The landscapemetrics and motif packages for measuring landscape patterns and processes

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Abstract:

This book chapter emphasizes the significance of categorical raster data in ecological studies, specifically land use or land cover (LULC) data, and highlights the pivotal role of landscape metrics and pattern-based spatial analysis in comprehending environmental patterns and their dynamics. It explores the usage of R packages, particularly **landscapemetrics** and **motif**, for quantifying and analyzing landscape patterns using LULC data from three distinct European regions. It showcases the computation, visualization, and comparison of landscape metrics, while also addressing additional features such as patch value extraction, sub-region sampling, and moving window computation. Furthermore, the chapter delves into the intricacies of pattern-based spatial analysis, explaining how spatial signatures are computed and how the **motif** package facilitates comparisons and clustering of landscape patterns. The chapter concludes by discussing the potential of customization and expansion of the presented tools.

Keywords: categorical raster data, land use, land cover, landscape metrics, pattern-based spatial analysis, spatial ecology

Introduction

Categorical raster data, such as ones representing land use or land cover (LULC), is often used in ecological studies (Fassnacht et al. 2006; Wulder et al. 2018; Chandra Pandey et al. 2021). This data is typically derived using remote sensing data, for example, satellite images in combination with statistical learning (Talukdar et al. 2020; Wang et al. 2022; Wang and Mountrakis 2023). LULC describes the spatial distribution of different anthropogenic uses of land or the natural land cover in a landscape. Thus, it provides information about human activities (usage) and natural features (physical material at the surface) in a given area within a specific time frame (Fisher et al. 2005). This information can then be used to better understand the processes and changes taking place in the landscape, such as urbanization (Fu and Weng 2016), deforestation (Floreano and De Moraes 2021), or the spread of invasive species (Manzoor et al. 2021).

From a computational perspective, LULC data can be conceptualized as a collection of cells organized in a regular grid, with each cell assigned to a specific category (With 2019). This framework enables us to analyze the data in terms of its two fundamental components: the composition, referring to the number of cells for each category, and the configuration, pertaining to the spatial arrangement of cells within each category (Riitters 2019). These components jointly create spatial patterns of categorical raster data, or landscape patterns, in short, which are commonly used to characterize the structure of landscapes. Furthermore, additional characteristics of a categorical

raster, for example, the diversity of categories, connectivity, or patch shape, can also be considered (Gustafson 1998; Uuemaa et al. 2013).

The aim of this chapter is to provide an overview of the methods and tools that allow to quantify and analyze landscape patterns. We will focus on the methods that are mainly implemented in two R packages: **landscapemetrics** (Hesselbarth et al. 2019) and **motif** (Nowosad 2021). The **landscapemetrics** package allows to compute a collection of landscape metrics, which quantify the composition and configuration of categorical raster data. The package also provides a set of additional functions, making it possible to visualize the results of the calculations, extract values of patches, sample metrics within sub-regions, or apply a moving window computation. Thus, its main purpose is to provide a set of tools to describe landscape patterns. The **motif** package, on the other hand, is focused on the analysis of these patterns. It allows to compare landscape patterns between different times, search for areas with resembling landscape patterns, or cluster areas with similar landscape patterns.

In this chapter, we will consistently utilize a set of example data. These data consist of spatial raster representing the LULC of three distinct regions in Europe: the Centre-Val de Loire region in France, the Noord-Brabant region in the Netherlands, and the Norra Mellansverige region in Sweden. We obtained the data from the Copernicus mission 2018 (European Environment Agency (EEA) (2023), available at https://land.copernicus.eu/), and cropped them to the respective regions. Additionally, all original 45 LULC classes were re-classified into five general classes (i.e., "urban", "agriculture", "vegetation", "marshes", "water") to simplify all examples. To reproduce the results presented in this chapter, you can download the corresponding data and code from the GitHub repository at https://github.com/Nowosad/landscapemetrics_motif_2024.

Landscape metrics

Landscape metrics allow to quantify the composition (i.e., amount) of and configuration (i.e., arrangement) of spatial landscape characteristics within the context of categorical raster data (Gustafson 1998, 2019; Uuemaa et al. 2013). The advantages of the landscape metrics approach include their easy application, interpretation, and communication, especially in landscapes with clear distinctions between classes (Lausch et al. 2015). Thus, they are a common tool in landscape and spatial ecology (Kupfer 2012; Lausch et al. 2015; Frazier and Kedron 2017). Even though the first conceptual developments date back to the 1980s (Turner 1989; Gustafson 1998, 2019), the application of landscape metrics gained popularity with the release of the FRAGSTATS software (McGarigal et al. 2012) in 1995, which allows to calculate an extensive collection of metrics (Kupfer 2012; Gustafson 2019).

While FRAGSTATS pioneered the field and made landscape metrics available to many scientists using a graphical user interface, more recently, the **landscapemetrics** R package (Hesselbarth et al. 2019) allows to calculate a large collection of metrics using the R programming environment, which is popular among ecologists (Lai et al. 2019; Hesselbarth et al. 2021). The **landscapemetrics** package is based on the **terra** R package (Hijmans 2021), but additionally supports raster objects from the **stars** (Pebesma 2019) and **raster** (Hijmans 2019) packages. Furthermore, some functionality also supports vector data (e.g., sample points) using the **sf** package (Pebesma 2018).

Following McGarigal et al. (2012), landscape metrics can be classified depending on the characteristics they describe, namely: area and edge, shape, core area, contrast, aggregation, and diversity metrics. Furthermore, landscape metrics can be calculated on patch-, class- and landscape-scale. While patch level metrics describe each patch, i.e., contiguous cells belonging to the same class as identified by a connected components labeling algorithm, class level metrics describe all patches belonging to the same class, and finally, landscape level metrics describe the entire landscape Figure 1. In this chapter, we will demonstrate how to calculate all these types of landscape metrics.

In order to use all functionality of the landscapemetrics package and to pre- and post-process data, we need to



Figure 1: A) Patch level: patches of an exemplary class indicated by color, i.e., all connected cells belonging to the same LULC class. B) Class level: exemplary class indicated by color, i.e., all patches belonging to the same LULC class. C) Landscape level: exemplary landscape including all LULC classes

load several packages related to spatial analysis and data wrangling. This includes the **terra** and **sf** packages for methods related to predominantly raster and vector data, respectively. Furthermore, the **dplyr** (Wickham et al. 2019) and **tidyr** (Wickham et al. 2023) packages provide a grammar for data manipulation and cleaning, while **ggplot2** (Wickham 2016) is a data visualization package. Additionally, we are creating a color scheme for all maps we are going to create in later examples.

Next, we import the three raster objects using the **terra** package representing the LULC data of the three exemplary regions as **SpatRaster** objects.

```
france <- rast("data/raster_france.tif")
netherlands <- rast("data/raster_netherlands.tif")
sweden <- rast("data/raster_sweden.tif")</pre>
```

Before calculating metrics, we need to check if the input raster fulfills certain requirements of the **landscapemetrics** package. For this, we are using the check_landscape() function. The function checks if the coordinate reference system (CRS) is projected (i.e., using Cartesian coordinates on a planar surface), the units of the map, and the number of classes. If some of the checks fail, we are still able to calculate all metrics, however, especially metrics relying on distances might not be correct or hard to interpret, e.g., due to the decimal degrees units of most

geographic CRS (on the contrary metric distance units of most projected CRS). In this case, the function will return a corresponding warning.

check_landscape(france)

layer crs units class n_classes OK 1 1 projected m integer 5 v

The input raster, france, has a projected CRS with units in meters and 5 discrete classes in total. Because the raster does not violate any of the checks, the function returns an OK check mark.

Deriving landscape metrics

All functions to calculate metrics start with the prefix $lsm_{,}$ followed by an abbreviation for the level (either p = patch, c = class, l = landscape), and finally, an abbreviation of the metric. We can get an overview of all 133 metrics that are currently provided by the **landscapemetrics** package using the $list_lsm()$ function. Additionally, we can use the function to display only a certain subset of metrics based on type or level.

list_lsm()

```
# A tibble: 133 x 5
  metric name
                                                              level function_name
                                        type
  <chr>
        <chr>
                                        <chr>
                                                              <chr> <chr>
                                        area and edge metric patch lsm_p_area
1 area
         patch area
2 cai
         core area index
                                        core area metric
                                                              patch lsm_p_cai
                                                              patch lsm_p_circle
3 circle related circumscribing circle shape metric
# i 130 more rows
list_lsm(type="area and edge metric", level="class")
# A tibble: 11 x 5
  metric name
                                           level function_name
                     type
  <chr>
          <chr>
                     <chr>
                                           <chr> <chr>
```

1 area_cv patch area area and edge metric class lsm_c_area_cv 2 area_mn patch area area and edge metric class lsm_c_area_mn

3 area_sd patch area area and edge metric class lsm_c_area_sd # i 8 more rows

To calculate a singular metric on patch-, class- or landscape-level, we simply use the function name and provide the input raster.

```
df_p_shape <- lsm_p_shape(france)
df_c_area <- lsm_c_area_mn(france)
df_l_lpi <- lsm_l_lpi(france)</pre>
```

Thus, to calculate the shape index of each patch, the mean patch area of each class i, or the largest patch index of the landscape, we use the three functions shown above. The returned data frames always include the same columns regardless of the specified metric.

df_l_lpi

#	A tibb	ole: 1 x 6				
	layer	level	class	id	metric	value
	<int></int>	<chr></chr>	<int></int>	<int></int>	<chr></chr>	<dbl></dbl>
1	1	landscape	NA	NA	lpi	65.1

These are an identifier of the raster layer, the level of the calculated metric, the class identifier, the patch identifier, the name of the metric, and finally, the metric value. If any of the columns are not applicable (e.g., the patch identifier on the landscape level), the column will contain NA values. This allows us to combine different data frames or apply the same post-processing workflow, even for different metrics and/or levels. For example, we can use the rbind() function to combine all three results into a single data frame and use functions from the **dplyr** package to calculate the minimum and maximum value for each metric.

```
result_combined <- rbind(df_p_shape, df_c_area, df_l_lpi)
result_range <- group_by(result_combined, metric) |>
    summarise(min=min(value), max=max(value))
result_range
# A tibble: 3 x 3
```

#	A LIDDIE	9: 3 X	3
	metric	min	max
	<chr></chr>	<dbl></dbl>	<dbl></dbl>
1	area_mn	64.4	3049.
2	lpi	65.1	65.1
3	shape	1	84.5

If we want to derive more than a few metrics, we can also use the calculate_lsm() function, which allows to calculate several metrics with only one function call. However, as pointed out by other authors (Gustafson 2019), "metric fishing" is an issue, i.e., computing as many metrics as possible and searching for any signal. Thus, we strongly advise not to calculate all metrics, but rather select metrics based on research questions and hypotheses. The calculate_lsm() function has many options for how to specify metrics, e.g., a vector of function names or the types and levels of metrics that can be specified.

For many metrics, we can specify further arguments, such as the direction of the connected labeling algorithm, which cells are considered core or edge cells, or the potential number of maximum classes. To see what arguments are available, we can have a look at the help page of a function, e.g., ?lsm_p_core, but all arguments of a specific metric function can also be used with calculate_lsm(). For example, we can change the directions of the connected labeling algorithm and calculate the number of patches on the class level. Comparing the results using a workflow including the dplyr package, we can see that the number of patches is larger when using "rook's" (4-neighborhood) instead of "queen's" rule (8-neighborhood; the default).

```
mutate(value.diff=abs(value.queen - value.rook))
df_comparison
```

#	A tibl	ble: 5	x 8					
	layer	level	class	id	metric	value.queen	value.rook	value.diff
	<int></int>	<chr></chr>	<int></int>	<int></int>	<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
1	1	class	1	NA	np	3231	4589	1358
2	1	class	2	NA	np	1541	3592	2051
3	1	class	3	NA	np	5512	9242	3730
#	i 2 mo	ore rou	VS					

We can also use the calculate_lsm() function (or any other lsm_ function) to calculate metrics of several raster layers or objects simultaneously. For this, we need to use a SpatRaster with several layers or a list of SpatRaster's as input. We are using the later example to calculate the perimeter and area of each patch for two regions in Europe. For this example, we only want to keep the vegetation class, i.e., class 3. Additionally, because some of the patches within each landscape are disproportional large, we are going to use the 95% quantiles of each region and metric to remove some larger values. Next, we are re-labeling the unique layer identification column using the country names. Last, we are reshaping the data frame from a long to a wider format to produce a ggplot2 figure in the final step Figure 2.

```
df_perim_core <- list(nl=netherlands, fr=france) |>
  calculate_lsm(what=c("lsm_p_perim", "lsm_p_area")) |>
 filter(class %in% 3) |>
 mutate(layer=case_when(layer==1~"Netherlands",
                         layer==2~"France")) |>
 pivot_wider(names_from=metric, values_from=value) |>
 filter(area<=quantile(area, probs=0.95) &</pre>
         perim<=quantile(perim, probs=0.95))</pre>
ggplot(data=df_perim_core, aes(x=area, y=perim, color=layer)) +
  geom point(alpha=0.1) +
  geom_smooth(se=FALSE, method="lm", formula="y ~ x") +
  scale_color_manual(name="Country",
                     values=c(Netherlands="#F79400",
                              France="#001E96")) +
 labs(x="Patch area [m2]", y="Patch perimeter [m]") +
  theme_classic() + theme(legend.position = c(0.9, 0.1))
```

This example also demonstrates how easily the **landscapemetrics** package can be incorporated into larger workflows. As expected, there is a strong relationship between the patch area and perimeter. Logically, as the patch area also increases the perimeter increases and this trend is comparable between the two regions.

Visualization of landscape metrics

We can also use built-in functions to visualize the landscapes or calculated metrics. All visualization functions start with the **show_** prefix and return a list storing **ggplot2** objects. This is done to be type-stable (i.e., always returning the same data type) regardless of the number of raster objects/layers or selected metrics. First, we can visualize all patches, i.e., all connected cells as specified by the **directions** argument of the connected components



Figure 2: Relationship between the patch area and patch perimeter in the Centre-Val de Loire region in France (blue) and Noord-Brabant region in the Netherlands (orange)

labeling algorithm. We can show the patches of the entire landscape (using the argument class="global"), or only patches of specific classes (e.g., using class=3). Here, we show all patches of the vegetation class in the French region Figure 3.

show_patches(france, class=3)



Figure 3: Patches of the natural vegetation class in the Centre-Val de Loire region in France

Furthermore, showcasing a more advanced approach, we have the capability to fill each cell of a patch accordingly to a specific landscape metric. For instance, in the following example, the fill color of each patch in the vegetation class corresponds to its area. Since we utilize a list to store two landscapes, the resulting list contains two elements, each representing a landscape and storing the associated ggplot2 objects. It becomes apparent that the landscape in France is dominated by a single large patch situated at the center of the region Figure 4.

```
list_gg_area <- list(fr=france, nl=netherlands) |>
    show_lsm(class=3, what="lsm_p_area")
plot_grid(plotlist=list_gg_area, ncol=2, labels=c("NL", "FR"))
```



Figure 4: Visualization of the patch area for the natural vegetation LULC class in the Centre-Val de Loire region in France (left) and the Noord-Brabant region in the Netherlands (right)

Correlation between several metrics can be an issue (Cushman et al. 2008; Schindler et al. 2008; Nowosad and Stepinski 2018), especially in combination with the previously discussed practice of "metric fishing". Thus, we can use the show_correlation() function to check correlations between metrics that were previously calculated using either calculate_lsm() or singular metric functions Figure 5.

Additional features

The **landscapemetrics** also provides some more advanced functionality. This includes extracting values of patches, sampling of metrics within sub-regions, or applying a moving window approach. In terms of metrics selection or arguments passed on to the metric functions, all these functions behave similarly to the calculate_lsm() function.

In order to demonstrate the extraction and sampling of metrics, we first need to create sample points. For this, we are going to randomly create 10 points within a region Figure 6.

```
samplepoints <- spatSample(france, size=10, as.points=TRUE) |>
st_as_sf()
```

Now, we can extract patch level metrics of all patches that contain a sample point. For this, we use the extract_lsm() function. The resulting data frame has 20 rows, one for each metric and sample point. It is worth noting that compared to previous result data frames, there is an additional column named extract_id, which facilitates matching the metric results with the respective sample points.



Figure 5: Correlation matrix of all class level metrics for the Noord-Brabant region in the Netherlands



Figure 6: Location of exemplary sample points used to extract and sample landscape metrics in the Centre-Val de Loire region in France

```
df extract <- extract_lsm(france, samplepoints,</pre>
                            what=c("lsm_p_area", "lsm_p_perim"))
df extract
# A tibble: 20 x 7
  layer level class
                        id metric
                                    value extract_id
  <int> <chr> <int> <int> <chr>
                                     <dbl>
                                                <int>
                                     15202
1
      1 patch
                   3
                      5207 area
                                                     1
2
      1 patch
                   3
                      5207 perim
                                   297200
                                                     1
                   3
                                                     2
3
      1 patch
                      7899 area
                                      7652
# i 17 more rows
```

Similarly, we can also sample metrics within a buffer around each sample point. For this, we need to additionally provide a size of the sampling buffer and its shape (either a square or circle), but it is also possible to directly use polygon objects as a sampling buffer.

```
# A tibble: 47 x 8
```

	layer	level	class	id	metric	value	<pre>plot_id</pre>	<pre>percentage_inside</pre>
	<int></int>	<chr></chr>	<int></int>	<int></int>	<chr></chr>	<dbl></dbl>	<int></int>	<dbl></dbl>
1	1	class	1	NA	pland	3.54	1	101.
2	1	class	2	NA	pland	48.6	1	101.
3	1	class	3	NA	pland	46.8	1	101.
#	i 44 m	nore ro	ows					

The resulting data frame has two additional columns. First, similar to the metrics extraction, an additional column identifies the sampling buffer. Second, an additional column stores information about the actual clipped sampling buffer area. Theoretically, this value should be equal to 100%. However, it includes all of the raster cells whose centroids are inside the selector polygon (Lovelace et al. 2019), and thus the actual sampling buffer area might be slightly larger or smaller than the specified area resulting in a deviation from the theoretical value. Furthermore, sample points at the edge of the landscape might include a smaller area than specified by the size argument. In these cases, a warning is returned and these sample plots can potentially be excluded from further analyses.

Similar to the previously used show_lsm() function, patch level metrics can be returned as a raster object in which each cell stores the metric value of the patch it belongs to. Thus, each cell in the raster object stores its corresponding metrics value. For this, the function spatialize_lsm() can be used. However, in order to be type-stable, this functions always returns a nested list for each layer and metric (even if only one layer and/or metric is present). The first level of the list corresponds to the number of layers, while the second level of the list corresponds to the number of selected metrics. So we need to use some indexing in order to get only one raster, e.g., the fractal dimension index raster, which we now can use for further analysis, such as calculating kernel density estimates (results not shown).

class(list_shape)

```
str(list_shape)
values(list_shape$layer_1$lsm_p_frac, mat=FALSE) |> density()
```

Last, **landscapemetrics** provides a moving window approach, i.e., metrics can be calculated for the local neighborhood of each focal cell. For this, the **window_lsm(**) function can be used. Similar to the **focal(**) function of the **terra** package, a local neighborhood must be specific using a matrix object. As with the previously discussed functions, metrics can be selected using the type of metric, or specific metrics using the **what** argument. However, currently only landscape level metrics are implemented. Depending on the size of the landscape and the local neighborhood matrix, this can be computationally demanding with a long run time.

mat_window <- matrix(1, nrow=501, ncol=501)
window_lsm(netherlands, window=mat_window, what="lsm_l_pr")</pre>

Utility functions

Many of the functions internally used by the **landscapemetrics** package might also be useful for users during pre- or post-processing of raster data or to develop new methods to quantify landscape characteristics. All of these functions start with the get_ suffix and usually return a (nested) list to be type-stable for different inputs.

One of the most fundamental functions of the package is the get_patches() function, which returns the patches of each class using the connected components labeling algorithm. Yet, the result is a nested list in which the first level refers to the number of raster layers/objects and the second level stores all patches separated by class i. All other cells not belonging to the current class i are set to NA. In the following example, we are first getting all patches of the region in French separated by class. Next, we are using all wetland and water-related classes and combining them into one SpatRaster object as layers. Last, we use raster algebra to sum all cells which returns a singular layer in which all cells are labelled by their cell identifier and all other cells are NA. This results in a single raster layer combining all patches of one of the two water-related classes.

```
list_patches <- get_patches(france)</pre>
ras_water <- list_patches$layer_1[4:5] |>
  rast() |>
  sum(na.rm=TRUE)
ras_water
class
            : SpatRaster
dimensions
            : 2860, 2333, 1 (nrow, ncol, nlyr)
resolution : 100, 100 (x, y)
            : 3568800, 3802100, 2619700, 2905700 (xmin, xmax, ymin, ymax)
extent
coord. ref. : ETRS89-extended / LAEA Europe (EPSG:3035)
source(s)
            : memory
name
            :
                sum
            : 10285
min value
max value
            : 10844
```

The get_boundaries() function returns a raster in which all boundary/edge cells of a patch are labeled 1 and all core cells are labeled 0. We define an edge cell as a cell that shares a neighboring cell with a different LULC value than itself. Usually, we apply the function to previously connected components labeled landscapes and receive a list with one element for each layer/object. This list can be used for further analysis, such as counting the number of

edge and core cells.

```
ras_boundaries_urban <- get_boundaries(list_patches$layer_1$class_1)
lapply(ras_boundaries_urban, freq, wide=TRUE)</pre>
```

```
[[1]]
layer 0 1
1 1 304595 164282
```

We can use the two functions get_unique_values() and get_adjacencies() to receive a vector with all unique class values and their adjacency matrix, respectively. Because both return a list in order to be type-stable, we can directly index the first element if we only provide one raster layer/object. Of course, the dimensions of the adjacency matrix must be identical to the length of the unique class values given.

```
vec_unique <- get_unique_values(sweden)[[1]]
mat_adjacencies <- get_adjacencies(sweden)[[1]]
dim(mat_adjacencies)</pre>
```

[1] 5 5

```
length(vec_unique)
```

[1] 5

Related, we can use the get_nearestneighbour() function on a previously connected component labeled landscape, which returns a data frame with the minimum Euclidean distances to the nearest patch of the same class. In the following example, we calculate the minimum distances between all patches of class 1, i.e., urban areas. There are 1,175 patches in total and the distance, as well as the identifier of the nearest neighbor, is included. We see that the distance between patches 626 and 650 of the urban class is the largest in the LULC data of Sweden.

```
sweden_cl1 <- get_patches(sweden, class=1)
df_neighbour <- sweden_cl1$layer_1$class_1 |>
  get_nearestneighbour(return_id=TRUE) |>
  arrange(-dist)
```

Last, there are two utility functions related to the shape of the patches. First, the function get_circumscribingcircle() returns a data frame with the diameter of the smallest circumscribing circle around each patch and the x- and y-coordinate of it. Similar to this, the get_centroids() function returns a data frame with the coordinates of the centroids of each patch. For this example, we will filter the data frame to include only the centroids of the marshes class and create a map plotting the patches as well as all the centroids Figure 7.

```
df_circle <- get_circumscribingcircle(netherlands)
df_centroids <- get_centroids(netherlands) |>
    dplyr::filter(class==4)
as.data.frame(netherlands, xy=TRUE) |>
    ggplot(aes(x=x, y=y)) +
    geom_raster(aes(fill=as.factor(cover))) +
    geom_point(data=df_centroids, aes(x=x, y=y), shape=3, size=2.5) +
    scale_fill_manual(values=color_scale) +
    coord_equal() + theme_void() + theme(legend.position="none")
```



Figure 7: Patch centroids of all marsh patches in the Noord-Brabant region in the Netherlands

Pattern-based spatial analysis

Pattern-based spatial analysis is a set of methods allowing for performing various tasks on landscape patterns, such as comparing landscape patterns or searching for areas with similar landscape patterns to the query one (Wickham and Norton 1994; Jasiewicz et al. 2015; Netzel et al. 2018; Nowosad 2021). Instead of treating each cell independently, this approach focuses on considering local composition and configuration. Firstly, each area, a group of adjacent cells encompassing a landscape pattern, is described numerically as spatial signatures. Next, the similarity between spatial signatures for two areas can be measured using various dissimilarity measures. Low dissimilarity values suggest that the two areas have similar composition and configuration. These ideas allow, for example, to compare spatial pattern change between an area in time, search for similarities between areas of interest, or group areas with similar patterns together. Spatial signatures may also be used directly as new variables, for example, in machine learning models.

The pattern-based spatial analysis methods are available in the R package **motif** (Nowosad 2021), which allows to describe spatial patterns of one or more categorical raster data for any defined regular and irregular regions. It accepts spatial raster objects from the **terra** (Hijmans 2021) and **stars** (Pebesma 2019) R packages as inputs. All **motif** functions use the $lsp_$ (*local spatial pattern*) prefix consistently, allowing users to find the desired tool quickly. Most functions in the package are based on a computationally fast C++ code and the software is designed to work on larger-than-RAM raster datasets.

We need to start by attaching the **motif** package for pattern-based spatial analysis, and two main packages for handling spatial data, **terra** and **sf** (Pebesma 2018).

```
library(motif)
library(terra)
library(sf)
```

Our main dataset for the following examples will be the spatial raster representing land cover classes in the Centre-Val de Loire region in France for the year 2018.

```
france <- rast("data/raster_france.tif")
plot(france) # result not shown</pre>
```

Spatial signatures

The backbone of pattern-based spatial analysis is the concept of spatial signatures. A spatial signature is a short numerical descriptor of landscape patterns featured in a particular area, and represented by a categorical raster. Landscape patterns can be described in various ways, and thus many possible spatial signatures exist. That being said, they usually express the composition and/or configuration (arrangement) of categorical raster cells (Table 1). It is also worth noting that spatial signatures can be calculated for a large area or many smaller subareas divided by regular or irregular zones (*windows*).

Spatial signatures are derived using the lsp_signature() function. We need to provide two arguments to calculate a single spatial signature: our input categorical raster data (x) and the spatial signature type (type). The most basic spatial signature is "composition": it is a share of cells of each category in a given area.

```
france_comp <- lsp_signature(france, type="composition")
france_comp
# A tibble: 1 x 3
    id na_prop signature
* <int> <dbl> <list>
```

0 <dbl [1 x 5]>

The lsp_signature() function always returns a data frame with three columns: a unique identifier (id), the proportion of cells in an area with missing values (na_prop), and the calculated signature (signature). This last column is a list containing a single signature per area of interest. We can see the obtained spatial signature by accessing the first element of the signature list.

france_comp\$signature[[1]]

1

1

1 2 3 4 5 [1,] 0.07027133 0.7041287 0.2184272 0.0004055524 0.0067673

It shows that $\sim 70\%$ of the area is covered by agriculture (2), $\sim 22\%$ by vegetation (3), and $\sim 7\%$ by the urban class (1).

While the "composition" signature is straightforward to understand, it does not encompass the spatial arrangement of the categories: it does not tell if a given category represents one large continuous area or if it is distributed as many small patches. Thus, more complex and informative signatures should be used in most cases. For instance, when dealing with a single categorical raster, a co-occurrence vector ("cove") serves as an appropriate choice for such a signature.

The co-occurrence vector is a spatial signature that encapsulates both the composition and configuration of raster classes in a given area (Haralick et al. 1973; Jasiewicz et al. 2015; Nowosad and Stepinski 2021). This is achieved by counting not how many times each class occurs but how often a pixel with a given class is adjacent to another pixel of some class. Thus, the result is a long vector (15 elements in this example) that counts how many times pairs of pixels with given classes are adjacent, e.g., urban cells are adjacent to other urban cells, and how many times urban cells are adjacent to, for example, vegetation cells. In general, you can think of spatial signatures as a way to

compress information: our original raster has 6,672,380 values, which we now compressed into a vector of only 15 elements.

```
france_cove <- lsp_signature(france, type="cove")
france cove</pre>
```

As shown above, spatial signatures may be used as multi-value descriptors of landscape patterns of a given area. This allows us to calculate spatial signatures of two or more areas and then compare them using a dissimilarity measure.

By default, the window argument is set to NULL, and **motif** performs calculations for the entire area. However, the package also offers the flexibility to compute numerous spatial signatures for a single large area by dividing it into multiple subareas referred to as "local landscapes". This partitioning is achieved by specifying either a numeric value or an **sf** polygon data as the **window** argument.

When a numeric value is provided, the input raster is subdivided into square-shaped subareas, with each side length equal to the specified numeric value, measured in cells. In the following example, we demonstrate the calculation of co-occurrence vectors for square subareas measuring 50 by 50 cells, which is equivalent to 5 by 5 kilometers in this example.

```
france_cove2 <- lsp_signature(france, type="cove", window=50)
france_cove2</pre>
```

```
# A tibble: 2,726 x 3
        id na_prop signature
* <int>        <dbl> <list>
1        1        0 <dbl [1 x 15]>
2        2        0 <dbl [1 x 15]>
3        3        0 <dbl [1 x 15]>
# i 2,723 more rows
```

Now, notice that the output here is still a data frame with three columns, but instead of having only one row, we now have 2,726 rows – one row per subarea. We may visualize these subareas by creating a new sf object with lsp_add_sf() and then using the plot() function (Figure 8).

```
france_cove2_sf <- lsp_add_sf(france_cove2)
plot(france, ext=ext(france_cove2_sf))
plot(st_geometry(france_cove2_sf), add=TRUE)</pre>
```

The window argument can also accept an sf polygon, allowing for the independent derivation of spatial signatures within each polygon-defined area. In the provided example, we begin by randomly selecting 100 sample points within the study area. For each point, we create a buffer of 300 meters, resulting in a corresponding buffer polygon. By setting this buffer polygon as the window argument, we can obtain a spatial signature for the 300-meter buffer surrounding each input point.



Figure 8: Land cover of the study area overlayed with a grid with each subarea of 50 by 50 input raster cells

type	name	description
composition	Composition	A representation of the share of cells for each category within a local landscape. The length of the composition vector corresponds to the number of unique categories in a raster. Input: one categorical raster.
cove	Co-occurrence	A count of all of the pairs of the adjacent cells
	vector	for each category in a local landscape. By default, its length equals to $(n^*n-n)/2+n$, where n is a number of unique categories. Input: one categorical raster.
wecove	Weighted	A modification of a co-occurrence vector, in
	co-occurrence	which each adjacency contributes to the
	vector	output based on the values from the weight
		raster. By default, its length equals to $(n^*n n)/2 \pm n$ where n is a number of unique
		categories. Input: one categorical and one numerical raster.
incove	Integrated	A count of all of the pairs of the adjacent cells
	co-occurrence	for each category in a local landscape for all
	vector	of the input rasters. Input: two or more categorical rasters.
-	A user-defined	Any user-defined function that can summarize
	function	categorical spatial raster data.

Table 1: Spatial signatures available in the motif package

```
sample_points <- read_sf("data/france_sample_points.gpkg")
sample_polys <- st_buffer(sample_points, dist=300)
france_cove3 <- lsp_signature(france, type="cove", window=sample_polys)
france_cove3 # result not shown</pre>
```

Landscape patterns' comparison

Landscape patterns change through time and we are able to evaluate and measure such a change. Here, we will use a second dataset, land cover classes for the Centre-Val de Loire region in France for the year 2000.

```
france2000 <- rast("data/raster_france2000.tif")</pre>
```

Now that we have two datasets, for the years 2000 and 2018, we can proceed with their comparison. In pattern-based spatial analysis, the comparison involves calculating the dissimilarity between the spatial signatures derived from both rasters. This approach is complementary to the pixel-based comparison that is based on comparing all the values for each dataset, as it allows us to evaluate the change in the landscape pattern.

To perform this comparison, we utilize the lsp_compare() function, and provide our two datasets, france2000 and france, along with specifying the type of spatial signature (type) and the chosen dissimilarity measure (dist_fun). Additionally, we have the option to obtain the results in one of several output classes. For instance, we can choose to use the SpatRaster class from the terra package by setting output="terra".

```
lc_change1["dist"]
```

```
class : SpatRaster
dimensions : 1, 1, 1 (nrow, ncol, nlyr)
resolution : 233300, 286000 (x, y)
extent : 3568800, 3802100, 2619700, 2905700 (xmin, xmax, ymin, ymax)
coord. ref. : ETRS89-extended / LAEA Europe (EPSG:3035)
source(s) : memory
name : dist
min value : 0.0002682711
max value : 0.0002682711
```

The above example compared the change in landscape patterns using the co-occurrence vector signature ("cove") and the Jensen-Shannon distance ("jensen-shannon") for the whole area. However, we can change the spatial scale of our analysis and look at the spatial pattern changes also for smaller subareas. This can be done by adding a value to the window parameter. In the example below, we set the window parameter to 50, meaning each subarea will consist of 50 by 50 cells from the input rasters Figure 9.

The highest values in the right panel of Figure 9 represent areas with the most prominent change of land cover landscape patterns. They mainly relate to the change of herbaceous areas into shrubs. We can also find examples of



Figure 9: (Left) land cover data for year 2000; (center) land cover data for year 2018; (right) change in land cover landscape patterns between 2000 and 2018 for 50 by 50 cells areas (Jensen-Shannon distance)

the areas with the largest changes by subsetting only the local landscapes with dissimilarity above some threshold. Then, the lsp_extract() function can be used to extract a local landscape with a given id.

Figure 10 shows a local landscape with the largest change of land cover landscape patterns between 2000 and 2018. This location is an example of an area with a large loss of natural vegetation (to agriculture) and a small expansion of urban areas.

Landscape patterns' search

Another example of pattern-based spatial analysis is searching for areas with similar landscape patterns to a query one. Pattern-based search is a comparison of a spatial pattern of a given local landscape to many subareas of a larger raster.

Here, we start by reading polygon data with our study area and cropping the **france** raster to its borders. Thus, the **france_study_area** object is a raster storing LULC data for the study area.

```
study_area <- read_sf("data/france_study_area.gpkg")
france_study_area <- crop(france, study_area, mask=TRUE)</pre>
```

Search can be performed with the lsp_search() function, while providing two raster datasets (an area of interest



Figure 10: An example of a local landscape of 5 by 5 kilometers with the largest change of land cover landscape patterns between 2000 and 2018

and a larger area), the signature type, distance measure and the window size.

plot(nlcd_search[["dist"]])

Its output is a **terra** object with three raster layers: a unique id, the proportion of cells in an area with missing values (na_prop), and the calculated dissimilarity (dist) (Figure 11 D). The areas with the smallest dissimilarity values are the ones that have the most similar spatial pattern to the area of interest.

```
nlcd_search_df <- as.data.frame(nlcd_search)
subset(nlcd search df, dist<0.001)</pre>
```

	id	na_prop	dist
1303	1303	0	0.0003939899
1677	1677	0	0.0007520309
1867	1867	0	0.0007956902

To extract a selected local landscape, the lsp_extract() function can also be used here (Figure 11 C). search_1 <- lsp_extract(france, window=50, id=1303)

Landscape patterns' regionalization and clustering

Spatial structures derived with lsp_signature() may also be converted to spatial objects of sf, stars and terra classes. The lsp_add_terra() function, for example, takes a spatial signature object and converts in into a terra raster object.



Figure 11: (A) Area of interest, (B) Search area divided into a set of regular local landscapes, (C) A local landscape with the most similar land cover spatial pattern to the area of interest, (D) Dissimilarity between land cover landscape patterns of the area of interest and the search area

```
france_cove2 <- lsp_signature(france, type="cove", window=10)
france_cove_terra <- lsp_add_terra(france_cove2, metadata=FALSE)
france_cove_terra</pre>
```

class	:	SpatKaster					
dimensions	:	286, 234, 15 (n	nrow, ncol, nly	r)			
resolution	:	1000, 1000 (x,	y)				
extent	:	3568800, 3802800), 2619700, 290	5700 (xmin	, xmax,	ymin,	ymax)
coord. ref.	:	TRS89-extended	/ LAEA Europe	(EPSG:3035)			
source(s)	:	nemory					
names	:	X1, X2, X	X3, X4,	X5, 1	X6,		
min values	:	0, 0.0000000,	0, 0.0000000,	0.0000000,	0,		
max values	:	1, 0.3191489,	1, 0.3055556,	0.3944444,	1,		

This new object has several raster layers representing spatial signature elements. This opens new possibilities for using the information of landscape patterns in other workflows related to spatial regionalization, clustering, and machine learning.

A regionalization example below uses the **supercells** package to group adjacent local areas with similar landscape patterns. We can apply the **supercells** algorithm (Nowosad and Stepinski 2022), which expects four essential arguments: input raster data, k: a number of regions desired by the user, **compactness**: a compactness value, where larger values cause clusters to be more compact, and **dist_fun**: a distance function.

The output here is a spatial vector with a set of polygons, where each polygon represents a larger area with a certain level of homogeneity of its landscape patterns (Figure 12 A).

```
plot(france)
plot(st_geometry(france_sc), add=TRUE, border="red") # result not shown
```

You may notice that, while the land cover landscape patterns are homogeneous internally, there are several examples of similar adjacent polygons. In cases like this, we could merge such polygons, for example, using a clustering method, such as hierarchical clustering or k-means. Firstly, we need to drop the geometry column from the france_sc object, as it is not needed for the clustering, and then calculate the value distances between the landscape patterns of each supercell. Next, we can apply the hierarchical clustering method with the hclust() function. Based on the dendrogram visualization (plot(hc)), we can select the number of clusters: here we choose four clusters. Finally, we can assign a cluster number to each supercell using the cutree() function.

The hierarchical clustering method assigns a cluster number to each, previously derived supercell. Thus, to obtain a

separate polygon for each cluster, we need to perform a postprocessing step: aggregate() the clusters to dissolve the borders between clusters.

france_sc2 <- aggregate(france_sc, by=list(france_sc\$k), FUN=mean)</pre>

The dissolved areas of clusters are shown on panel B of Figure 12, while the C panel shows the final created polygons. The first cluster represents mostly agricultural areas, the third cluster represents mostly forested areas, and the fourth cluster represents mostly urban areas. The second cluster is a bit more complex, as it contains a mosaic of forested and agricultural areas. The result seems mostly satisfactory, where most created polygons are internally homogeneous and visibly distinct from their neighbors. At the same time, there are a few areas in which homogeneity needs to be improved. This suggests that the result could still be improved, for example, by using a larger number of initial supercells or changing the number of expected clusters.



Figure 12: (A) Study area divided into supercells of homogeneous land cover landscape patterns, (B) Supercells grouped into four clusters using the hierarchical clustering method, (C) Borders of the polygons derived with the hierarchical clustering method

Conclusions

In conclusion, this chapter has highlighted the significance of categorical raster data, specifically land use or land cover (LULC) data, in ecological studies. We have explored the role of landscape metrics and pattern-based spatial analysis in quantifying and analyzing landscape patterns, using the R packages **landscapemetrics** and **motif**.

Landscape metrics, computed using the **landscapemetrics** package, have proven to be valuable tools in spatial ecology and landscape ecology. They allow us to quantify the composition and configuration of spatial landscape characteristics, enabling a deeper understanding of environmental processes and changes. By calculating metrics at various levels and visualizing them, researchers can gain insights into the patterns and structures present in the landscape. However, it is crucial to select metrics purposefully, aligned with research questions and hypotheses, to avoid the pitfall of "metric fishing" (Gustafson 2019).

Moreover, pattern-based spatial analysis, facilitated by the **motif** package, offers a robust framework for analyzing and comparing landscape patterns. By considering local groups of adjacent cells as landscape patterns and calculating spatial signatures, we can capture both composition and configuration information. This approach allows us to compare landscape patterns over time, identify areas with similar patterns, and group similar areas together. The **motif** package's ability to handle large raster datasets is particularly advantageous.

The chapter has provided practical examples and code snippets demonstrating the calculation of landscape metrics and spatial signatures, as well as their visualization. We have shown how to use these techniques to analyze landscape patterns, explore changes over time, and extract local landscapes with significant pattern variations. By combining the power of landscape metrics and pattern-based spatial analysis, researchers can gain a comprehensive understanding of landscape dynamics, composition, and configuration. These techniques facilitate the investigation of the pattern-process link that is a central framework of many ecological fields, but specifically landscape ecology (Turner 1989). For example, the pattern-process link using LULC data was studied for species distributions (Marshall et al. 2018), (functional) connectivity (Vogt et al. 2009), or genetic population structure (Borthwick et al. 2020). However, patterns and processes are often in an interacting relationship influencing each other, and many drivers and processes act simultaneously - such as climate, disturbances, succession, biotic competition and dispersal, or human land use (Turner 2005). The pattern-process link is a complex and challenging topic, and the analysis of landscape patterns is only one part of the puzzle. Nevertheless, landscape metrics and pattern-based spatial analysis are powerful tools to investigate the pattern-process link and to gain a better understanding of the landscape.

Both packages, being open-source, offer extensive possibilities for customization and expansion. This enables researchers to tailor them to their specific inquiries and requirements. The **landscapemetrics** package, for instance, allows for the integration of new metrics through the utilization of diverse utility functions, thereby enhancing its capabilities. Similarly, the **motif** package can be expanded by incorporating user-defined spatial signatures, which can be used to measure similarities between different properties of landscape patterns. Consequently, contributions to both packages are highly encouraged and welcomed. You can actively participate in the development of these packages at https://github.com/r-spatialecology/landscapemetrics and https://github.com/Nowosad/motif.

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