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APPLICATION

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r.pi: A GRASS GIS package for semi-automatic spatial pattern analysis of remotely sensed land cover data

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Abstract

1. Analysing the changing spatial patterns of landscapes due to climate change or anthropogenic impact is important for various disciplines. Land cover change and its resulting modification of spatial patterns in the landscape influence various geographical or ecological parameters. Changing formerly continuous into discontinuous ecosystems due to land cover conversion causes isolated fragments in the landscape. Maintaining the connectivity of a fragmented landscape is relevant for, e.g. in nutrient cycle, water-runoff or species population persistence.
2. Satellite imagery derived land cover can be used to analyse continuously the changing spatial arrangement of land cover types. However, analyses are computer intensive and require robust and efficient processing routines.
3. We developed a patch-based spatial analysis system (*r.pi*) integrated natively into a Free and Open Source GIS (GRASS GIS) to be able to analyse large amounts of satellite derived land cover data in a semi-automatic manner, and to ensure high reproducibility and robustness.
4. Various established and newly developed indices for spatial pattern analysis are provided in this program, to derive further meaningful information like spatial configuration, patch irreplaceability or connectivity of fragments based on a dispersal model approach.

KEYWORDS
connectivity, GIS, landscape fragmentation, patch irreplaceability, remote sensing, spatial ecology

1 | INTRODUCTION

In the last decades, a global decrease of unaltered and undisturbed land cover has been observed (Hansen et al., 2013; Laurance et al., 2002; Margono, Potapov, Turubanova, Stolle, & Hansen, 2014; Mayaux et al., 2005). Human activities result in habitat fragmentation, degradation or complete habitat loss. Fragmentation is regarded as human induced increase in numbers, decreased connectivity or decreased size of fragments (Fahrig, 2003) and is a key focus of quantitative landscape ecology (Gustafson, 1998; O'Neill et al., 1988; Turner, 1989). Downstream effects include changes to the nutrient and water cycles or the disruption of species migration, and hence, a diminished chemical and biotic exchange eventually leading to the depletion of landscapes with respect to their environmental conditions (Collinge, 1996; Fischer & Lindenmayer, 2007; Saunders, Hobbs, & Margules, 1991). Hence, when analysing connectivity, it is important to take the surrounding landscape into account in order to derive information concerning landscape friction which influences the functional connectivity between fragments (Debinski, 2006; Ricketts, 2001).

Monitoring of land cover changes, such as fragmentation, is increasingly accomplished using remote sensing data with increasing focus on high spatial and temporal resolution satellite imagery (Achard et al., 2007).

There is already a long record of software developed for the analysis of spatial patterns (Elkie, Rempel, & Carr, 1999; Mladenoff & DeZonia, 2000; Perera, Baldwin, & Schnekenburger, 1997; Turner, 1990; Vogt et al., 2009) or for spatial statistical analysis (Baddeley, 2008; Macchi, 2008; Rangel, Diniz-Filho, & Bini, 2006; Rosenberg, 2008). The most widely known software package for spatial pattern analysis is probably *Fragstats* (Turner, 2005) which provides a wide range of landscape-, class- and patch-based metrics (McGarigal, Cushman, Neel, & Ene, 2007). One of the major bottlenecks in some analytical process is the access to the source code in order to modify and adapt it to specific needs. Furthermore, interoperability between software packages is often challenging and not always solved. The application of remote sensing and GIS techniques in the same framework as spatial pattern analysis is therefore important as large datasets needed to be analysed repetitively. The *r.pi* (raster patch index) GRASS GIS 7.2 plugin we present here was developed because no other program offered semi-automatic and extendable and modifiable patch-based connectivity analysis, implemented in an open-source software. The open-source GIS and remote sensing software GRASS GIS (Neteler & Mitasova, 2008; Neteler, Bowman, Landa, & Metz, 2012) provides all necessary remote sensing and GIS techniques in order to process satellite imagery and the *r.pi* plugin offers subsequent spatial pattern analyses without the need for intermediate data transformations or conversions. This software provides established and new ecologically relevant spatial patch-based indices. This paper outlines the capabilities of *r.pi* and its potential for further development approaches in various fields of geographical or ecological research. All the presented functions are also available in the GRASS GIS 7.2 Addons Manual page at: https://grass.osgeo.org/grass72/manuals/addons/.

2 | FUNCTIONALITY

The *r.pi* module is composed of a set functions for raster processing in GRASS GIS. The functionalities of the *r.pi* tool are split up into several modular components with each focusing on one specific task (Table 1). Major focus is given to patch-based indices which assess the connectivity of patches and their relative importance to maintain patch connectivity in homogeneous or heterogeneous environments.

2.1 | General settings

The nomenclature of the *r.pi* modules is defined in concordance with other GRASS modules. All main inputs have to be categorical rasters out of which one land cover class is treated as the class of interest that is the class constituting the patches. Patches are defined as an agglomeration of connected cells of the same land cover type (defined by *keyval* argument), which are permeable for any type of spatially dynamic factors like water or organisms (Pearson & Gardner, 1997) using the Rook (4) or Queen (8) neighbourhood rule (Fortin & Dale, 2005). Outputs are mostly rasters with the computed values assigned to each patch pixel, tables per patch or distance matrices.

2.2 | Classical patch indices

A simple module *r.pi.corearea* provides different calculations of the core area of a patch. In contrast to common core area calculations with fixed edge effects values, this module takes the landscape values surrounding a patch into account, which delivers more meaningful results with respect to ecologically useable habitat areas for, e.g. viable population size or climate–forest interactions (Laurance, 2004). The value of the landscape attributes using distanced weights is taken to shrink the patch area. The distance weight ranges from 0 to 1 and influences if close landscape attributes (e.g. 0) or far landscape attributes (e.g. 0.7) are weighted more to calculate the edge depth.

The second module *r.pi.index* allows the computation of common spatial attributes of patches, like shape, compactness, asymmetry and euclidean nearest neighbour (ENN) (see McGarigal & Marks, 1995).

2.2.1 | Distance to neighbouring patches (ENN, FNN)

Complementing the *r.pi.index* module, the *r.pi.enn* module expands the neighbourhood consideration beyond the nearest neighbour. It works on a pre-defined *n*-th nearest neighbour neighbourhood for the calculation of indices. These are the distance of focus patch to *n*-th ENN and the area, SHAPE and perimeter of the *n*th ENN, and the

TABLE 1 List of some applications and the corresponding *r.pi* modules

Function	Application	Module
Spatial attributes	Area, perimeter, SHAPE index, etc.	*r.pi.index*
	Values of neighbouring patches, e.g. proximity index	*r.pi.prox*, *r.pi.neigh*
Connectivity	Using homogeneous matrix (euclidean nearest neighbour)	*r.pi.enn*, *r.pi.odc*
	Using heterogeneous matrix (functional nearest neighbour)	*r.pi.fnn*
	Using individual-based dispersal models considering a heterogeneous matrix	*r.pi.searchtime*, *r.pi.energy*
	Analysing cluster of connected patches/graph theory	*r.pi.graph*
Relevance	Analysing patch relevance for other fragments concerning connectivity	*r.pi.searchtime.pr*, *r.pi.energy.pr*, *r.pi.graph.pr*, *r.pi.enn.pr*

distance between all ENN patches. Statistics (e.g. average, sum) of the values across all ENN are supplied. Optionally, the full distance and adjacency matrix can be returned.

In many ecological cases, the euclidean distance assumption is inappropriate, e.g. for species movement hampered by certain land cover types, requiring the definition of a heterogeneous landscape matrix. This is available via the *r.pi.fnn* module, which provides the same functions as *r.pi.enn* but accounts for a heterogeneous environment by assigning different levels of *friction* to different landscape elements. Hence, instead of ecological distance, this module estimates the ecological or functional distance to the nearest neighbours.

2.2.2 | Omnidirectional connectivity (ODC)

The connectivity analysis without the restrictions of *a priori* defined nearest neighbours has been applied in some studies, e.g. using Voronoi polygons (Bender, Tischendorf, & Fahrig, 2003), but this could be so far only applied for points. The module *r.pi.odc* extends this analysis to polygons and calculates the distance to all neighbouring patches, no matter how distant they are.

2.2.3 | Buffer neighbourhood analysis (NEIGH and PROX)

Information on the attributes of patches in a defined buffer around the focus patch is provided by *r.pi.neigh*. The minimum and maximum buffer distance around the focus patch and the statistics of the patches located in this buffer can be defined. The module *r.pi.prox* adds the proximity (Turner, Gardner, & O'Neill, 2001) and modified proximity index (Bani, Massimino, Bottoni, & Massa, 2006) for patches in a defined buffer zone.

2.2.4 | Graph theory (GRAPH)

Graph theory which is described in detail in, e.g. Urban and Keitt (2001), Fortin and Dale (2005) or James, Rayfield, Fortin, Fall, and Farley (2005), provides a robust theoretical background for investigating and quantifying the connectivity of a landscape. This functionality has been added to *r.pi* as well. Currently, the following nearest neighbour hierarchy methods are implemented in *r.pi.graph*: nearest neighbour, relative neighbourhood graph, Gabriel graph and minimum spanning tree (Fortin & Dale, 2005). Indices describing the resulting clusters attributes are, e.g. diameter of cluster, amount of links or area. Moreover, the individual patch relevance for the maintenance of the cluster attributes can be retrieved.

2.3 | Individual-based modules (SEARCH and ENERGY)

This kind of analysis uses so called "individuals" or "agents" are released from each patch into the landscape matrix and move with a certain perception of different land cover types. The calculated patch statistics are then based on the time taken to immigrate into a patch, the path taken and the number of immigrants per patch (Pe'er & Kramer-Schadt, 2007; Tischendorf & Fahrig, 2000; Tischendorf, Bender, & Fahrig, 2003).

TABLE 2 List of relevant parameters as an example for *r.pi.searchtime* and *r.pi.energy* dispersal modules

r.pi.searchtime	*r.pi.energy*
Amount of released "individuals"	*r.pi.searchtime* parameters plus
Step length (px)	Cost matrix
Finished individuals (%)	Starting energy
Perceptions radius/angle (px/degree)	
Power of attraction to other patches	

Technically, the movement characteristics of the individuals are determined by a step length, suitability of the matrix and their perception range and angle (Table 2). The latter point is related to the attractiveness to disperse towards patches which modifies the dispersal pattern towards patches in the perception range. These analyses provide information on immigrant counts, abundance and binary (based on a threshold) and the diversity of immigrants related to their source patches, and resemble a model for the potential ecological connection between patches.

2.3.1 | Searchtime

The searchtime module *r.pi.searchtime* is a well-established measure for the analysis of connectivity (Kindlmann & Burel, 2008; Tischendorf & Fahrig, 2000). It measures the time until immigration into a different patch other than the original one occurs. Optionally, the land-cover dependent suitability of the environment for migration can be accounted for in this analysis by defining a cost matrix.

2.3.2 | Immigrants/migrants

Additionally to the influencing parameters described above, *r.pi.energy* requires a defined starting energy for each individual, which is reduced for each step based on a cost matrix. The minimum of the cost matrix value is 1, the maximum value is without limit. This results in individuals which might not immigrate successfully, hence "die" in the landscape. Moreover, they have the possibility to migrate through a patch and emigrate again, which increases the migrant not the immigrant counter. Hence, the output delivers information about percentage successful emigrants, immigrants and migrants.

2.4 | Patch relevance (PR)

The four modules, *r.pi.enn.pr*, *r.pi.searchtime.pr*, *r.pi.energy.pr* and *r.pi.graph.pr*, are providing the same functions as the corresponding modules described above but these indices are analysing the patch metrics with and without each patch and assigning the differences to the respective patch. The statistical difference can be described as change in average, median or standard deviation. Moreover, the analysis of

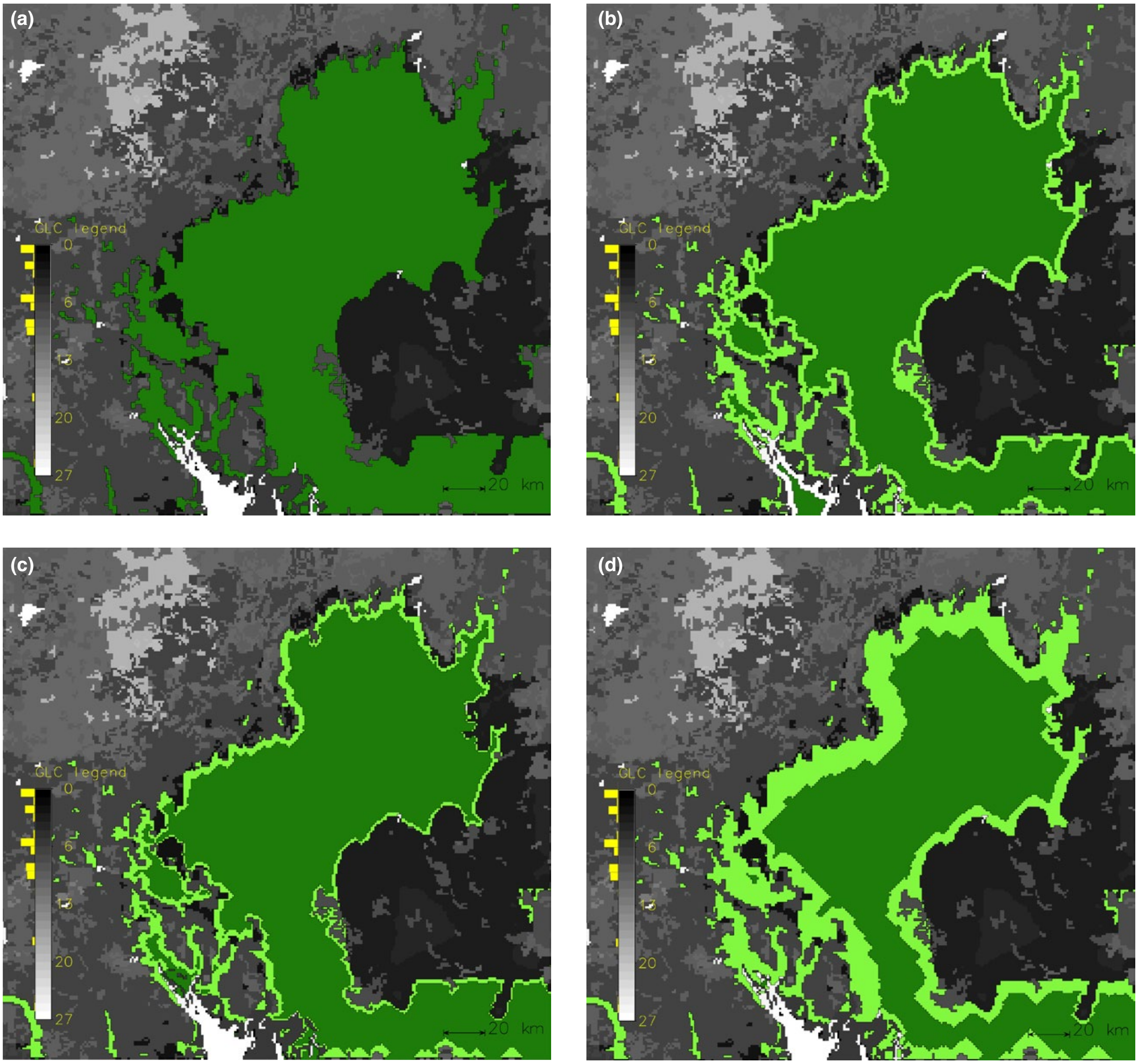

FIGURE 1 The results of *r.pi.corearea* applied on rainforest fragments (dark green) using influences of the surrounding landscape (bright/less to dark/high) and depicting the visible edge effects in light green. Different edge effects methods were used to take the surrounding landscape into account (c,d) compared to the established homogeneous edge effect calculation (b)

the relevance of single patches to maintain a high connectivity can also be applied on the graph theory. The two modules, *r.pi.graph.dec* and *r.pi.graph.red*, are providing information concerning successive patch removal due to size, amount of links, etc. of single fragments and the reduction of neighbourhood distance definition, respectively.

2.5 | Neutral landscape models (NLM)

The approach to generate neutral landscapes for hypothesis testing (Gardner, Milne, Turner, & O'Neill, 1987; Gardner & Urban, 2007) while controlling for shape and coverage, has been used in various studies (Gardner & Urban, 2007; O'Neill, Gardner, & Turner, 1992; Pearson & Gardner, 1997; With, 1997; With & King, 1997). This functionality is provided by *r.pi.nlm* and *r.pi.nlm.stats*. The *r.pi.nlm* module generates a single neutral landscape. It is complemented by *r.pi.nlm.stats* provides statistics on the randomization procedure for selected indices. Neutral landscapes of pre-defined land cover classes are either randomly generated or defined by the percentage coverage or agglomeration of patches.

2.6 | Further modules: Moving window, Monte-Carlo, import and export

The module *r.pi.searchtime.mw* provides the same functions as *r.pi.searchtime* but with the modification that individuals are placed randomly in the landscape. The module *r.pi.prob.mw* calculates the probability inside a moving window or in the whole landscape to place two random points in the same patch with a Monte Carlo permutation.

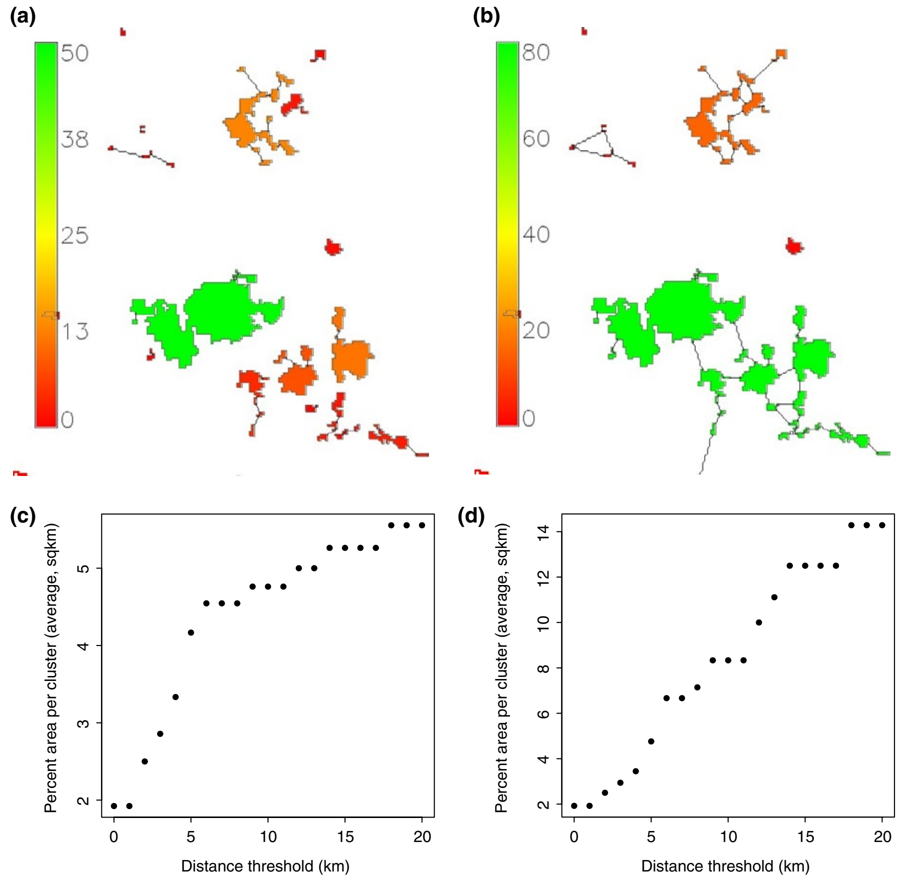

FIGURE 2 The results of percentage area per cluster using a threshold of 20 km (a,b, *r.pi.graph*) and the decreasing amount of average area within one cluster using a decreasing threshold from 20 to 1 km (c,d, *r.pi.graph.dec*) applied on rainforest fragments in West Africa

The distance between two patches to be regarded as one continuous patch can be specified, which could be oriented on species-specific dispersal distances. Another module, *r.pi.grow* grows patches either regularly or irregularly depending on a suitability matrix. This can be used to model for instance urban growth on the basis of eligible areas. The two modules *r.pi.import/-export* are providing the capability to export patch-based data and import them again as patch-based raster, e.g. after *R* (R Development Core Team, 2016) processing.

3 | RESULTS: CASE STUDY EXAMPLES OF RAINFOREST FRAGMENTS IN WEST AFRICA

West Africa experienced high deforestation rates, resulting in distinct fragmentation patterns (Bryant, Nielsen, & Tangley, 1997; Chatelain, Dao, Gautier, & Spichiger, 2004; Chatelain, Gautier, & Spichiger, 1996). In this section, some of the above-described indices are applied

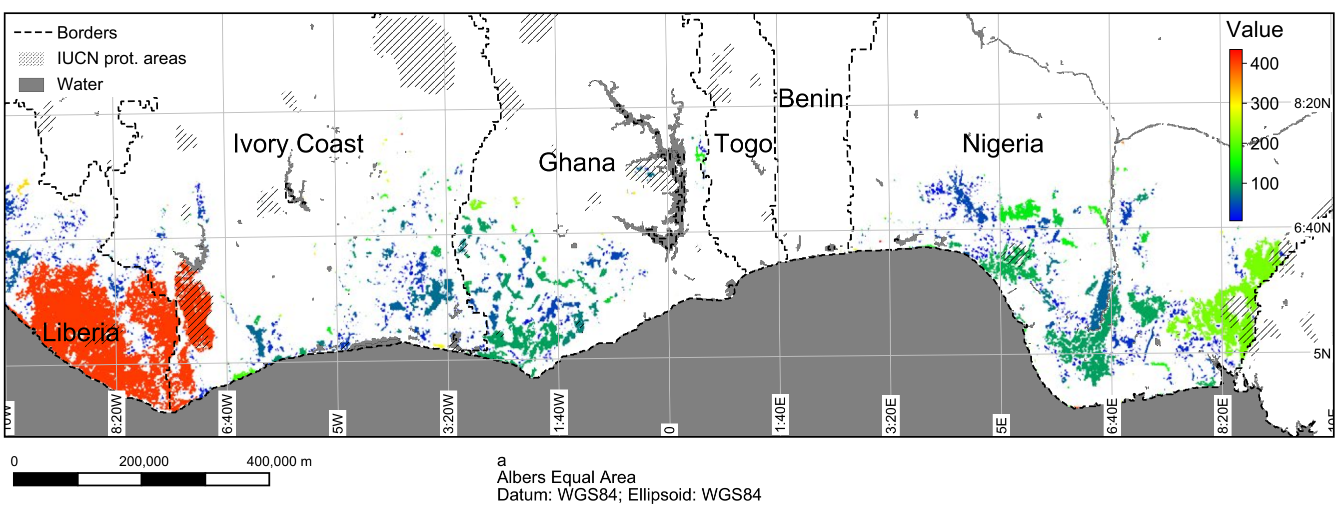

FIGURE 3 The results of *r.pi.searchtime* applied on West African rainforest fragments based on a classification of MODIS 2001–2006 data (average searchtime (steps), *n*: 10,000 per patch, 1 km resolution)

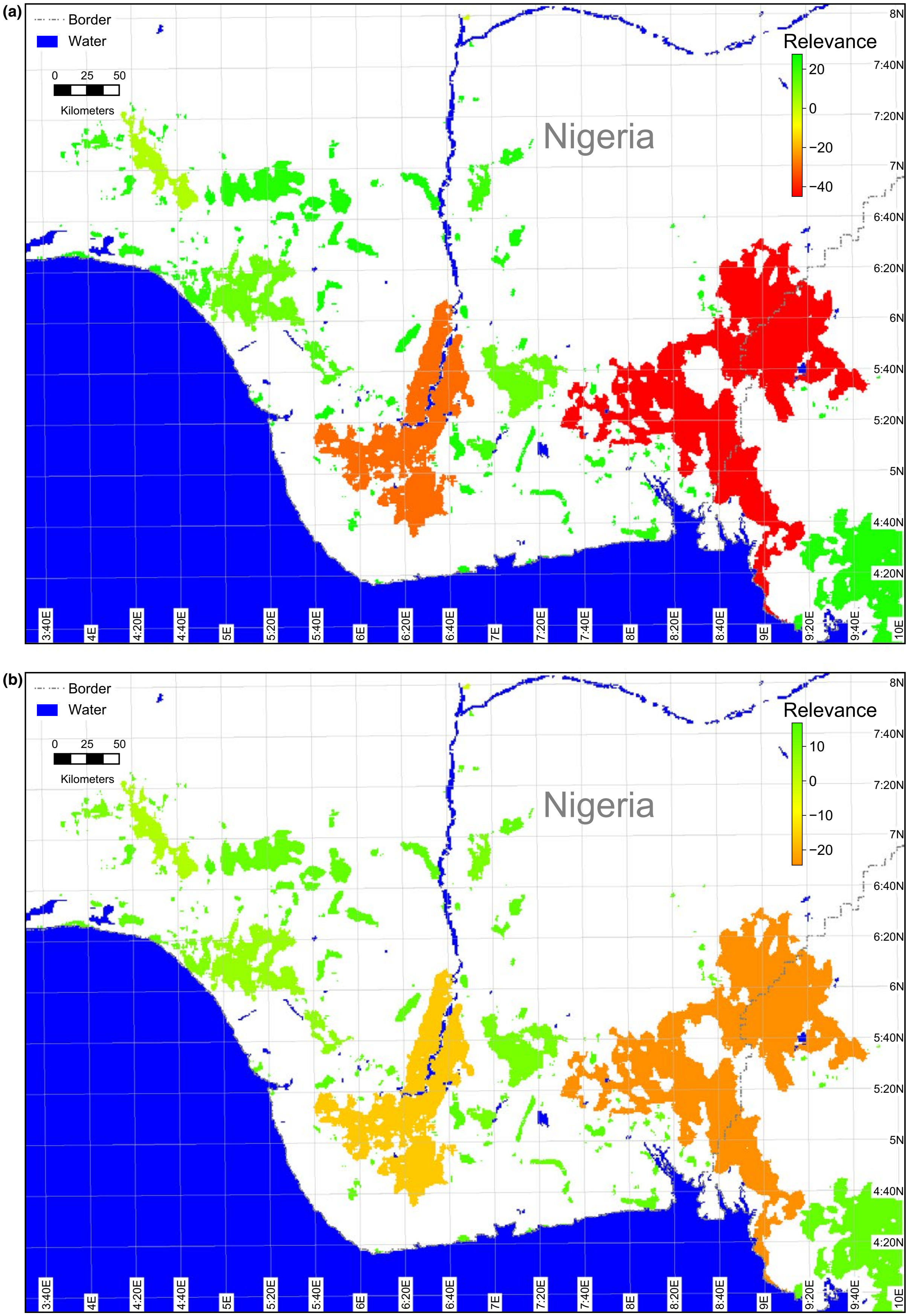

FIGURE 4 The difference of successful emigrants in percentage for all remaining patches if this patch is removed from the landscape (*r.pi.energy.pr*, *n*: 10,000 per patch, 1 km resolution)

exemplarily to describe the spatial arrangement of the remaining rainforest fragments.

A small part of West African rainforest fragments is shown in Figure 1 with an actually mapped rainforest fragment (Figure 1a) based on remote sensing data (GLC2000; Bartholomé & Belward, 2005). The results of the common approach to compute edge effects can be seen in Figure 1b. However, the surrounding landscape has differing impacts on the rainforest edges and hence changes the remaining core area. These surrounding landscape attributes are accounted for using different distance weight factors which are weighting close (Figure 1c) and distant landscape attributes higher (Figure 1d). The impact of the red areas (high impact on edges) is clearly visible and results in a lower core area compared to the common approach (Figure 1b). This shows, that accounting for the surrounding of fragments is crucial to derive ecological meaningful results; however, the settings need to be curtailed to the specific species environmental perception or parameter studied.

Further relevant analysis can be conducted ranging beyond the first nearest neighbour analysis by applying graph theory approaches as described in Fortin and Dale (2005). Here, two different distance definitions, nearest neighbour graph (NNG) and Gabriel graph (GG), have been applied to specify clusters of patches using *r.pi.graph*. The distance threshold was set to 20 km and the index used was "percentage area of cluster" (Figure 2a,b). The black lines indicate linkages while the colour shows low (red) to high (green) percentage of area within the respective cluster. The differences in resulting clusters and index values is clearly visible, with NNG resulting in a higher amount of clusters and hence partly lower percentage of area within one cluster. Applying a decreasing distance threshold starting from 20 up to 1 km and computing the average percentage area per cluster shows as well distinct differences between the two distance definitions NNG and GG. The average area is increasingly declining below a threshold of 6 km using NNG while the GG patterns results in a linear decrease in average area per cluster (Figure 2c,d). Moreover, the GG approach results in nearly constantly higher average cluster areas than the NNG method. This outlines that different neighbourhood definitions and thresholds are resulting in different findings and need to be considered when analysing landscape fragmentation.

The results of the searchtime between fragments for all rainforest fragments in West African is depicted in Figure 3. Fragments with a high searchtime (hence a low connectivity) are shown in red. The large fragments in Ivory Coast and Liberia show a low connectivity due to missing fragments in the north and east, while the small fragments in Ghana show a moderate to high connectivity, which is caused by the agglomeration of fragments. These results arise from the spatial agglomeration but also from spatial alignment. Patches which are surrounded by perpendicular located fragments have a higher chance of low searchtime values. These information need to be linked to other indices like the size and surrounding of fragments in order to provide meaningful information, for, e.g. conservation.

The aforementioned output provides information about the fragment itself but not how much this fragment is relevant to support a high connectivity for other patches in the landscape. This can be achieved by removing each patch and calculating the differences to the original value. Here, we apply the count of successful emigrants using a dispersal model approach. The results of the successful emigrants for two different matrix suitability settings are shown in Figure 4. Fragments in red are most important for the maintenance of high connectivity within the landscape. All other patches have lower "*patch relevance*" values for the maintenance of the applied index value for all patches in the landscape. The suitability of the matrix in-between the patches can be changed based on species specific dispersal requirements. This parameter is important for the result of successful emigrants as the difference between Figure 4a and b shows. Hence, the environmental settings cause significant differences concerning the connectivity of patches and therefore also for their relevance to support a high connectivity in the landscape. These values need to be defined in concordance with scientists of the respective fields (e.g. zoologist for landscape perception of specific species) in order to determine relevant influencing parameters.

These examples showed the differences in the spatial arrangement, connectivity and relevance of rainforest fragments which is relevant for botanical or zoological studies as well as future prediction how fragments can deteriorate due to climate land cover interaction (Laurance, 2004). The potential of some of the available modules to describe the landscape concerning the spatial arrangement of rainforest fragments has been shown.

4 | CONCLUSION AND OUTLOOK

The *r.pi* modules already provide a large amount of different established and novel methods to analyse spatial patterns in the landscape. The modules provide supplementary functions to the *r.le* (Baker & Cai, 1992) or its successor *r.li* module in GRASS which delivers class or landscape index analysis. Thus, *r.pi* expands the *r.li* functionality by patch-based indices and introduces new innovative spatial metrics such as connectivity of individual habitat patches. The resulting index values were also validated against Fragstats output for equivalent functions. The advantages of *r.pi* over other programs is the potential to combine functions and native GIS functions provided by GRASS in a batch environment to process input data automatically. Moreover, due to the open source licensing it is feasible to extend, modify and add further functions through the scientific community. Further new algorithms will be added in the future.

The new *r.pi* modules can be applied in various disciplines like remote sensing, fragmentation analysis or landscape management because they provide fast and automatic processing of satellite imagery and incorporate at the same time meaningful, adaptable and extendable functionality.

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AUTHORS' CONTRIBUTION

M.M. and D.R. contributed to the development of the methods; B.L. and M.M. contributed with coding; S.D. and M.M. contributed to the structure and the aim of the paper. All authors contributed to the preparation of the manuscript.

DATA ACCESSIBILITY

The dataset used in this paper is the Global Land Cover 2000 of the European Commission (Joint Research Centre) and it is freely available at: http://forobs.jrc.ec.europa.eu/products/glc2000/products.php.

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