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APPLICATION

ecochange: An R-package to derive ecosystem change indicators from freely available earth observation products

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Abstract

1. Spatial resources accessible for the derivation of biodiversity indicators of the class ecosystem structure are sparse and disparate, and their integration into computer algorithms for biodiversity monitoring remains problematic. We describe ecochange as an R-package that integrates spatial analyses with a monitoring workflow for computing routines necessary for biodiversity monitoring.
2. The ecochange comprises three modules for data integration, statistical analysis and graphics. The first module currently downloads and integrates diverse remote sensing products belonging to the essential biodiversity class of structure. The module for statistical analysis calculates RasterStack ecosystem-change representations across areas of interest; this module also allows focusing on species habitats while deriving changes in a variety of indicators, including ecosystem areas, conditional entropy and fractal dimension indices. The graphics module produces level and bar plots that ease the development of indicator reports.
3. Its functionality is described with an example workflow to calculate ecosystem-class areas and conditional entropy across an area of interest contained in the package documentation.
4. We conclude that ecochange features procedures necessary to derive ecosystem structure indicators integrating the retrieval of spatially explicit data with the use of workflows to calculate/visualize biodiversity indicators at the national/regional scales.

KEYWORDS
biodiversity monitoring, biodiversity reports, data integration, ecosystem remote sensing products, essential biodiversity variables, statistical analysis, workflows to derive biodiversity indicators

1 | INTRODUCTION

The growing availability of freely shared remote sensing products has brought about new opportunities for scientists and decision-makers to monitor ecosystems, deriving essential biodiversity variables and ecosystem indicators (Hardisty, Belbin, et al., 2019; Kissling et al., 2015; Kissling, Walls, et al., 2018; Lai et al., 2019; Pereira et al., 2013). A variety of products available in free-shared global repositories (Table 1) enable the derivation of indicators of change in ecosystem structure such as ecosystem extent (Skidmore et al., 2015), fragmentation (Taubert et al., 2018) and configurational complexity (Nowosad & Stepinski, 2019), among others (de la Barra et al., 2022). These data products offer the opportunity to the assessment of biodiversity change at national and regional scales (Kissling et al., 2015). However, such spatial resources are sparse and disparate, and their integration into computer algorithms for biodiversity monitoring remains troublesome (Anderson, 2018; Hardisty, Michener, et al., 2019). Reconciling ecosystem spatial variables with user-defined areas of interest involves the need to perform a series of spatial operations, including data downloading, storing, retrieval, copying, merging and projection that limit their use and can compromise the integrity of calculations (Dantas de Paula et al., 2019; Hardisty, Michener, et al., 2019; Kissling, Ahumada, et al., 2018).

The R package ecochange supports biodiversity monitoring by assisting users in the integration of remote sensing products to compute ecosystem structure indicators. The package includes a workflow to calculate and visualize structural indicators at the regional level or national scale (Figure 1). The workflow implemented make use of thematic maps derived from remote sensing spectral information for a given area of interest. The applicability to other raster datasets and the interpretability of the results should be assessed by the user. The package does not require field data to work. It operates on RasterStack data covering an area of interest represented by a user-defined polygon geometry or area of interest representing the border of a Geographic Administrative Data Map (GADM). Currently, the package can download up to 16 ecosystem remote sensing products (Table 1). The package routines automatically integrate ecosystem variables to calculate ecosystem structural indicators (Table 2) across areas of interest and over time.

Currently, there is a variety of packages available in R to calculate biodiversity indicators (Figure 2). Some packages include modules to download spatially explicit data: for example, the getSpatialData (Kwok, 2018) and gfcanalysis (Cooper & Zvoleff, 2019). Others include functions to derive indicators associated with ecosystem structure in a spatially explicit manner. Yet, most packages lack mechanisms to integrate spatial analyses within user-defined monitoring workflows to derive indicators suitable for biodiversity monitoring. The ecochange extends the functionality of these packages by enabling the downloading, reprojection and alignment of remote sensing products and the derivation of structural indicators of biodiversity change.

2 | PACKAGE DEPENDENCIES AND INSTALLATION

Descriptions and applications included here correspond to ecochange_2.9 (Lara, Gutierrez-Velez, et al., 2022). This package version embodies four dependencies (raster, sf, parallel and rasterVis), a variety of imports (e.g. landscapemetrics, tibble and ggplot2) and several suggested libraries (e.g. viridis and rvest). Users can install the package, imports and dependencies by running the command: install.packages('ecochange'). Users are also encouraged to install the suggested library viridis. The installation of geospatial binaries required for the dependency sf relies on geospatial binaries that are system dependent. In Windows systems, R configures these binaries during the package installation. In Linux-like distributions, users must preinstall such binaries. For instance, Ubuntu users must run either the terminal or a package manager to install the following binaries: libpq-dev, gdal-bin, libgdal-dev and libudunits2-dev. In Mac systems, the users must install similar binaries via Homebrew.

TABLE 1 Examples of ecosystem spatial resources processed by ecochange

Product	Scene names	Format and size	Pixel size	Web resource and authentication requirements	Essential biodiversity variable
Geographic Administrative Data Maps (GADM)	The name of any approximate GADM around the world	User-defined	-	https://gadm.org/ Unrequiredy login	Ecosystem-Class Areas (ECA)
Forest Change (Hansen et al., 2013)	treecover2000, lossyear, gain, datamask, first, last	scenes (tif) 10x10^{o}	30 m	https://glad.earthengine.app/view/global-forest-change Unrequired login	ECA; Fragmentation
Tree-Canopy Cover (Sexton et al., 2013)	TC_2000, TC_2005, TC_2010, TC_2015	scenes (tif) in compressed (zip) files 170 km N-S by 183 km E-W	30 m	https://e4ftl01.cr.usgs.gov/MEASURES/GFCC30TC.003 Required login: LP-DAAC user and password	ECA
Surface Water (Pekel et al., 2016)	Occurrence, change, seasonality, recurrence, transition, extent	scenes (tif) 10x10^{o}	30 m	https://global-surface-water.appspot.com/download Unrequired login	ECA; Inundation

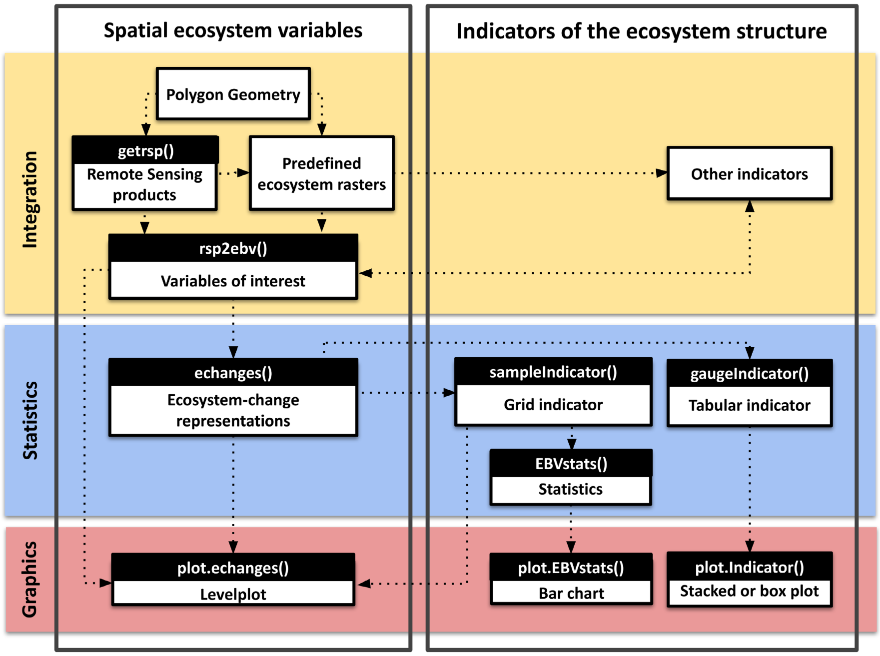


FIGURE 1 Flowchart indicating modules and functions of ecochange.

TABLE 2 Examples of indicators in the class ecosystem structure derived by ecochange using integrated remote sensing products. Routines used are indicated

Name	Equation	Metric
Ecosystem-class Area In-package raster tabulation routines Landscapemetrics dependence (Hesselbarth et al., 2019)	Area = $\sum_{i=1}^{K} \sum_{j=1}^{K} w_{ij}a$ Where w_{ij} is the number of cells in the class ij; a is the area	Ecosystem horizontal extent
Conditional entropy at class level Landscapemetrics dependence (Nowosad & Stepinski, 2019)	$H(y \vee x) = -\sum_{i=1}^{K} \sum_{j=1}^{K} p(x = c_i, y = c_j) \log_2 p(y = c_i \vee x = c_j)$; where $\{c_1, \ldots, c_K\}$ are K landscape classes assigned to a landscape of grid cells; x is a class of a focus cell; y is a class of an adjacent cell; $p(x = c_i, y = c_j)$ is a probability of the focus cell having a class c_i and an adjacent cell having a class c_j	Configurational complexity; ecosystem degradation; Landscape diversity
Perimeter-area Fractal Dimension at class level Landscapemetrics dependence (Hesselbarth et al., 2019)	PAFRAC = $\frac{2}{\beta}$; where β is the slope of a regression of the area against the perimeter logarithm: $n_i \sum_{l=1}^{n} \ln a_{il} = a + \beta n_i \sum_{l=1}^{n} \ln p_{il}$; where l is the number of patches; i is the class; a is the area and p is the perimeter	Shape; complexity; ecosystem fragmentation
Other metrics	See documentation of landscapemetrics (Hesselbarth et al., 2019; Nowosad & Stepinski, 2019)	Metric dependent

3 | INPUTS FOR DATA RETRIEVAL

In order to run, ecochange functions minimally require a polygon representing an area of interest and one RasterStack object (Dantas De Paula et al., 2019; O'Connor et al., 2015; Pettorelli et al., 2016). Alternatively, the package offers users the option of selecting the name of a Geographic Administrative Data Map (GADM) as the area of interest and the name of a raster data product available to download directly through the use of the package using the arguments roi and lyrs (Table 3). Other arguments correspond to a file path where downloaded products will be stored and mc.cores to speed up computation processes through the implementation of multi-core processing (see Appendix S1). These arguments have defaults that guide users during the implementation of the functions. For instance, NULL defaults in roi and lyrs make the functions print character vectors describing available GADM, and remote sensing products to download, respectively. Users can then choose any element in the list and re-run the functions for subsequent applications. By default, a folder named 'ecochange' and located in a temporary directory is used as the path to download the data. Likewise, lyrs controls internal

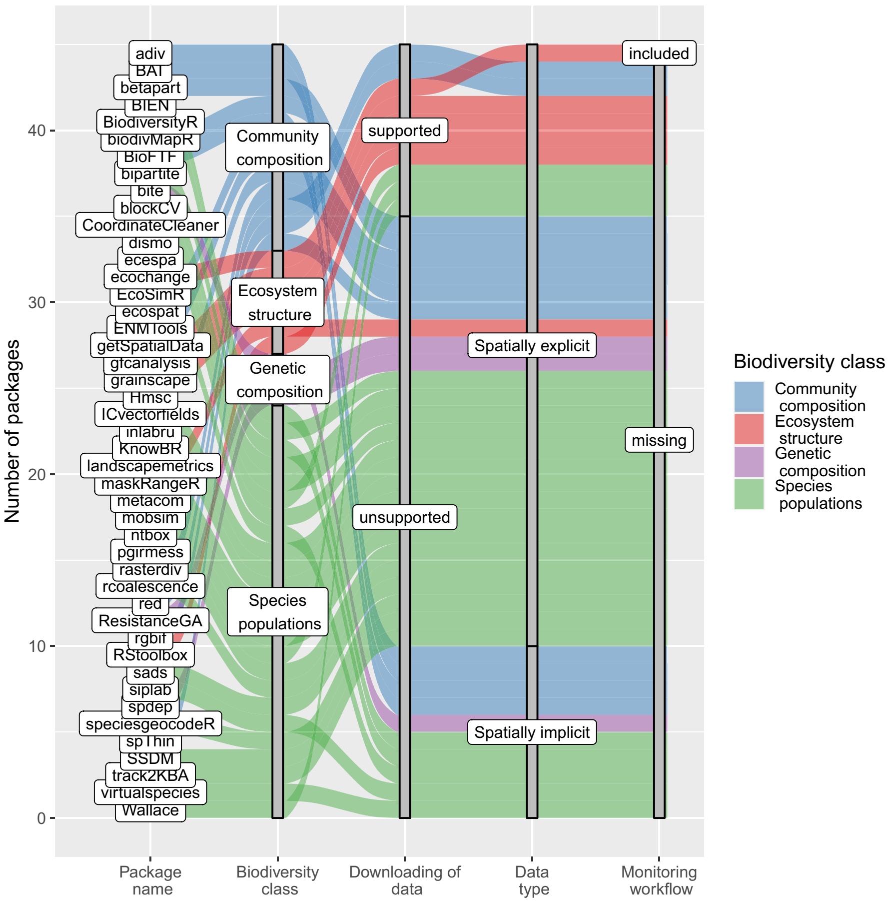


FIGURE 2 R packages available to compute biodiversity indicators ordered according to the classes defined by Pereira et al. (2013). To support biodiversity monitoring at regional and national scales, the packages should include routines to download spatially explicit data and workflows to compute and visualize indicators.

methods that simplify the formulation of ecosystem variables with long names (Table 3). In Linux-like machines, the mc.cores argument is set to use 60% CPU capacity by default. In Windows systems, this argument is automatically set to 1 because Windows system administrators usually restrict the use of multiple cores.

The ecochange features three modules for data integration, statistical analysis and graphics (Figure 1). Routines in the modules are inheritable and operate on diverse typologies (Figure 3).

4 | DATA INTEGRATION MODULE

This module incorporates routines that download, integrate and format spatial ecosystem variables into a standard geometry, helping users to focus the analysis on areas of interest (Figure 1).

4.1 | Downloading spatial data

Function getrsp() downloads ecosystem remote sensing products for any polygon worldwide. To download tree cover (TC) datasets, the getrsp() asks for user authentication through the NASA Earth Data Login. Users can register on the earth-data web page[1] and authenticate through the package using their credentials. The function asks for authentication just once during a given R session by storing the credentials in its internal options. Thus far, downloading other remote sensing products available (Table 1) does not require authentication.

Once users specify arguments and credentials, the getrsp() checks whether the requested variables are stored in the path, in which case, the function retrieves their file paths. Otherwise, the image is downloaded. Downloading times depend on the file sizes and the internet speed available to users. After downloading the data, the function retrieves their corresponding file paths (Figure 3).

4.2 | Data integration

The function rsp2ebv() derives raster data representing the ecosystem variable of interest defined by lyrs. The produced data are cropped to the extent of the selected area of interest defined by the argument roi. The projection and pixel resolution of the output are defined by entering an appropriate string and a number to the optional arguments sr and ofr, respectively. By default, these arguments reproject the raster dataset to the UTM metric system with a 30 m pixel size. Although users can change such defaults, we recommend maintaining at least the default of sr because internal routines to derive indicators require scenes to have a metric system.

The function integrates input data products for the area of interest through six steps: first, routines in the function crop scenes

TABLE 3 Arguments for data retrieval and graphics

Arguments and defaults	Classes	Definition and functionality
Data retrieval		
roi = NULL	character, SpatialPolygonsDataFrame or NULL	The name of a Geographic Administrative Data Map (GADM), or a predefined polygon, or NULL. By default, this argument prints character vectors with names of downloadable GADM
lyrs = NULL	character or NULL	The names of downloadable remote sensing products (Table 2) and/or predefined ecosystem variables. By default, this argument prints character vectors with names of downloadable remote sensing products. Users can provide regular expressions matching complicated names; for instance, the regular expression lyrs = 'TC_2010' can match a dataset with the name 'GFCC30TC_p008r060_TC_2010.zip'
path = file. path (tempdir(), 'ecochange')	character	A file path. By default, the functions store downloaded data in a folder named 'ecochange' located in a temporary directory
mc.cores = round (detectCores() *0.6,0)	numeric	A number of machine cores used to fasten the function excecutions. By default, the argument make the functions to use 60% of the machine cores. In Linux-like systems, the argument tells the functions to evaluate parallel routines. In Windows systems, this argument is automatically set to 1 because Windows-system administrators usually restrict the use of multiple cores
Graphics		
y	character	Colour palette. If this argument is missing, or the suggest viridis is not installed then the palette terrain. colours() is implemented
type	character	Type of plot: 'p' for level plots, 'b' for barplots, 's' for stacked bar plots. Each plot method can support one or two types: plot.echanges () supports the 'p' and 'b'; plot. Indicator () supports the 's' and 'b'; and plot.EVBstats () supports the 'b' only
cex = 1	numeric	Adjustment for most text values. If a main title is specified, then it is increased up to 1.4*cex
xlab and ylab	character or numeric	Titles for the *x* and *y* axes
main	character or numeric	A text for the main title
sub	character or numeric	A text for the sub title. This argument is not available in level plots
fill	character	A text for the legend title

into sections covering the polygon; second, they create a temporary directory and store the scene sections in the directory; third, they reproject the scene sections; fourth, they use original scene names to mosaic the reprojected scene sections; fifth, they load the mosaics in the R environment as a RasterStack (Figure 2); and sixth, they remove the temporary files created during the previous steps.

5 | STATISTICAL ANALYSIS MODULE

Routines in this module operate on the RasterStack areas of interest to compute both grid and tabulated user-defined indicators (Figure 1). The module includes a core function to derive ecosystem-change representations necessary to calculate and visualize changes in the selected indicators.

5.1 | Ecosystem changes

Representing spatial and temporal dimensions of ecosystem variables is necessary to operationalize biodiversity monitoring (Schmeller et al., 2017). The function echanges() constructs spatial datasets representing ecosystem change across space and over time. Each layer contains the spatial distribution of a set of ecosystem variables after excluding (masking-out) pixels according to values in an individual ecosystem layer that will be used as a criterion to select pixels of interest. Routines in the function also support

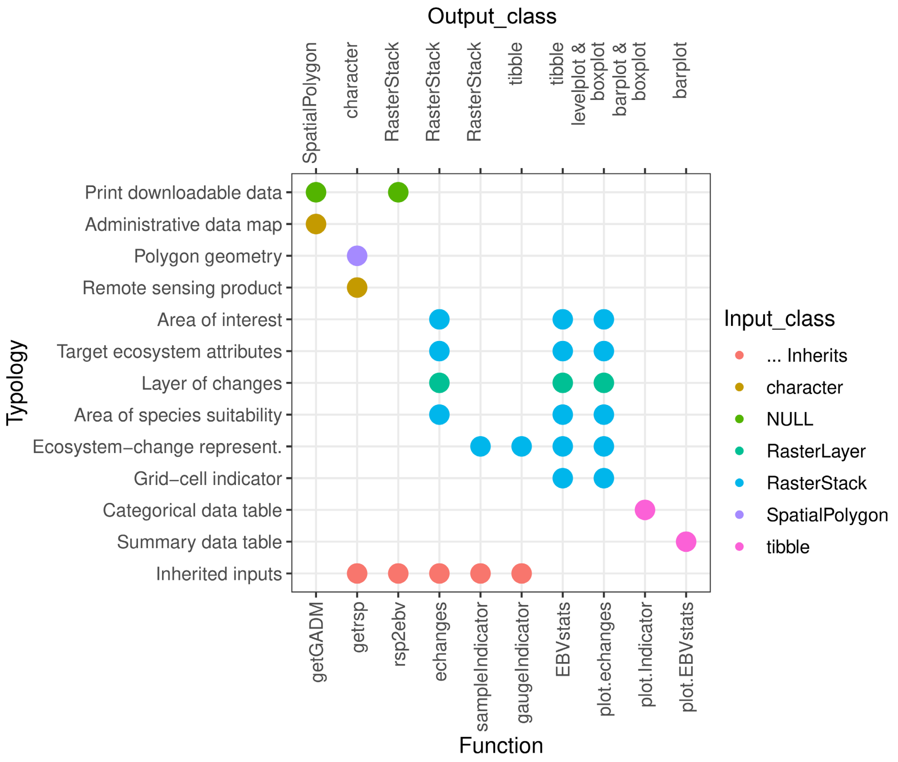


FIGURE 3 Typologies and R-classes processed by ecochange.

the computation of ecosystem variables for an area representing the spatial distribution range for a given species within the selected region of interest.

Users can derive the areas of interest specifying the arguments for data retrieval. Users can also provide any RasterStack object stored in the local machine (Figure 3). The input should include up to three variables: (i) a mandatory target layer or set of layers representing ecosystem attributes—that is, thematic or continuous ecosystem types, such as 'treecover2000' or 'TC' (Table 1); (ii) a mandatory layer with pixels labels representing change—for example, forest 'lossyear' or water 'recurrence'; and (iii) an optional layer representing a species distribution range within the area of the region of interest. By default, echanges() considers the first layer of the RasterStack area of interest as the target ecosystem attributes and the last layer as the raster representing changes. If either the variables have a different order, the target ecosystem attributes comprise more than one layer, or the inputs incorporate a species distribution range, users must employ three arguments eco, change and sp_dist to specify the names of the layers representing the three corresponding variables. Using the argument sp_dist makes pixels outside the corresponding layer become NA.

The function also incorporates three numeric arguments: eco_range, change_vals and sp_dist_range to define the values considered in the three variables (Figure 4). Values in change_vals determine the dimensionality of the output. By default, this argument considers all the values in the layer representing changes.

Finally, two logical get_unaffected and binary_output control the types of variables to be extracted. The first get_unaffected specifies whether or not the analysis must focus on unchanged areas (default TRUE). The second binary_output determines whether the output must be binary or thematic (default FALSE).

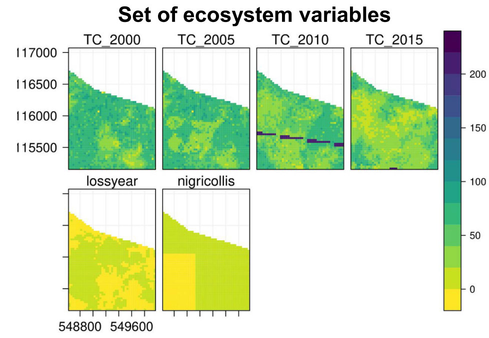
5.2 | Gauge biodiversity indicator

The function gaugeIndicator() computes categorical indicators at the patch, class or landscape levels. It operates on a RasterStack ecosystem-change representation projected in a metric system. This input can be pre-processed using the arguments for data retrieval or directly provided. The function includes routines with improved performance to calculate ecosystem areas at the class level while maintaining the dimensionality of the ecosystem representations. This indicator is commonly used in ecosystem decision-making. The default metrics = 'area_ha' controls higher-order functions that iterate and fork over routines for raster tabulation, counting pixel classes and calculating areas faster than analogous routines in the dependency landscapemetrics (Hesselbarth et al., 2019).

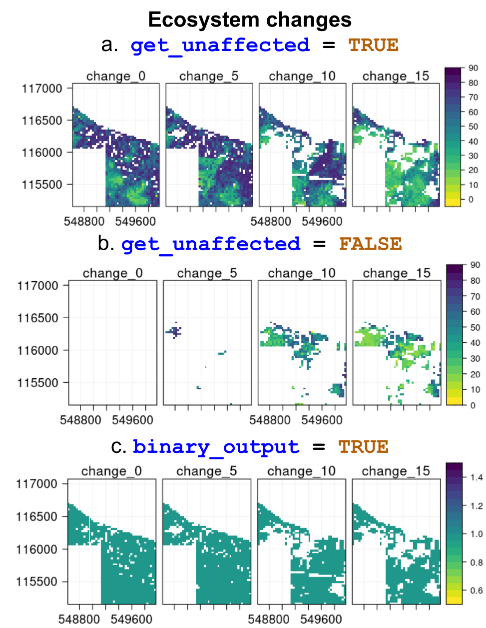
Formulation of other indicators makes the function invoke the landscapemetrics dependence. Users can dispatch parameters using the list smp_lsm (Figure 4). For instance, the what argument in the list dispatches a dash_separated string with three commands that control the wrapper, aggregation level and name of the desired indicator. Currently, the wrapper is always 'lsm', a short for

R code	Output

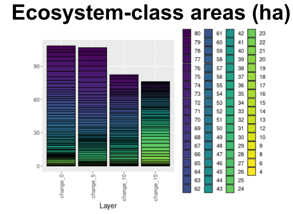
```
# (Step 1)
# Example of RasterStack Area of Interest:

> AOI <- system.file('amazon.grd',
     package = 'ecochange')
> amazon <- brick(AOI)

# Subset of ecosystem variables
  (see panel names):

> nm <- names(amazon)[c(3:6,2,7)]

# Levelplot:

> plot.echanges(amazon)
```




```
# (Step 2)
# Ecosystem-change representation:

> ech <- echanges(amazon,
     eco = 'TC',
     change = 'loss',
     sp_dist = 'nigri',
     eco_range = c(1,80),
     change_vals = c(1,5,10,15),
     get_unaffected = TRUE,
     binary_output = FALSE,
     mc.cores = 2)

> plot.echanges(ech)

# See other arguments in echanges().

 ?echanges
```




```
# (Step 3)
Landscape-class metric:

> areas  <- gaugeIndicator(ech,
    metric = 'area',
    smp_lsm = list(what = 'lsm_c_ca'))

> plot.Indicator(areas)
```




```
# (Step 4)
# Grid metric (Conditional entropy):

> H  <- sampleIndicator(ech,
     metric = 'condent',
     min = 1,
     max = 80,
     classes = 5)

> plot.echanges(H)
```

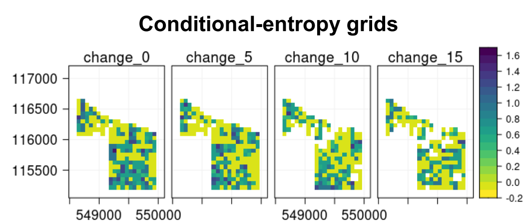


FIGURE 4 Example workflow to calculate ecosystem-class areas and conditional entropy processing a predefined RasterStack area of interest included in the package.

landscapemetrics. The aggregation level can be 'p', 'c' or 'l' for 'patch', 'class' or 'landscape' levels, respectively. The indicator name might be 'ca', 'pafrac' and 'condent' for 'class areas', 'perimeter-area fractal dimension' and 'conditional entropy', respectively. For instance, what = 'lsm_c_ca' calculates ecosystem areas at the class level using the landscapemetrics dependence. Users can read more about these and other parameters to tune the computation of indicators in the documentation of the dependence. The output of the function is a tibble of categorical variables, including layer name, level (class, landscape, patch), class number, name of the indicator and value of the indicator.

5.3 | Sample biodiversity indicator

The function sampleIndicator() helps users to identify hotspots of ecosystem degradation via the calculation of a RasterStack grid indicator (Nowosad & Stepinski, 2019; Taubert et al., 2018). This function precomputes or uses a raster layer representing contextual metrics of variations in ecosystem structure for groups of pixels within user-defined gridded areas. The function wraps over the dependence landscapementrics to sample a user-defined indicator per grid-cell at the landscape level while keeping the dimensionality of the input layer representing ecosystem change (Figure 4). The default metrics = 'condent' estimates conditional entropy per grid-cell by wrapping over the landscapemetrics dependence. This indicator is a measure of the ecosystem integrity that combines pixel adjacencies and pixel diversity into a metric of ecosystem degradation—or entropy (Table 2). The higher the entropy measured, the lower the ecosystem integrity and the higher the ecosystem degradation observed. Users can compute other indicators using arguments available in functions of the dependence landscapemetrics.

The argument side controls a size (m) for the grid-cell used to calculate local metrics. By default, the function finds an optimal grid-cell size suitable for the ecosystem shape. The optimization consists of iterating the calculation over grid-cell sizes proportional to the ecosystem extent and formulated in decreasing orders of magnitude (10^5, 10^4, …, 10^1). The iteration runs until converging into a grid-cell size that samples the most grids with non-missing values across the area of interest. Smaller grid sizes will increase grid resolutions, improving visualization of indicator patterns across the ecosystem-change representation. Users can utilize this default routine as a reference to tune grid sizes appropriate for their research.

Arguments min and max indicate the range of values in the ecosystem variables to be processed, and the argument classes provides aggregation classes (Figure 4). This can be either an integer between 1 and 30 (default 5) or a NULL term—to avoid reclassification. Users can set classes = NULL, but they must be aware that avoiding reclassification might increase the execution times of the functions, depending on the complexity of the ecosystem variables inputs and the specifications of the machine used for the analysis. The output is a RasterStack object (Figure 4).

5.4 | Statistics

Function EBVtats() tabulates statistics for changes in remote sensing products. This function operates on any RasterStack object, including those calculated by the other functions (Figure 4). It contains two arguments ccp and stats to specify the remote sensing product and to define the type of statistics to be computed, respectively. By default, the argument stats computes summary statistics, including the scene names, cell sizes/numbers; mean, extremes, sd and skewness. The output is a tibble containing the requested statistics (Figure 4).

6 | GRAPHICS MODULE

The graphics module incorporates routines to display visual representations of the spatial variables and derive reports for indicators produced with functions in the statistical analysis module. This module has three methods: plot.echanges(), plot.Indicator() and plot.EBVtats(). Such methods operate on corresponding classes and display statistical illustrations (Figure 4), including level, bar, stacked bar and box plots, depending on the graphics arguments (Table 3, Graphics). The level plots are panel representations that preserve the dimensionality of RasterStack inputs displaying panels with an improved colour palette and scale bar (Figure 4). The stacked bar plots allow users to measure changes in ecosystem areas. The box plots permit users to see the distributional characteristics and levels of RasterStacks and tabular data generated by ecochange. Colours in the bar and box plots usually correspond to the colour-palette formula used in the plot.echanges(), enabling users to compare spatial and statistical variables.

7 | APPLICATION TO REAL DATA AND PERFORMANCE TEST

We have implemented the ecochange to study the effect of changes in forest integrity between 2000 and 2015 across a tamarin distribution range (*Leontocebus nigricollis*) and test the package performance (see Appendix S1).

8 | CONCLUSIONS

ecochange features routines useful to derive ecosystem structure indicators integrating the retrieval of spatially explicit data with the use of workflows to calculate and visualize biodiversity indicators at the national/regional scales. Their routines are efficient, modular and adaptable to R classes and methods. It makes the package suitable for users to create customized workflows for the computing of indicators. Users can implement functions and wrappers of the package to reproduce, modify or create new biodiversity workflows, expanding the package functionality through integration with other routines accessible in open-source repositories developed for the R environment, including the CRAN and GITHUB. Modules in the package contribute to strengthening biodiversity infrastructures adaptable to user-defined workflows for indicators efficiently.

AUTHOR CONTRIBUTIONS

Wilson Lara, Victor H. Gutierrez-Velez and Maria C. Londoño conceived the ideas and designed methodology; Wilson Lara, Victor H. Gutierrez-Velez and Ivan Gonzales programmed the software; Wilson Lara, Victor H. Gutierrez-Velez and Maria C. Londoño collected the data; Wilson Lara and Victor H. Gutierrez-Velez led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest associated with this publication.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/2041-210X.13986.

DATA AVAILABILITY STATEMENT

The spatial data processed in the example workflow are available in the ecochange package binaries (Lara, Gutierrez-Velez, et al., 2022). We have shared the data and R code necessary to reproduce Figures 2–4 in Zenodo (Lara, Londoño, et al., 2022). The polygon and the earth observation products processed in the Appendix S1 are available in the web resources described in Table (1). The layer of the primate distribution range—Leontocebus nigricollis_veg.tif (Appendix S1)— belongs to the Colombian von Humboldt Institute (Velásquez-Tibatá et al., 2019).

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ENDNOTE

[1] https://urs.earthdata.nasa.gov/users/new

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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