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Empowering ecological remote sensing learning: The imageRy R package to help students and instructors

Duccio Rocchini [a,*,1], Ludovico Chieffallo [a,1], Michele Torresani [b,c,1], Daniel McInerney [d], Ruben Remelgado [e], Giovanni Andrea Nocera [a], Giacomo Panza [f], Giovanni Bacaro [g], Rocìo Beatriz Cortès Lobos [a], Emanuela Cosma [a], Vítězslav Moudrý [h], Elisa Padulosi [h], Diletta Santovito [a], Petra Simova [h], Elisa Thouverai [g]

[a] BIOME Lab, Department of Biological, Geological and Environmental Sciences, Alma Mater Studiorum University of Bologna, via Irnerio 42, 40126, Bologna, Italy

[b] Free University of Bozen/Bolzano, Faculty of Agricultural, Environmental and Food Sciences, Piazza Università/Universitätsplatz, 39100, Bozen/Bolzano, Italy

[c] Competence Centre for Plant Health, Piazza Università 5, 39100 Bolzano, Italy

[d] Coillte Teoranta, Irish State Forestry Board, Castletroy Business Park, Limerick, Ireland

[e] Institute of Crop Science and Resource Conservation (INRES), University of Bonn, Germany

[f] University of Siena, Italy

[g] Department of Life Sciences, University of Trieste, Trieste, Italy

[h] Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Department of Spatial Sciences, Kamýcka 129, Praha - Suchdol, 16500, Czech Republic

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ABSTRACT

Remote sensing is widely used in ecology to estimate key properties such as biodiversity, species distributions, and habitat dynamics. The increasing availability of free satellite imagery has expanded its use in teaching, but has also introduced challenges related to data handling, workflow fragmentation, and the interpretation of analytical outputs.

To address these issues, we introduce the `imageRy` R package, a pedagogically oriented framework that integrates data, analytical functions, and visualization within a single reproducible environment. Rather than focusing solely on the implementation of standard remote-sensing methods (e.g., spectral indices, classification, spatial variability, and multivariate analysis), `imageRy` emphasizes the connection between spatial outputs and their statistical interpretation.

The main contribution of the package lies in the integration of statistical visualization as a native analytical layer within remote-sensing workflows. Functions for ridgeline plots, boxplots, and barplots enable users to move seamlessly from maps to quantitative summaries of data structure, including class separability, variability, and relative abundance. This dual perspective links pixel-level information to aggregated ecological interpretations, improving both analytical clarity and pedagogical effectiveness.

By coupling controlled in-package datasets with a unified analytical and visualization framework, `imageRy` reduces technical variability, enhances reproducibility, and supports a structured transition from introductory learning to more advanced remote-sensing applications. The package is therefore positioned as a conceptual and computational bridge between spatial analysis and statistical interpretation in ecological informatics.

1. Introduction

Remote sensing has become a crucial tool in various fields, including climate change monitoring (Zellweger et al., 2019), disaster analysis (Van Westen, 2000), and biodiversity surveys (Skidmore et al., 2021; Rocchini et al., 2022). In ecology, it is extremely useful for estimating a variety of ecological variables, including population size temporal behavior (Koshkina et al., 2020), species community diversity assessment (Rocchini et al., 2010, 2018; Torresani et al., 2024), species distributions (Feilhauer et al., 2012; He et al., 2015; Sillero

* Corresponding author.
E-mail address: duccio.rocchini@unibo.it (D. Rocchini).

[1] Authors equally contributed to the manuscript.

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et al., 2026), vegetation structure (Moudrý et al., 2021), and habitat changes (Kerr and Ostrovsky, 2003; Amici et al., 2015). Indeed, remote sensing is key for mapping Essential Biodiversity Variables (EBVs, Reddy et al., 2021), which will serve as a basis for monitoring the progress of the post-2020 Global Biodiversity Framework (see https://geobon.org/tag/indicators/). Hence, given the societal and political relevance of remote sensing, we must enable scientists and practitioners to use this technology effectively.

Lectures in remote sensing are now based on free images provided by different institutions like the National Aeronautics and Space Administration (NASA; e.g., the Landsat program) or the European Space Agency (ESA; e.g., the Copernicus program). These data have become increasingly accessible thanks to platforms such as Google Earth Engine, enabling planetary computing from the classroom (Pham-Duc et al., 2023).

In addition, analyzed data and related ecological stories are also available to speed up image gathering and ecological storytelling about the main processes driving the patterns found during data analysis: an example of this is provided by the Earth Observatory (NASA, https://earthobservatory.nasa.gov/), which includes data and stories on different ecological processes at various spatio-temporal scales.

In this perspective, the use of Free and Open Source Software (FOSS, Stallman, 1985; Perens, 1999, see also Rocchini and Neteler, 2012 for its application in ecology) is fundamental in providing students with the experience of a completely free possibility to learn remote sensing data analysis (Rocchini et al., 2017). Furthermore, FOSS enhances both robustness and reproducibility of any kind of scientific analysis, fostering interactions among students and collaboration, by guaranteeing transparency and flexibility/scalability (Rocchini et al., 2017).

Providing students with software code facilitates teaching, allowing them to understand the different commands and functions. In turn, it ensures that the use and application of the software is standardized among students, with an easier capability to detect errors by the instructors. In this paper, we propose the `imageRy` R package, which includes free remotely sensed data and functions to handle and analyze them from an ecological perspective.

Several educational resources for remote sensing are currently available as collections of external tutorials, web portals, or platform-specific workflows. While valuable, these solutions often require learners to switch between multiple websites, interfaces, or software ecosystems, which can fragment the learning experience and increase the technical overhead (e.g., data handling, authentication, export/import steps). In addition to web-based resources, R itself offers mature and powerful remote-sensing packages, most notably `RStoolbox` (Muller et al., 2025), which provides an extensive framework for image preprocessing, classification, and spectral analysis. Such packages are widely used in research and advanced teaching contexts due to their methodological depth and analytical flexibility. However, their breadth and parameter richness can present a steep learning curve for beginners. `imageRy` does not aim to replicate this comprehensive functionality; instead, it focuses on providing a pedagogically streamlined interface that emphasizes conceptual clarity, reproducible teaching workflows, and ecological interpretability. In this sense, `imageRy` is designed as a self-contained R package that bundles lightweight example imagery together with lecture-oriented functions, enabling a complete, reproducible workflow within a single environment. This integration is particularly relevant in classroom settings, where reducing logistical complexity helps instructors focus on analytical concepts rather than troubleshooting heterogeneous toolchains. At the same time, we acknowledge that imageRy is not intended to replace advanced cloud platforms or specialized software; rather, it provides a structured entry point and a pedagogical bridge toward more complex, real-world workflows.

One of the main aims of `imageRy` is to support remote-sensing teaching through a coherent analytical environment in which spatial analysis and statistical interpretation are tightly connected. Rather than only accelerating lecture flow, the package is designed to help students and instructors move from raw remotely sensed data to ecologically meaningful representations, and from maps to explicit summaries of data structure such as class separability, variability, and relative abundance.

In this sense, the development of `imageRy` is guided by three explicit informatics objectives: (i) to provide a controlled and versioned coupling between data and code for classroom use; (ii) to minimize technical variability arising from heterogeneous data acquisition, file handling, and software configurations; and (iii) to integrate statistical visualization as a native analytical layer within remote-sensing workflows, thereby linking spatial outputs to quantitative and distributional interpretation in a single reproducible environment.

In this paper, we describe the novelties, with respect to existing R-based frameworks, of the `imageRy` package , available in the GitHub repository https://github.com/ducciorocchini/imageRy. A Comprehensive R Archive Network (CRAN) version is also available at https://CRAN.R-project.org/package=imageRy. However, the GitHub version – installable via the `devtools` or `remotes` packages – is used here because it provides access to the most recent developments and full version control, ensuring transparency and reproducibility of the workflows presented. We will focus on the two main components of `imageRy`, namely the data design philosophy and the statistical visualization layer. The full set of functions provided by the package – including those related to data import and remote sensing image visualization, as well as data analysis – are summarized in Tables 1 and 2, respectively.

2. The philosophy under the data of `imageRy`

The data of `imageRy` are lightweight to facilitate easy and quick lectures and encompass significant free data from various sources such as the NASA Earth Observatory (https://earthobservatory.nasa.gov/) and readily available Copernicus data (https://www.copernicus.eu/). A list of data available for the package can be extracted by the `im.list()` function, which shows the data contained in the `inst/images` folder in the GitHub version of the package. Data can then be imported by the `im.import()`.

Table 1
Functions for data import and remotely sensed image visualization in `imageRy`.

Category	Function	Description
Data discovery	`im.list()`	Lists the remotely sensed datasets available within the package, providing a structured overview of the internal data repository.
Data import	`im.import()`	Imports selected raster datasets as `SpatRaster` objects, enabling direct use without external data handling.
Image visualization	`im.plotRGB()`	Displays multispectral raster data as RGB composites, supporting visual interpretation of spectral information.
	`im.ggplot()`	Produces raster visualizations using `ggplot2`, enabling flexible and publication-ready graphical outputs.
	`im.ggplotRGB()`	Generates RGB composite images within the `ggplot2` framework, linking remote sensing visualization with statistical graphics.

Table 2
Functions for data analysis in `imageRy`.

Category	Function	Description
Spectral indices	`im.dvi()` `im.ndvi()`	Computes the Difference Vegetation Index (DVI). Computes the Normalized Difference Vegetation Index (NDVI).
Image classification	`im.classify()` `im.fuzzy()`	Performs k-means clustering on raster data. Applies fuzzy classification to assign probabilistic memberships.
Image variability	`im.kernel()`	Computes moving-window statistics (e.g., mean, SD, variance).
Multivariate analysis	`im.pca()`	Performs Principal Component Analysis.

Statistical visualization	`im.ridgeline()`
	`im.barplot()`
	`im.boxplot()`
		Generates ridgeline plots of raster distributions.
		Summarizes class frequencies or percentages.
		Visualizes spectral distributions across classes.

A central design principle of `imageRy` is the deliberate inclusion of datasets with different levels of complexity and computational demand. Rather than providing a single type of input data, the package integrates both fully georeferenced remote sensing products (e.g., Sentinel-2 Level-2 A imagery) and simplified, lightweight raster datasets. This dual structure is intended to support heterogeneous teaching environments, where students may have access to computers with very different computational capabilities. This choice addresses a fundamental trade-off between realism and accessibility. On the one hand, georeferenced datasets preserve the full spatial, spectral, and radiometric properties required for ecologically meaningful analyses, enabling students to work with data that are consistent with real-world remote sensing workflows. On the other hand, lightweight datasets reduce memory usage and computational overhead, allowing the same analytical concepts to be explored on low-performance machines without technical barriers.

This design supports a progressive learning pathway. At early stages, students can interact with simplified datasets to understand core concepts such as spectral signatures, vegetation indices, clustering, and spatial variability, without being distracted by issues related to data size, file handling, or computational constraints. Subsequently, the same analytical logic can be transferred to fully georeferenced datasets, reinforcing the connection between conceptual understanding and real-world applications.

Importantly, all datasets included in `imageRy` are curated and version-controlled within the package repository (https://github.com/ducciorocchini/imageRy/tree/main/inst/images), ensuring that teaching workflows remain fully reproducible across different machines and over time. Metadata and documentation are provided in a structured format (https://github.com/ducciorocchini/imageRy/tree/main/man), allowing users to trace data provenance, understand sensor characteristics, and interpret the ecological meaning of the variables.

By embedding both data and documentation within the same software environment, `imageRy` minimizes external dependencies and reduces variability in classroom execution. This approach reflects a broader informatics objective of tightly coupling data, code, and documentation, thereby enhancing reproducibility, transparency, and consistency in remote sensing education.

3. Statistical visualization as a unifying analytical layer in `imagery`

The analytical design of `imageRy` is structured around a coherent framework that links spectral information, spatial representation, and statistical interpretation within a unified workflow. A distinctive contribution of `imageRy` lies in the explicit integration of statistical visualization as a native component of remote sensing workflows. Traditional approaches in remote sensing primarily emphasize spatial outputs such as maps — based on e.g., spectral indices, classification, multivariate analysis, kernel based calculations, also present in `imageRy` (Table 2). `imageRy` introduces a complementary analytical layer that focuses on the statistical structure of the data.

Statistical visualization functions – including `im.ridgeline()`, `im.barplot()` and `im.boxplot()` – operate on the distribution of pixel values rather than their spatial configuration. These functions enable the transformation of raster data into aggregated representations that summarize key properties such as class separability, within-class variability, and relative abundance. From a methodological perspective, these representations provide essential information that is not directly visible in spatial maps. For example, ridgeline plots (see Cremonini, 2024) – by the `im.ridgeline()` function (Fig. 1B) – extend the user's perspective by representing full distributions across multiple groups or temporal steps, enabling fine-grained comparison of spectral responses. Once an image has been classified, barplots – by the `im.barplot()` function (Fig. 1C) – automatically summarize class frequencies or proportions, linking pixel-level classifications to landscape-level composition. Furthermore, boxplots – by the `im.boxplot()` function (Fig. 1D) – allow the comparison of spectral distributions across classes, revealing both central tendencies and dispersion. In addition to conventional boxplot summaries, the function overlays kernel density estimates of a continuous variable (e.g., near infrared reflectance values) across classes, enabling a more detailed assessment of class separability in feature space. Together, such approaches share a common informatics structure: raster outputs are transformed from spatial objects into tabular representations, summarized according to layers or classes, and then represented as statistical graphics. This shared logic is summarized in Algorithm 1. From an informatics perspective, this statistical layer implements a transformation from high-dimensional raster data to lower-dimensional statistical representations. This transformation reduces data complexity while preserving key distributional properties, thereby facilitating comparison, interpretation, and communication of results. By abstracting from spatial detail, statistical visualization enables users to focus on underlying data structure, including variability, overlap among classes, and relative dominance.

To our knowledge, this explicit coupling between remote sensing outputs and statistical visualization is not systematically implemented in existing R-based remote sensing frameworks, which are primarily oriented toward raster processing and image rendering. In contrast, `imageRy` treats statistical visualization as a first-class analytical component, enabling a seamless transition between spatial and statistical domains.

The integration of statistical visualization within the analytical workflow has important implications for both interpretation and evaluation. By providing distributional summaries of pixel values, these tools enable the direct assessment of analytical results. For example, the separability of clusters obtained through classification can be evaluated by examining the overlap of their spectral distributions, while class proportions provide an immediate quantitative description of landscape composition (Foody, 2002).

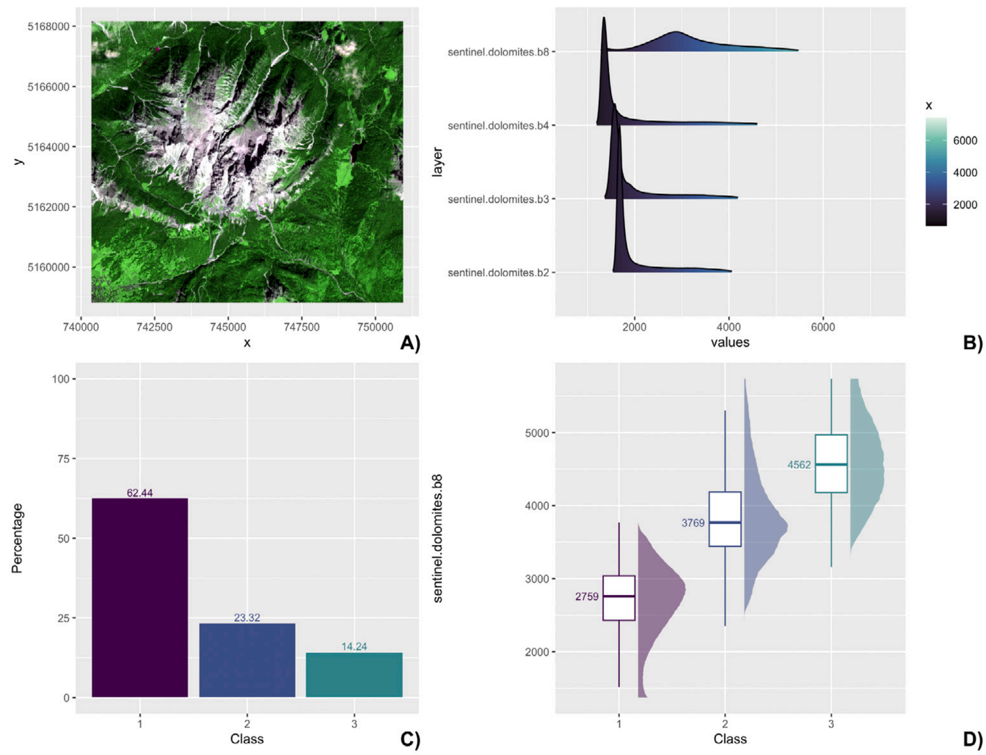

Fig. 1. Conceptual representation of statistical visualization as a unifying analytical layer in `imageRy`. Remote-sensing workflows traditionally emphasize spatial outputs (e.g., maps derived from spectral indices, classification, or multivariate analysis). In `imageRy`, these spatial representations are complemented by statistical visualizations, including ridgeline plots, barplots, boxplots with kernel densities which summarize the distribution of pixel values and class properties. This integration enables a seamless transition from spatial patterns to quantitative interpretation, linking pixel-level information to aggregated descriptors such as class separability, variability, and relative abundance. In this example, the bands of a Sentinel-2 A image of Tofane (norther Italian Alps, four bands available in `imageRy`, shown in R=4 G=8 B=3, (A)) can be represented by ridgeline plots showing their frequency distribution in a continuous space, by the function `im.ridgeline()` (B). Once the image has been classified – in this case with three clusters – barplots (C) (function `im.barplots()`) and boxplots (function `im.boxplots()`) with an overlaid continuous variable, e.g. B8 (D), can automatically be built. The description of the parameters for every function is available through the `.Rd` files of the `imageRy` manual (https://github.com/ducciorocchini/imageRy/tree/main/man) while the specific settings for the figure are available at: https://github.com/ducciorocchini/imageRy_paper/blob/main/Visualization_plot.R.

From a pedagogical perspective, this dual representation enhances interpretability by making implicit assumptions explicit. It allows users to move between spatial patterns and their statistical characterization, reducing the risk of over-interpreting spatial outputs without considering underlying variability and uncertainty (Goodchild, 2013). From a computational standpoint, statistical summaries are efficient, as they operate on aggregated representations rather than full spatial datasets. This contributes to the scalability of the framework and supports its application in teaching environments with limited computational resources.

Overall, the integration of statistical visualization transforms `imageRy` from a collection of analytical tools into a structured framework that connects spectral analysis, spatial representation, and statistical interpretation. This integration represents the primary contribution of the package to ecological informatics.

4. Discussion

In this paper, we described the main strengths of the `imageRy` R package. The package is designed as an intentionally scoped educational tool for ecological remote sensing, addressing the needs of a diverse community of instructors and students, offering standardized workflows and a wealth of low-maintenance imagery with various spatial and spectral resolutions that support lectures with varied ecological focuses. Due to its versatility and open-source framework, `imageRy` stands to improve the accessibility and efficacy of remote sensing education.

A key and unique feature of `imageRy` is its "all-in-one" design: teaching datasets, import utilities, visualization tools, and core analytical functions are provided within a single R package, minimizing, as stated in Section 1, the need to navigate across multiple external resources. This supports consistent classroom execution and reduces variability introduced by heterogeneous platforms. However, this design also implies clear limitations. First, the in-package imagery is intentionally lightweight and cannot substitute large-scale, frequently updated archives or computational infrastructures offered by cloud platforms (e.g., planetary-scale processing). Second, `imageRy` prioritizes transparency and pedagogical clarity over maximum performance or breadth of algorithms; advanced or domain-specific methods can be accessed by interfacing `imageRy` outputs with specialized R packages (as discussed below). Therefore, `imageRy` should be viewed as a deliberately engineered informatics intervention for ecological remote-sensing education: it enforces controlled data provenance, version consistency, and standardized workflows at early learning stages, while explicitly delineating its limits with respect to inference-ready and large-scale analytical pipelines.

This intentional design choice necessarily constrains the scope of `imageRy`. By embedding a limited set of curated datasets and focusing on lecture-oriented workflows, the package does not aim to provide exhaustive data coverage, real-time data access, or computational scalability. Instead, it deliberately trades analytical breadth and performance for reproducibility, interpretability, and ease of use in educational contexts. As a result, `imageRy` is not intended to support fully automated or computationally intensive analyses, nor to replace

Algorithm 1 Statistical visualization of raster outputs in `imageRy`

```
Require: Raster data R, optional classified raster C, visualization type V
Ensure: Statistical visualization P
Check that input raster data are valid SpatRaster objects
if V = im.ridgeline() then
    Convert raster stack R into long-format table
    Associate each pixel value with its corresponding raster layer
    Estimate value distributions for each layer
    Build ridgeline plot of distributions across layers
    return plot P
end if
if V = im.barplot() then
    Check that classified raster C contains a single layer
    Extract class labels from C
    Count pixels assigned to each class
    if percentage output is required then
        Convert class counts into percentages
    end if
    Build barplot of class frequencies or percentages
    return plot P
end if
if V = im.boxplot() then
    Check that raster R and classified raster C are valid
    Select target raster layer from R
    Extract pixel values from the selected layer
    Extract corresponding class labels from C
    Combine pixel values and class labels into a table
    Compute class-wise distributions of raster values
    Build boxplot, optionally including density and median summaries
    return plot P
end if
```

dedicated remote-sensing infrastructures. Rather, its role is to provide a controlled and transparent environment in which students can learn core remote-sensing concepts before transitioning to more specialized, data-intensive, or inference-oriented tools.

As a consequence, several commonly used remote-sensing tasks are explicitly out of scope for imageRy. These include large-area and long time-series processing, automated ingestion of remote repositories, sensor-specific atmospheric correction pipelines, advanced machine-learning workflows, and inference-ready ecological modeling at regional or global scales. Such tasks are more appropriately addressed by specialized platforms and packages developed for those purposes.

With the data stored in `ImageRy`, a wide range of spatio-statistical analyses can be performed. Moreover, additional code could be implemented to expand the potential of the package with more sophisticated techniques, linking `imageRy` to other R packages devoted to specific analysis types, such as: (i) the development of RS-Essential Biodiversity Variables (e.g., Skidmore et al., 2021) through the link with the `ecochange` R package Lara et al., 2022; (ii) species distribution models (through the `sdm` Naimi and Araújo, 2016 and the `ecospat` Di Cola et al., 2017 R packages); (iii) advanced variability measurements with the link to the `rasterdiv` R package (Rocchini et al., 2021).

The strict link between imageRy and the `ggplot2` package (Wickham, 2016) increases the power of visual learning (Rocchini et al., 2017), since such package is devoted to elegant graphics which enhance the appealing of the proposed remote sensing analyses during lectures (e.g., Fig. 1). This might be further empowered linking additional functions from the advanced graphics and image processing packages like the `magick` package (Ooms, 2021).

The `imageRy` package is designed specifically as an entry point for students who are at the very beginning of their journey with both remote sensing and computer science. In many ecological and environmental science programs, student cohorts come with widely varying levels of prior programming experience. This disparity often leads to unequal classroom engagement and can slow down collective progress (Rocchini et al., 2017). By offering clearly structured functions and a self-contained dataset, `imageRy` helps to equalize the starting conditions in the classroom, enabling all students to begin exploring key remote sensing concepts without being immediately overwhelmed by technical complexities such as file handling, data formats, or software dependencies. Of course, understanding how computers handle files, data structures, and input/output operations is a crucial part of a students' learning path; however, we view these skills as best introduced after students have gained some initial confidence and context. While more advanced environmental, geological, and geographical datasets can be accessed using external packages such as `geodata` (Hijmans et al., 2024), the primary aim of `imageRy` is to streamline and support early-stage learning by simplifying lectures and avoiding the typical challenges associated with importing and exporting images. Once students become comfortable with the basic workflow and gain confidence, the course progressively transitions to teaching standard R programming practices and direct use of external tools like `terra`. In this way, `imageRy` functions as a pedagogical bridge that supports early engagement while ultimately preparing students to work independently with real-world data and more advanced analytical workflows.

All the documentation of `imageRy` has been written in MarkDown, a lightweight markup language designed to produce plain-text documents that are easy to read, write, and convert into multiple output formats. By adopting Markdown, the package metadata and documentation rely on a standardized and widely used format, which facilitates the development of vignettes, tutorials, and additional educational material aimed at explaining how to use the package (https://github.com/ducciorocchini/imageRy/blob/main/vignette/vignette.md).

Finally, the graphs shown in this manuscript are colorblind friendly (see Rocchini et al., 2024). In other words, all the color palettes used can be seen by colorblind people based on the `viridis` R package (Garnier et al., 2024). This is a crucial point also during lectures. Color blindness is the result of the inability to perceive peculiar wavelengths depending on the type of disease: (i) protanopia, i.e., the inability to perceive the red color (560 nm); (ii) deuteranopia, i.e., the inability to recognize the green color (530 nm); (iii) tritanopia, i.e., the inability to distinguish the blue color (420 nm, Vienot et al., 1995). In general, maps based on rainbow color palettes are meaningless for colorblind people. Several packages have been devoted to solve the issue (see Rocchini et al., 2024), focusing on a number of different aspects, like: (i) the simulation of colorblindness (e.g., the `colorspace` Zeileis et al., 2020, the `colorblindcheck` Nowosad, 2019, the `colorblindr` McWhite and Wilke, 2023 or the `colorBlindness` Ou, 2021 R packages); (ii) the development of colorblind-friendly color palettes (e.g., the `RColorBrewer` Neuwirth, 2013, the `viridis` Garnier et al., 2024, the `cols4all` Tennekes, 2023 or the `rcartocolor` Nowosad, 2018 R packages), and (iii) the creation of graphs with improved color palettes (e.g., the `cblindplot` R package Rocchini et al., 2023). It would be important during lectures to instruct and guide attendees to produce their maps avoiding the contrast between green and red, under a colorblind friendly framework to let everyone appreciate the results coming out from remote sensing data analysis.

CRediT authorship contribution statement

Duccio Rocchini: Writing – original draft. **Ludovico Chieffallo:** Writing – original draft. **Michele Torresani:** Formal analysis, Data curation. **Daniel McInerney:** Validation, Methodology. **Ruben Remelgado:** Writing – review & editing, Methodology. **Giovanni Andrea Nocera:** Conceptualization. **Giacomo Panza:** Methodology. **Giovanni**

Bacaro: Conceptualization. **Rocìo Beatriz Cortès Lobos:** Methodology. **Emanuela Cosma:** Data curation. **Vítězslav Moudrý:** Conceptualization. **Elisa Padulosi:** Formal analysis. **Diletta Santovito:** Methodology. **Petra Simova:** Conceptualization. **Elisa Thouverai:** Software.

Declaration of competing interest

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Data and code availability

The `imageRy` package development version is available in GitHub at https://github.com/ducciorocchini/imageRy. In addition to the development version of the imageRy package a CRAN release (https://CRAN.R-project.org/package=imageRy) is also available. A vignette including all the functionalities of the package is available at: https://github.com/ducciorocchini/imageRy/blob/main/vignette/vignette.md.

The whole code to reproduce the figure of this manuscript is available at: https://github.com/ducciorocchini/imageRy_paper/blob/main/Visualization_plot.R.

The datasets used in `imageRy` are available in the `inst/images` folder of the GitHub repository of the package at: https://github.com/ducciorocchini/imageRy. Their description is provided at: https://github.com/ducciorocchini/imageRy/blob/main/data_description.md.

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