

Original Software Publication

LandScriptDeforestMap: An R package to evaluate deforestation in remote sensing images

Thiago Lappicy^{a,*}, Ana I.R. Cabral^{b,c}, Romero Gomes P. Da Silva^a, Juliana Sobreira Arguelho^a, Samira Pinho B. de Andrade^a, Ana Karine Pereira^a, Anne-Elisabeth Laques^d, Carlos Hiroo Saito^{a,e}

^a University of Brasília, Center for Sustainable Development, Campus Darcy Ribeiro, 70.910-900, Brasília, Brazil

^b Forest Research Center (CEF), School of Agriculture, University of Lisbon, Tapada da Ajuda, 1349-017, Lisbon, Portugal

^c Laboratory for Sustainable Land Use and Ecosystem Services, School of Agriculture, University of Lisbon, Tapada da Ajuda, 1349-017, Lisbon, Portugal

^d Research Institute for Development, UMR Espace-Dev, 34093, Montpellier, France

^e University of Brasília, Institute of Biological Sciences, Department of Ecology, 70-910-900, Campus Darcy Ribeiro, Brasília, Brazil

ARTICLE INFO

Keywords:

R package

GIS

Deforestation

Amazon

Mapbiomas

Sustainable development goal 15

ABSTRACT

The **LandScriptDeforestMap** R package was developed for mapping and measuring deforestation dynamics using classified satellite images. It can be applied to different land cover types and grid sizes and was widely tested throughout the Amazon. This package allows providing information to different stakeholders focused on assessing and detecting deforestation and identifying possible driving causes (e.g. agriculture, pasture, urban growth, mining). This tool is of great value when designing new public policies dedicated to the sustainable management of land/forest, and contributes to the Sustainable Development Goal 15, aiding in a more transparent discussion and focusing on public policies driven by data.

Metadata

Nr	Code metadata description	Please fill in this column
C1	Current code version	V1.0
C2	Permanent link to code/repository used for this code version	https://github.com/Lappicy/LandScriptDeforestMap
C3	Permanent link to reproducible capsule	https://github.com/Lappicy/LandScriptDeforestMap/blob/main/README.md
C4	Legal code license	MIT
C5	Code versioning system used	none
C6	Software code languages, tools and services used	R
C7	Compilation requirements, operating environments and dependencies	R packages: <i>dplyr</i> , <i>ggplot2</i> , <i>ggspatial</i> , <i>raster</i> , <i>sf</i> and <i>stats</i> .
C8	If available, link to developer documentation/manual	https://github.com/Lappicy/LandScriptDeforestMap/blob/main/README.md
C9	Support email for questions	lappicy@gmail.com

1. Motivation and significance

Tropical Forests are home to many species, corresponding to the most biologically diverse ecosystem on land around the world. They play an important role in the mitigation of climate change by carbon storage, and they also strongly contribute to biodiversity conservation and the stability of hydrological regimes [1]. Recognizing this importance, the 2030 Agenda for Sustainable Development established in the Sustainable Development Goal 15, a specific Target 15.2: Halt deforestation and restore degraded forests [2].

Although the recognition of the importance of monitoring the status of forest covers, the necessity of continuous long-term assessment of forest degradation and the identification of the main disturbance contributors persists [3]. These assessments must be done globally and regionally, because even considering a future scenario in which deforestation rates will slow down by 2030 at global level, this result can masque the existence of large regional differences [4]: in some regions, forest losses can be expected to continue at alarming rates.

This reinforces the statements that despite the advances in remote sensing, data availability and storage by cloud computing facilities,

* Corresponding author.

E-mail address: lappicy@gmail.com (T. Lappicy).

detailed spatial information about the long-term cover changes, including both forest degradation and post deforestation recovery, is still lacking [1].

Nevertheless, to use remote sensing data to overcome forest cover loss monitoring requires specific skills (in the geoprocessing scope) for the treatment and processing of the data. Furthermore, the unrefined data with pixel-by-pixel information, without any grouping or geo-statistical treatment (of forest loss, for example) makes it difficult to locate critical or priority areas for land management. Thus, data analysis at pixel-by-pixel level usually requires additional processing to extract meaningful information and identify relevant spatial patterns [5–7].

These techniques may include image segmentation, supervised or unsupervised classification, texture analysis, amongst others [8,9]. With proper clustering and geostatistical treatment, it is possible to identify the most critical areas, to detect different patterns of deforestation, land use change and other relevant information for decision support on territory management [10]. These methods help to simplify unrefined data and extract more useful and understandable information for decision-making [11,12].

In this perspective, the objective of this work is to present the LandScriptDeforestMap, an R script developed to analyse deforestation behaviour, at multitemporal level, through remote sensing derived products. This package can detect and account for cover changes at different spatial and temporal scales, at a pixel-by-pixel basis, build

intervals of change, and represent them in different spatial resolutions. Moreover, it relates possible drivers of deforestation (such as Agriculture, Mining, Pasture and Urban areas) with the deforestation oscillations, aiding in a better understanding of their relations.

Even when using a pixel-by-pixel analysis from satellite images to attempt to explain deforestation patterns [13,14], some studies tend to aggregate the data in specific areas, such as the limits of a given state, city, or specific protected land [15]. This can lead to a problem of not being able to realize where the deforestation is happening inside these areas and towards where it might be growing. Either the pixels are too small to be visually appealing or there is a loss of information when making a generalization to a larger area. This leads to the discussion about appropriate spatial resolutions for the analysis of the target problem [16,17]. Our proposed R script serves as an alternative, to improve the visualization and understanding of the patterns that may exist behind the scenes, looking for the adequate scale of observe socio-environmental processes. An example is used in Section 3 ("Illustrative Examples") where it can be shown this improvement.

The product can help researchers, public managers, and other interested parties to obtain important information to design measures and policies to meet the different demands in the context of territorial and environmental management and planning. Our proposed R script is flexible for the users to determine the scale of analysis, so that the heuristics associated to their own background knowledge and intuition

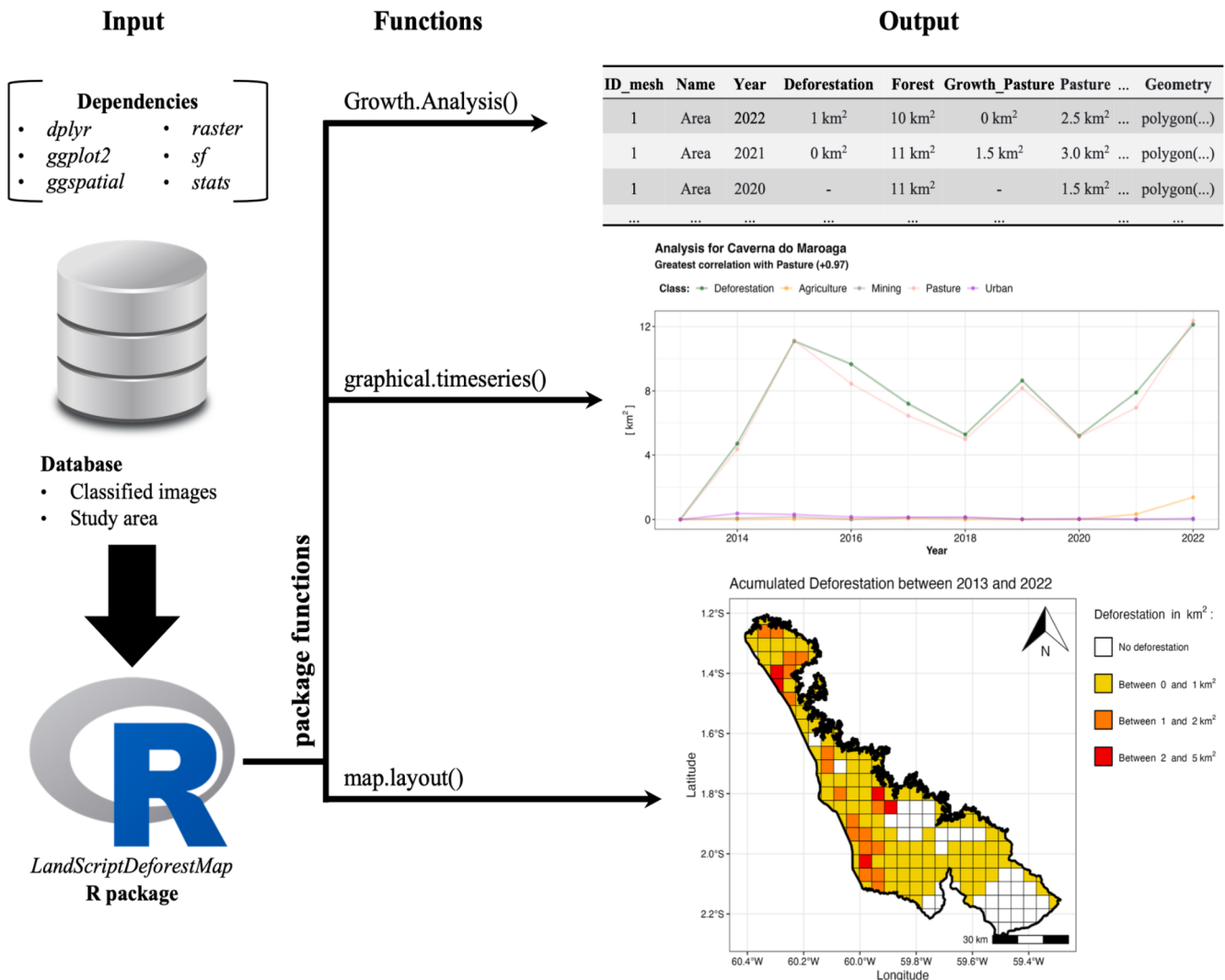


Fig. 1. Flowchart for the package proposed in this study with output examples.

can help in this choice. This is different from a pre-determined fixed scale where the investigation approach is already built-in the code. This freedom is committed to the recognition of system complexity and the heuristic in knowledge building in which experts and other stakeholders can choose what they consider to be the appropriate scale of analysis to produce the relevant outcomes [18].

LandScriptDeforestMap R efficiency was tested in evaluating the deforestation profile between 2013 and 2022 in the Amazon region using the Brazilian regional data obtained from the Brazilian Annual Land Use and Land Cover Mapping project called MapBiomias [19].

2. Software description based on land cover information

This section will explain the three steps (functions) of the LandScriptDeforestMap package considering its application to deforestation analysis and the use of MapBiomias data. There are three main functions: i) *Growth.Analysis()*; ii) *graphical.timeseries()*; iii) *map.layout()* - shown in Fig. 1. The inputs are the boundaries of the study area (vector file in any georeferenced format such as “.shp” or “.gpkg”) and at least one land cover classified images (raster files in any georeferenced format such as “.tif”). The deforestation analysis throughout the studied period, as well as the growth rate of different classes (e.g., forest, agriculture, pasture, mining, urban), were done using the *Growth.Analysis()* function. For the forest class, deforestation was calculated instead of its growth rate, as it is the main information necessary to evaluate and it corresponds to the inverse of growth.

First, the resulting information from *Growth.Analysis()* is represented in both a table (.txt) and a vector format (.gpkg). Then, a time series graph (.jpg or .png format) of these classes is created using the *graphical.timeseries()* function, which also calculates the correlation coefficient for deforestation against the other classes, and identifies the class with which has the highest correlation. Lastly, the *map.layout()* allowed for the creation of a map layout representing the dynamics of deforestation (or any land cover class) in different interval classes and different time periods (also in a .jpg or .png format).

2.1. The growth.analysis() function

Given a specific area and the land cover classified images, the *Growth.Analysis()* function (Fig. 2) analyses the overall behaviour of deforestation (or a specific land cover type) in a squared mesh that overlaps the study area for each image given. The analysis consists of accounting for the number of pixels of a specific class, considering that each pixel represents a certain area in km², as well as the positive net change between the time interval of each of the images specified - this positive net change is the growth between the images, if only one image is given as input, no growth can be calculated. The inputs are: i) a vector file of the studied area (geopackage, shapefile or the directory on which this file is); ii) a folder having at least one classified image (e.g. from MapBiomias).

The created function can be fractionated into a few steps. Firstly, the vector file is read into R and a square mesh is created on top of it. The refinement/resolution of the mesh can be adjusted, in degrees, with the “mesh.size=” argument with the default being a square with dimensions of 0.25° x 0.25°. Then, with the raster files found in the specified folder, the function makes sure that the projections are the same as the vector

file, if not, then the vector is reprojected to fit the images. Subsequently, *Growth.Analysis()* crops each of the raster files on top of the square mesh vector created. Afterwards, the function transforms the raster into a matrix format and then counts the number of pixels inside each square belonging to the mesh.

All pixel values (frequencies found for each square mesh) are transformed into km² assuming that the “mesh.size=” argument is in degrees. The categorical values from the classified images are then grouped into 8 classes: “Forest”, “NonForest”, “Agriculture”, “Mining”, “Pasture”, “Urban”, “Water” and “Others”. These classes are either a direct measure of the forest in the region or possible drivers of deforestation.

The MapBiomias legend codes corresponding to each land use category were obtained for collections 4.0, 7.1 and 8.0. *Growth.Analysis()* can be applied to any classified image, which can have different categories and codes. If the legend key uses the same categories of MapBiomias but has different codes is possible to define new values using the arguments: i) “num.forest=”; ii) “num.non.forest=”; iii) “num.agriculture=”; iv) “num.mining=”; v) “num.pasture=”; vi) “num.urban=”; vii) “num.water=”; and viii) num.others=”.

If these previous arguments are not listed, the algorithm will still run, and will return the aggregated value for each class contained in the images, the difference is only that the labels will be the same as the original raster files, thus they will need to be specified again when using the other two functions (to create a graph and a map).

The function will also count the positive net change of each class throughout the years - hereby called as “growth”. Hence there will be created the “growth” for agriculture, mining, pasture, urban, water and others, and added in table output. For the forest class, instead of “Growth of Forest”, we choose two other names: “deforestation”, representing the negative net change of forest throughout the years, and “reforestation”, representing the positive net change of forest throughout the years (the same as the “growth” for the other classes). With this additional information, the analysis and visualisation of deforestation throughout time can be more easily understood.

There are two outputs from this function, a table (.txt format) and a vector file (.gpkg format). The table output has the area inside each mesh created for the 8 classes proposed as well as for all the existing categories from the original raster files given (inputs). The output vector is the same as the table, with only adding the latitude and longitude of each square of the created mesh to facilitate any spatial analysis or creation of maps.

The *Growth.Analysis()* has the purpose of facilitating the analysis of land cover maps produced with satellite images by decision-makers. It was designed to be easy to use and simple enough so that it could be widely distributed and tested. Below there is a code snippet showing how to call this function in the R environment. As the function was tested over MapBiomias products, an example with this data is shown to understand the six inputs needed to execute the function as per Fig. 2: (i) a vector file for the studied area (“geo.file=”); (ii) the folder location with raster images (“tif.folder=”); (iii) the refinement of the mesh (“mesh.size=”), with a default value of 0.25°x0.25°; (iv) which collection of the MapBiomias dataset is used (“MAPBIOMAS=”), if other images are used, the user should leave this empty; (v) the path and the folder where to save the results (“output.folder=”); and (vi) the name of the file to be saved (“output.name=”).

```
FinalAnalysis <- Growth.Analysis(geo.file = "Caverna do Maroaga.shp",
                                tif.folder = "Mapbiomas8 folder/",
                                mesh.size = 0.045,
                                output.folder = "Results/",
                                output.name = "Analysis_CavernaMaroaga",
                                MAPBIOMAS = 8)
```

Fig. 2. Example for the *Growth.Analysis()* function used within RStudio.

2.2. The *graphical.timeseries()* function

Using the output table obtained from the *Growth.Analysis()* function as input, namely the growth variables, it is possible to compare them in a plotted in a time series graph along with the yearly deforestation (see code snippet in Fig. 3). The growth variables were selected using the argument “comparison.names=” of the snippet code shown. This may aid in better understanding the deforestation in the area along with the drivers that affect it (Growth_Agriculture, Growth_Mining, Growth_Pasture and Growth_Urban).

It is worth noting that although this function may run with a file other than the output from the *Growth.Analysis()* function, this is not recommended seeing that for it to properly work, the input must be very specific. It must be a sf (simple feature) object in R, with columns for each squared mesh (namely ID_mesh), for each year being analysed, for each class in the original raster files, and columns named for Forest, NonForest, Agriculture, Mining, Pasture, Urban and their Growth (same name but with “Growth_” stated before). Hence, it is recommended to run the *Growth.Analysis()* function to get the input needed for this function, even if a similar analysis was already done.

Besides the graphical representation of the variables obtained in the previous section, *graphical.timeseries()* also calculates the Pearson Correlation Coefficient between Deforestation and the different variables (defined within “comparison.names=”) and returns the highest correlation that is statistically significant. This allows for identifying the most significant driver (amongst the chosen ones) in the deforestation phenomena. The output obtained with this script is shown in Section 3, Fig. 5. Within the *graphical.timeseries()* function, the user may also change the colours of each drive (with the “comparison.colour=” argument) and the plot title (“title.name=”).

2.3. The *map.layout()* function

The *map.layout()* function within the LandScriptDeforestMap package is a visualisation tool tailored for showcasing the existing dynamics of land cover change over time, here with the focus on deforestation. It is designed to increase the interpretability of the output data resulting from the *Growth.Analysis()* function. The *map.layout()* will generate a map portraying the evolution of one of the existing classes (see 2.1 and 2.2 for the types of classes). The user may customise the output by explicitly specifying the land cover class of interest and the intervals of values for that class. Similarly as with the *graphical.timeseries()* function, this may run with another data as “proxy.table=”, but this is not recommended since it needs a very specific format, already specified in the previous section.

This visualisation tool focuses on providing a clear and intuitive display of the spatial distribution of land cover changes. Whether the users want to observe the studied area land cover for a specific year or to track changes over multiple years, the *map.layout()* function empowers users to grasp and communicate the complex patterns of land cover dynamics, contributing to the decision-making process related to land management and environmental planning. A code snippet on Fig. 4 shows how to call this function in R. The resulting output from using this code is shown in Section 3, by Fig. 6.

3. Illustrative examples

Examples of the outputs obtained by functions *graphical.timeseries()* and *map.layout()* were given in Fig. 5 and Fig. 6, respectively. These functions were tested in one protected area in the Brazilian Legal Amazon, named “Caverna do Maroaga (Presidente Figueiredo)” and located in the state of Amazonas, encompassing the municipalities of “Presidente Figueiredo” and “Rio Preto da Eva”. It was delimited in 1990 as a protected area, corresponding to the IUCN management category VI (Protected areas with sustainable use of natural resources). With a population of approximately 8772 habitants, it now has an extent of roughly 4000 km².

The data used for such analysis is readily available at the existing github, available at <https://github.com/Lappicy/LandScriptDeforestMap/tree/main/Example%20application/Data>, consisting of two datasets. The first one was taken from MapBiomias [16] collection 8, which produce land use and cover maps (classified images) from 2013 to 2022 in “.tif” format. The second dataset used was the limits of “Caverna do Maroaga” in the geopackage format, which is available at the Amazon Network of Georeferenced Socio-Environmental Information (RAISG) (<https://www.raisg.org/en/maps/>) and contains information about the boundaries of the protected areas located in the Amazon region.

Deforestation behaviour was analysed according to the main drivers affecting it (Fig. 5), all data extracted from the 8th collection of MapBiomias between 2013 and 2022 (10 years). The highest statistically significant correlation was obtained between deforestation and Pasture (with the Pearson correlation coefficient having a value of +0.97). This aids when one is trying to better understand the underlying mechanisms that led to deforestation as well as making it easier to comprehend the temporal variation on the deforestation itself as well as on the driver that led to it. In the example shown in Fig. 5, one could try to understand what led to the peaks of deforestation and pasture in the years of 2015 and 2022, or what led to the rise/downfall of them before/after said periods.

Fig. 6 shows a raster map where deforestation is represented in five class intervals. This representation facilitates the visualisation of the different levels of deforestation, as well as its spatial configuration and patterns, thus making it easier to understand where the main points of deforestation are occurring alongside with where other deforestation regions may be appearing. These four different classes for deforestation in km² are editable (as per Fig. 4 with the “col.limits=” argument).

4. Impacts

Here, we developed the LandScriptDeforestMap R package, an executable script that uses the land cover maps timeseries analysis to obtain a description of the forest and deforestation dynamics. The script can be used to analyse the behaviour of any land cover type and identify the factors that may impact it. With the availability of this script through R (via the package) and through other available online services (e.g. <https://github.com/Lappicy/LandScriptDeforestMap>), there will be a contribution to an increasing understanding of the spatial patterns of land covers and in particular of deforestation. This type of information may be easily available, not only to academic and political environments but also to the general society.

LandScriptDeforestMap R efficiency could present deforestation

```
graphical.timeseries(proxy.table = FinalAnalysis,
  comparison.names = c("Growth_Agriculture", "Growth_Mining",
    "Growth_Pasture", "Growth_Urban"),
  comparison.color = c("darkorange", "grey50", "#EA9999", "purple"),
  save.as = "Results/Maroaga Deforestation vs Growth.png",
  title.name = "Analysis for Caverna do Maroaga")
```

Fig. 3. Example for the *graphical.timeseries()* function used within RStudio.

```
map.layout(mesh.data = FinalAnalysis,
           class = "Deforestation",
           year.used = "all",
           col.limits = c(0, 1, 2, 5),
           save.map.as = "Results/Map acumulated deforestation.png")
```

Fig. 4. Example for the `map.layout()` function used within RStudio.

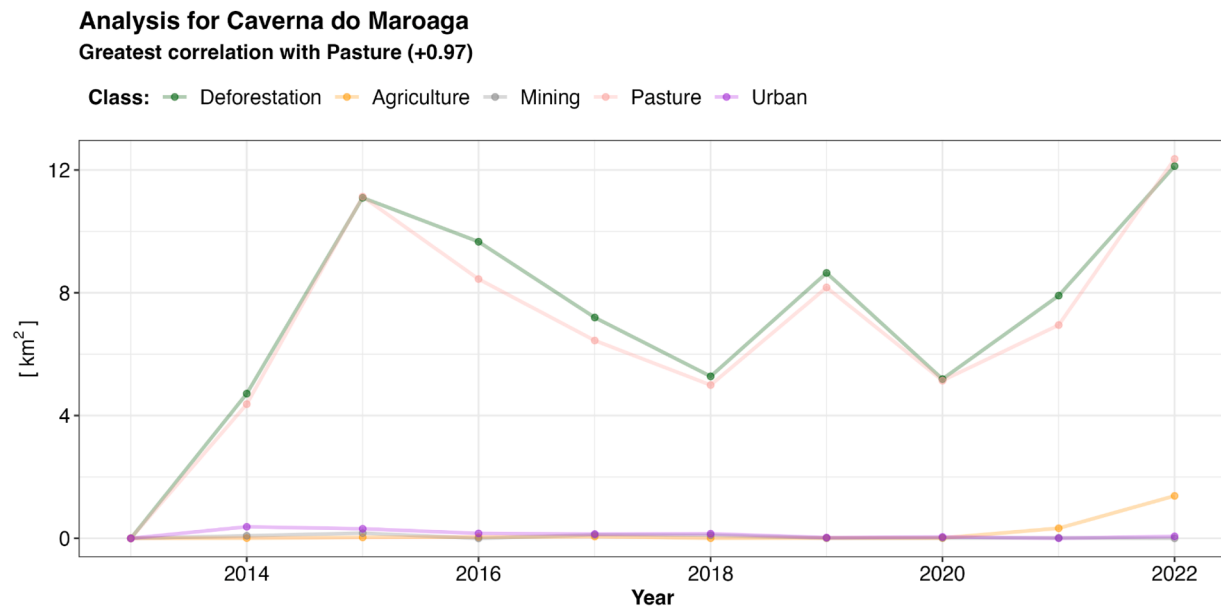


Fig. 5. `graphical.timeseries()` output example of Caverna do Maroaga.

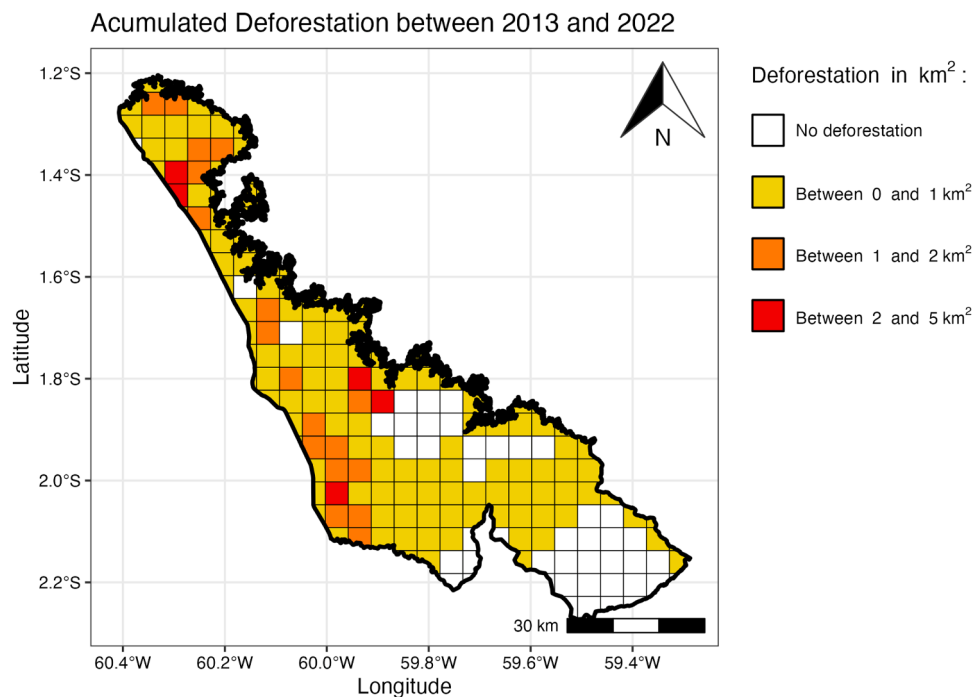


Fig. 6. `Map.layout()` output example of Caverna do Maroaga.

dynamic in Amazon between 2013 and 2022 in a sample region as a case study and validation as shown in the illustrative example. The data source was the Brazilian Annual Land Use and Land Cover Mapping

project called MapBiomas [19]. The R script was able to assess deforestation behaviour according to the main drivers affecting it which, in this case, was pasture – having a correlation of 0.97 between them

(pasture and deforestation). The capacity of the LandScriptDeforestMap to compare spatial patterns of different land use types could address a statistically significant correlation in the study area.

With respect to the analysis of deforestation in the Amazon, this package proved itself to be an important step to easily obtain data that allows quantifying forest loss over time and contributes to the delineation of prevention and mitigation policies.

5. Conclusions

The development of automated procedures helps to monitor forest/land cover by both government and civil society. For the stakeholders, the automated procedures, given by the LandScriptDeforestMap R package, will empower them to participate in public spheres and thus achieve the global sustainable development goals and targets defined by the United Nations.

Thus, free access to forest data obtained from using satellite images is not enough. There is also a need for routines that analyse all the multitemporal information, pixel-by-pixel, accounting and relating them according to class types to identify trends and drivers. This is particularly important on policy implementation and monitoring in low and middle (lower-middle or upper-middle) income countries where there is usually a present weakness in their human resources capacity and technical infrastructure.

Automating these steps can save researcher's time to perform a deforestation analysis, focusing on the preliminary choices about scale, and then concentrate their attention to the understanding of the results.

Additionally, this package is also important in the tropical regions of the globe, and in Brazil in particular, where deforestation has increased substantially in the last decades and where a lot of data may exist – which can make their analysis more difficult. Thus, using these types of routines (such as those proposed in this work) to understand the behaviour of deforestation is crucial for the sustainable management of forest areas. Another important output is its representation in the form of a cartographic mesh, which facilitates the visualisation of the different deforestation levels. When LandScriptDeforestMap R package permits users to choose the scale of analysis by establishing the grid resolutions, it can help these stakeholders to incorporate their background knowledge and intuition, in a heuristic manner, to produce new scale-dependant diagnosis.

This user's empowerment makes this tool of great value when designing new public policies in a very participatory way, contributing to the Sustainable Development Goal 15.

CRedit authorship contribution statement

Thiago Lappicy: Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ana I.R. Cabral:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Romero Gomes P. Da Silva:** Conceptualization, Data curation, Formal analysis, Investigation, Project administration, Supervision, Validation, Visualization, Writing – original draft. **Juliana Sobreira Arguelho:** Formal analysis, Investigation, Visualization, Writing – original draft. **Samira Pinho B. de Andrade:** Conceptualization, Investigation, Methodology, Visualization. **Ana Karine Pereira:** Investigation, Visualization, Writing – original draft. **Anne-Elisabeth Laques:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft. **Carlos Hiroo Saito:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft.

Declaration of competing interest

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

Data availability

I have shared the link to my data/code at the "Attach Files" step and all the data / code is available via the github directory.

Acknowledgements

The authors are grateful to INCT-ODISSEIA Project, “Observatório das Dinâmicas Socio-Ambientais” at Universidade de Brasília (UnB) for their technical support. This work was also supported by the research project PROGYSAT “Projet de coopération Régionale; Observation des GuYanes par SATellite”, Amazon Cooperation Program (PCIA) that contributes to the integrated development of French Guiana and its neighbors in the Guiana Shield. The authors are also grateful to Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Capes-Print Program), Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) and Fundação de Amparo à Pesquisa do Distrito Federal (FAP-DF) for their financial support with grant 00193-00000398/2024-11. Additional thanks to CEF (project reference UIDB/00239/2020 and DOI identifier [10.54499/UIDB/00239/2020](https://doi.org/10.54499/UIDB/00239/2020), <https://doi.org/10.54499/UIDB/00239/2020>, and project reference UIDP/00239/2020 and DOI reference [10.54499/UIDP/00239/2020](https://doi.org/10.54499/UIDP/00239/2020) <https://doi.org/10.54499/UIDP/00239/2020>) research centres, and the Laboratory for Sustainable Land Use and Ecosystem Services-TERRA (LA/P/0092/2020). We also thank FAP-DF (“Fundação de Apoio a Pesquisa do Distrito Federal”) for their financial support with the article processing charge.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.softx.2024.101799](https://doi.org/10.1016/j.softx.2024.101799).

References

- [1] Vancutsem C, Achard F, Pekel JF, Vieilledent G, Carboni S, Simonetti D, Gallego J, Aragão LEOC, Nasi R. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Sci Adv* 2021;7(10):eabe1603. <https://doi.org/10.1126/sciadv.abe1603>.
- [2] UN - United Nations. A/RES/70/1: transforming our world: the 2030 Agenda for Sustainable Development. https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf; 2015 [accessed 30 November 2023].
- [3] Feng M, Sexton JO, Huang C, Anand A, Channan S, Song XP, Song DX, Kim DH, Noojipady P, Townshend JR. Earth science data records of global forest cover and change: assessment of accuracy in 1990, 2000, and 2005 epochs. *Remote Sens Environ* 2016;184:73–85. <https://doi.org/10.1016/j.rse.2016.06.012>.
- [4] D'Annunzio R, Sandker M, Finegold Y, Min Z. Projecting global forest area towards 2030. *For. Ecol. Manag.* 2015;352:124–33. <https://doi.org/10.1016/j.foreco.2015.03.014>.
- [5] Basics of remote sensing De Jong SM, Van der Meer FD, Clevers JG. Remote sensing image analysis: including the spatial domain. In: De Jong SM, Van der Meer FD, editors. *5. Dordrecht, The Netherlands: Springer Science & Business Media; 2007. p. 16–30.*
- [6] Plaza A, Martínez P, Pérez R, Plaza J. Spatial/spectral endmember extraction by multidimensional morphological operations. *IEEE Trans Geosci Remote Sens* 2002;40(9):2025–41. <https://doi.org/10.1109/TGRS.2002.802494>.
- [7] Crosta AP. Digital processing of remote sensing images. Campinas State University (UNICAMP) /Institute of Geosciences - São Paulo (Brazil). Ed. Rev. 1992:170.
- [8] Blaschke T. Object based image analysis for remote sensing. *ISPRS J Photogramm Remote Sens* 2010;65(1):2–16. <https://doi.org/10.1016/j.isprsjprs.2009.06.004>.
- [9] Venturieri A, dos Santos JR. Image classification techniques for vegetation cover analysis. In: Assad DE, Sano EE, editors. *Geographic Information system, Applications in Agriculture. Brasília: Embrapa; 1998. p. 351–71.*
- [10] Américo-Pinheiro JHP, Benini SM. Hydrographic basins: fundamentals and applications. ANAP publisher 2018:220.

- [11] Kleemann J, Baysal G, Bulley HN, Fürst C. Assessing driving forces of land use and land cover change by a mixed-method approach in north-eastern Ghana, West Africa. *J Environ Manage* 2017;196:411–42. <https://doi.org/10.1016/j.jenvman.2017.01.053>.
- [12] Bocco G, Mendoza M, Velázquez A. Remote sensing and GIS-based regional geomorphological mapping-a tool for land use planning in developing countries. *Geomorphology* 2001;39(3–4):211–9. [https://doi.org/10.1016/S0169-555X\(01\)00027-7](https://doi.org/10.1016/S0169-555X(01)00027-7).
- [13] Diniz J.M.F.D.S., REIS A.A.D., ACERBI F.W. Spatial pattern analysis of deforestation in the northeast of Minas Gerais State, Brazil. *Anais da Academia Brasileira de Ciências*, 2023; 95(4), e20191247. doi: <https://doi.org/10.1590/0001-3765202320191247>.
- [14] Bragagnolo L, da Silva RV, Grzybowski JMV. Towards the automatic monitoring of deforestation in Brazilian rainforest. *Ecol Inform* 2021;66:101454. <https://doi.org/10.1016/j.ecoinf.2021.101454>.
- [15] Cabral AI, Saito C, Pereira H, Laques AE. Deforestation pattern dynamics in protected areas of the Brazilian Legal Amazon using remote sensing data. *Appl Geogr* 2018;100:101–15. <https://doi.org/10.1016/j.apgeog.2018.10.003>.
- [16] Malleson N, Steenbeek W, Andresen MA. Identifying the appropriate spatial resolution for the analysis of crime patterns. *PLoS One* 2019;14(6):e0218324. <https://doi.org/10.1371/journal.pone.0218324>. PMID: 31242224; PMCID: PMC6594600.
- [17] Ferrer Velasco R, Köthke M, Lippe M, Günter S. Scale and context dependency of deforestation drivers: insights from spatial econometrics in the tropics. *PLoS One* 2020;15(1):e0226830. <https://doi.org/10.1371/journal.pone.0226830>. PMID: 31995574; PMCID: PMC6988916.
- [18] Introduction Marchau VAWJ, Walker WE, Bloemen PJTM, Popper SW. *Decision Making under Deep Uncertainty*. In: Marchau VAWJ, Walker WE, Bloemen PJTM, Popper, editors 2019. Chain: Springer; 2019. p. 1–20.
- [19] Souza Jr CM, Shimbo JZ, Rosa MR, Parente LL, Alencar A, Rudorff BF, Hasenack H, Marsumoto M, Ferreira LG, Souza-Filho PWM, Oliveira SW, Rocha WF, Fonseca AV, Marques CB, Diniz CG, Costa D, Monteiro D, Rosa ER, Vélez-Martin E, Weber EJ, Lenti FEB, Paternost FF, Pareyn FGC, Siqueira JV, Viera JL, Neto LCF, Saraiva MM, Sales MH, Salgado MPG, Vasconcelos R, Galano S, Mesquita VV, Azevedo T. Reconstructing three decades of land use and land cover changes in Brazilian biomes with landsat archive and earth engine. *Remote Sens (Basel)* 2020; 12(17):2735. <https://doi.org/10.3390/rs12172735>.