; Saura and Pascual-Hortal, 2007; Tischendorf and Fahrig, 2000a,b). Little is gained from using a scale-robust metric if that metric is intrinsically not able to adequately identify the critical patches for connectivity. On the contrary, an adequate metric (in biological and landscape planning terms) may fail for practical applications if it is too sensitive to scale variations, since in practice landscape data present a limited degree of spatial detail and accuracy, which may ultimately have a considerable impact in the outcome of the analysis. Ideally, the best metric for biological and planning criteria would be also largely robust both to MMU and extent variations; if not, a trade-off between both aspects would preferably guide the metrics selection. In any case, scale studies are needed for providing complementary criteria for the choice and adequate use of the most suitable metric for connectivity analyses of this kind.

## 4. Conclusions

We have shown that the assessment of landscape connectivity may be critically influenced by the spatial scale of the analyzed maps, depending on the connectivity metric considered. We have tackled the scale issue from a decision-making perspective, studying how planning decisions derived from landscape connectivity analyses are influenced by the scale of the input data; previous scaling studies have not explicitly addressed this matter. Our analysis varied both MMU and map extent, and evaluated the degree of robustness of the analyzed metrics when prioritizing habitat patches according to their importance for the maintenance of landscape connectivity. Our experimental results on real forested landscapes have shown that certain connectivity metrics (AWF, PC, IIC, LCP and MSC) are considerably robust to changing scale when assigning conservation priorities. On the contrary, other metrics (NL, NC, CCP, GD and *F*) are highly sensitive both to MMU and extent variations. Hence, the use of these latter metrics should be avoided since it may lead to inappropriate and misleading planning conclusions, in the sense of being largely influenced by the particular scale characteristics of the analyzed landscape data.

Tackling scale-related studies from the perspective of just describing the variations of landscape metrics values with scale may be of little help in practice if ignoring the impact of scale on the management decisions taken from these landscape metrics. Overall sensitivity to scale is less relevant than prioritization sensitivity because (1) overall metric values alone are not directly used for decision making and (2) we have shown that, even though there is sensitivity on the overall metric value, the resultant patches prioritization may be robust and vice versa. Hence, we encourage further research on scale implications on actual landscape planning regarding spatial metrics.

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