

1 *crstools* 1.0.0: an R package for cartographic analyses

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## 26 **ABSTRACT**

27 Spatial analyses are central to ecological studies, underpinning applications ranging from  
28 species distribution modelling to conservation planning and macroecological inference.  
29 However, most of these require translating processes occurring on a spherical surface into a  
30 planar map, inevitably introducing distortion biases. Projection choice can therefore influence  
31 both visual interpretation and quantitative results. At the same time, assessing the level of  
32 distortion caused by each projection can be a demanding task. Despite the significance of  
33 these challenges, existing solutions are often restricted to proprietary software or stand-alone  
34 tools, creating friction for transparent and reproducible scientific workflows.

35 Here we introduce crstools, an R package designed to integrate projection selection,  
36 distortion visualisation and image georeferencing within a single reproducible environment.  
37 This package provides three core functionalities. First, building on established cartographic  
38 guidelines, crstools enables users to automate projection choice based on geographic extent  
39 and user-defined distortion preferences. Second, crstools allows users to assess projection-  
40 induced distortion by graphical visualisation of Tissot's indicatrices. Third, an interactive  
41 georeferencing workflow enables users to extract coordinates of locations of interest from  
42 non-georeferenced images.

43 By integrating these features within a single R-based framework, crstools reduces reliance on  
44 ad hoc graphical interfaces and promotes open, scriptable, and fully reproducible  
45 cartographic analyses.

46

## 47 **BACKGROUND**

48 Working with spatial and ecological data often involves representing spatial relationships on  
49 maps. This requires the simplification of complex real-world patterns into intuitive geometric

50 shapes (e.g. points, lines, polygons) (Battersby et al. 2017). However, this task poses a series  
51 of methodological challenges.

52 First, the representation of data originating from a spherical surface (i.e. the Earth) onto a  
53 plane unavoidably introduces biases associated with spatial distortion, which can lead to  
54 misleading interpretation of spatial patterns (Olson 2006, Jenny et al. 2017).

55 This process, known as map projection, is characterised by a series of limitations. Each  
56 projection type can only preserve some of the original spatial features: conformal projections  
57 aim to minimise distortion of angles and shapes; equidistant projections aim to preserve  
58 distances across two defined points or lines; equal-area projections aim to ensure relative  
59 spatial extent of geographic areas; finally, compromise projections aim to balance distortion  
60 across different spatial features (Snyder 1987, Gudmundsson and Alerstam 1998). Because  
61 map projections distort spatial properties (e.g., distances, areas, and angles) in different ways,  
62 no single projection can consequently preserve all spherical properties perfectly (see Jenny et  
63 al. 2017 for review). Selecting an appropriate projection is therefore essential for matching  
64 the map to the geographic extent and the spatial relationships most relevant to the analysis.  
65 Choosing an appropriate projection is not only fundamental for visualisation purposes, but it  
66 can also affect inference based on geographic relationships, as well as outcome perceptions  
67 (Lapon et al. 2020, Gosling and Symeonakis 2020, Berke 2024).

68 For example, Budic and colleagues (2016) highlighted how species distribution models can  
69 be affected by the projection used for environmental layers, by comparing models built under  
70 different projections for species with either high-latitude ranges or broad continental  
71 distributions. Skewed sampling due to stronger distortion at high latitudes affected parameter  
72 importance for the former group of species when a “lat-long” (conformal) projection was  
73 used, therefore advocating for the use of an equal-area projection to reduce such biases.

74 Similarly, ecological studies that involve measuring distances between locations (e.g.

75 migration patterns) may often be affected by the type of projection used to perform such  
76 calculations (Gudmundsson and Alerstam 1998, Technitis et al. 2015). While some  
77 approaches allow for the integration of spherical features and geodesic calculations into the  
78 analyses, to avoid the biases introduced by planar map projections (Meyer et al. 2025), this is  
79 not always applicable, and projected maps remain widely used across a multitude of  
80 disciplines such as species distribution modelling, ecological vulnerability, and  
81 epidemiological mapping (Hamid et al. 2024, Brambilla et al. 2025, Healey et al. 2025,  
82 Wampande et al. 2025).

83 When using map projections, an important challenge is the ability to infer the amount of  
84 spatial distortion caused by any chosen projection. For instance, equirectangular projections  
85 (which form a grid of equally spaced parallels and meridians) may appear deceptively  
86 straightforward but it introduce substantial (and often overlooked) distortion toward the poles  
87 (Mulcahy and Clarke 2001). One of the most effective visual tools for intuitively assessing  
88 distortion caused by map projections is Tissot's indicatrix (Laskowski 1989). This consists of  
89 a network of ellipses placed onto a projected map at grid intersections, whose deformation in  
90 shape and size illustrates how the chosen projection alters area, shape, distance, and direction  
91 across the map.

92 Finally, gathering geographic data from maps can sometimes pose its own complex  
93 challenge. In fact, over the last decade, there has been an exponential increase in publicly  
94 available geographic data (e.g. occurrence points) from published literature and citizen  
95 science databases (e.g. GBIF, iNaturalist). However, most historical records are often hard to  
96 access as they are only represented as geographic shapes on figures (often in paper format),  
97 rather than georeferenced maps or databases. Nonetheless, these historical data represent a  
98 critical source of information, useful to assess, for example, population trends through time or

99 investigate changes in species' geographic ranges (Tingley and Beissinger 2009, Turvey et al.  
100 2017).

101

102 Attempts have been made to address some of the challenges described above. In particular,  
103 when it comes to choosing the most suitable map projection, complete and automated  
104 selection tools were largely unavailable until recently (Gosling and Symeonakis 2020). For  
105 instance, a Python add-in for automatically selecting the most suitable map projection was  
106 recently developed and integrated in ArcGIS (Gosling and Symeonakis 2020). However, the  
107 latter is a licensed "point-and-click" software which is at odds with modern requirements for  
108 open and reproducible science (Alston and Rick 2021, Brunsdon and Comber 2021).

109 Projection Wizard (Šavrič et al. 2016) (<http://projectionwizard.org/>) represents an easily  
110 accessible tool for straightforward automated selection of map projections. Whilst  
111 convenient, it nevertheless constitutes a stand-alone web page that is not integrated into any  
112 coding environment, thus creating friction for scientific reproducibility and preventing  
113 seamless integration within spatial analysis workflows. Similarly, it is possible to extract  
114 occurrence data from non-georeferenced maps using the QGIS Georeferencer tool (Graser et  
115 al. 2025); however, this requires multiple complex steps and is still affected by the issues of  
116 reproducibility described above.

117 Here we present *crstools*, an R package designed to handle multiple cartographic tasks and  
118 overcome the above limitations. First, *crstools* allows the user to automatically choose the  
119 most suitable projection based on geographic extent and distortion preferences. Second, it  
120 provides functions to visualise projection distortions using Tissot's indicatrices. Last, it  
121 enables the user to extract coordinates from non-georeferenced maps. *crstools* provides its  
122 functionalities within the R environment (R Core Team, 2021), thus allowing for scientific

123 reproducibility as well as limiting the need for multiple platforms for data acquisition,  
124 analysis, and visualisation.

125

## 126 **METHODS AND FEATURES**

127 The core functionalities of *crstools* for automatic selection of map projections are derived  
128 from Projection Wizard (Šavrič et al. 2016). In *crstools*, users only need to provide the  
129 desired distortion type and the extent of the area of interest in the “suggest\_crs()” function in  
130 order to obtain the best projection(s) available, following Snyder’s selection guidelines  
131 (Snyder 1987) and further implementations by Jenny et al. (2017). The following distortion  
132 options are currently implemented: "equal\_area", "conformal", "equidistant", and  
133 "compromise". The geographic extent can be provided as a map extent (xmin, xmax, ymin,  
134 ymax), or as a “SpatExtent”, a “SpatRaster”, or an “sf” object. Currently, *crstools* supports 23  
135 projection options, which are summarised in Table 1 together with their relative distortion  
136 properties and extent inputs. The user can decide whether the “suggest\_crs()” function should  
137 return a single optimal projection or a set of the best suitable projections in the form of proj4  
138 and well-known text (WKT) strings.

139

140 Table 1. List of the available projection options in *crstools* with relative distortions and  
141 extents. Modified from Šavrič et al. 2016.

<b>Extent</b>	<b>Distortion Property</b>	<b>Projection</b>
World	Equal-area	Mollweide
		Hammer (or Hammer-Aitoff)
		Eckert IV
		Wagner IV (or Putnins P2')

		Wagner VII (or Hammer-Wagner)
		McBryde-Thomas flat-polar quartic
	Compromise	Natural Earth
		Winkel Tripel
		Robinson
		Patterson (cylindrical)
		Plate Carrée (cylindrical)
		Miller cylindrical I
	Equidistant	Azimuthal equidistant
		Two-point equidistant
Hemisphere	Equal-area	Lambert azimuthal equal-area
	Equidistant	Azimuthal equidistant
Continent, ocean, or smaller area	Equal-area	Lambert azimuthal equal-area
		Albers conic
		Cylindrical equal-area
		Transverse cylindrical equal-area
	Conformal	Stereographic
		Lambert conformal conic
		Mercator
		Transverse Mercator

	Equidistant	Azimuthal equidistant
		Equidistant conic

142

143 To visualise spatial distortion introduced by different map projections, we implemented the  
144 “geom\_tissot()” function, which calculates and plots Tissot’s indicatrices across a projected  
145 map of interest (Laskowski 1989) using a custom “ggplot2” (Wickham 2011) function.

146 “geom\_tissot()” computes a regular grid of circle centres within the spatial extent of the input  
147 data, which can be provided as either an “sf” or “SpatRaster” object. Each circle is projected  
148 into the map’s coordinate reference system (CRS), such that any deformation in shape or area  
149 reflects local projection-induced distortion. The resulting geometries are added as a layer to a  
150 ggplot object, allowing straightforward visualisation and further customisation. This

151 approach provides a reproducible and flexible method to assess and visualise the spatial  
152 effects of map projections directly within the tidyverse framework (Wickham et al. 2019).

153 Finally, *crstools* allows for georeferencing of images using the “choose\_gcp()”,  
154 “find\_gcp\_coord()”, “georeference\_img()”, and “extract\_coords()” functions. This workflow  
155 enables users to quickly extract coordinates for locations of interest from an image using a  
156 georeferenced map as a reference. Georeferencing in *crstools* relies on the use of Ground  
157 Control Points (GCPs), which are manually selected on both the image and the reference  
158 map. The implementation of georeferencing functions in *crstools* provides a reproducible  
159 workflow for transforming non-georeferenced images into spatially-explicit data for  
160 subsequent analysis.

161 Our R package *crstools* also provides a series of step-by-step tutorials aimed to help users  
162 explore the package functionalities, rendered as an easily accessible webpage  
163 (<https://evolecolgroup.github.io/crstools/>).

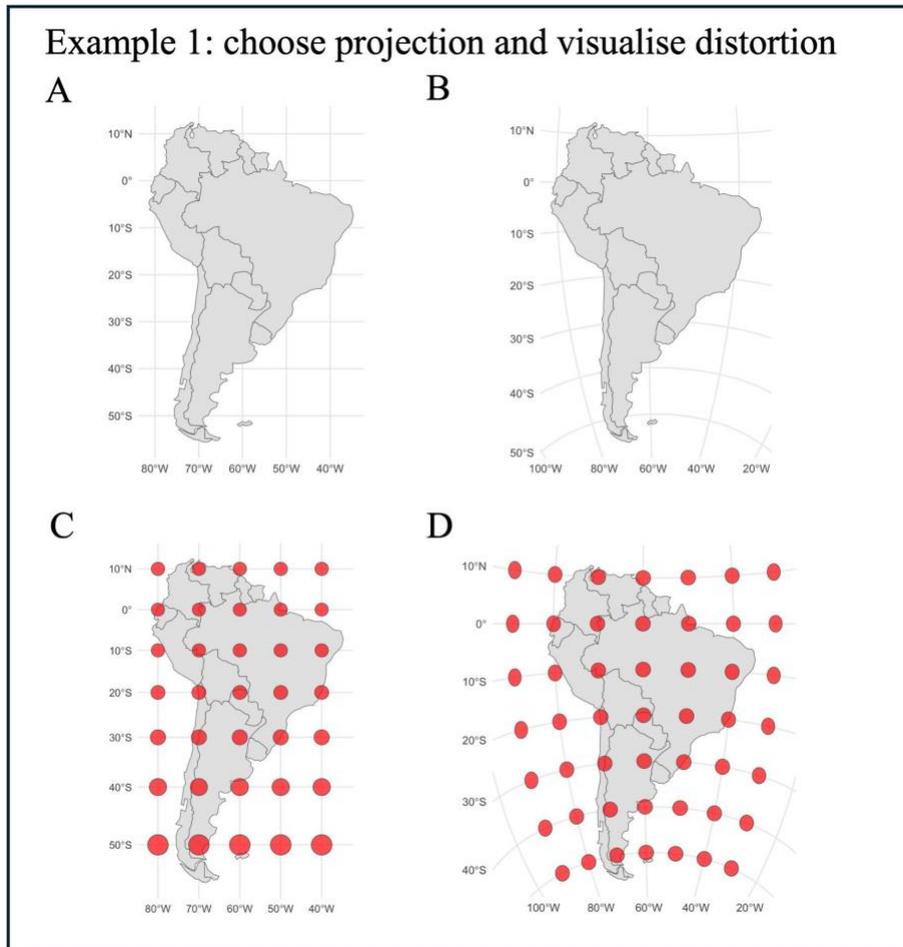
164

165 **EXAMPLES**

166 Applied example 1: choose the best projection and visualise the distortion on a map

167 This first example illustrates how to use *crstools* to choose the best projection for a desired  
168 geographic extent, and then how to visualise the projection distortion via Tissot’s indicatrix  
169 (code available in the “crstools” vignette and at the “Get started” section of the website:  
170 <https://evolecolgroup.github.io/crstools/articles/crstools.html>). As shown in Figure 1, an “sf”  
171 object with the extent of South America was obtained and plotted using the packages  
172 “rnaturalearth” (Massicotte and South 2025) and “ggplot2” (Figure 1A). The best projection  
173 was then automatically selected using the “suggest\_crs()” function with equal-area as the  
174 desired distortion parameter and the “sf” object for South America as the geographic extent  
175 of interest. The area of interest was then replotted using the suggested projection, which is  
176 returned as a list object containing both proj4 and WKT strings (Figure 1B). Finally, local  
177 distortion was assessed by overlaying Tissot’s indicatrix on both the original and the  
178 reprojected maps using the “geom\_tissot()” function (Figure 1C-D).  
179 The use of Tissot’s indicatrix allows for an easy assessment of map distortion, as illustrated  
180 in Figure 1, where strong distortion toward the South Pole is evident in Figure 1C but  
181 substantially reduced in Figure 1D.

182



183

184 Figure 1. Outputs from example 1: geographic extent of South America plotted in a  
185 latitude-longitude projection using “rnatrualearth” (A); reprojected map of South America  
186 using the suggested projection for the desired equal-area distortion (B); Tissot’s indicatrix  
187 showing projection-induced distortion in the original and reprojected maps (C-D).

188

189 Applied example 2: georeferencing an image and extracting coordinates of interest

190 This second example shows how to use *crstools* to georeference an image and subsequently  
191 extract coordinates from locations of interest (tutorial available in the “georeference\_image”  
192 vignette and at homonymous article on the website:

193 [https://evolecolgroup.github.io/crstools/articles/georeference\\_image.html](https://evolecolgroup.github.io/crstools/articles/georeference_image.html)). The procedure

194 focuses on selecting Ground Control Points (GCPs) interactively, using a georeferenced map

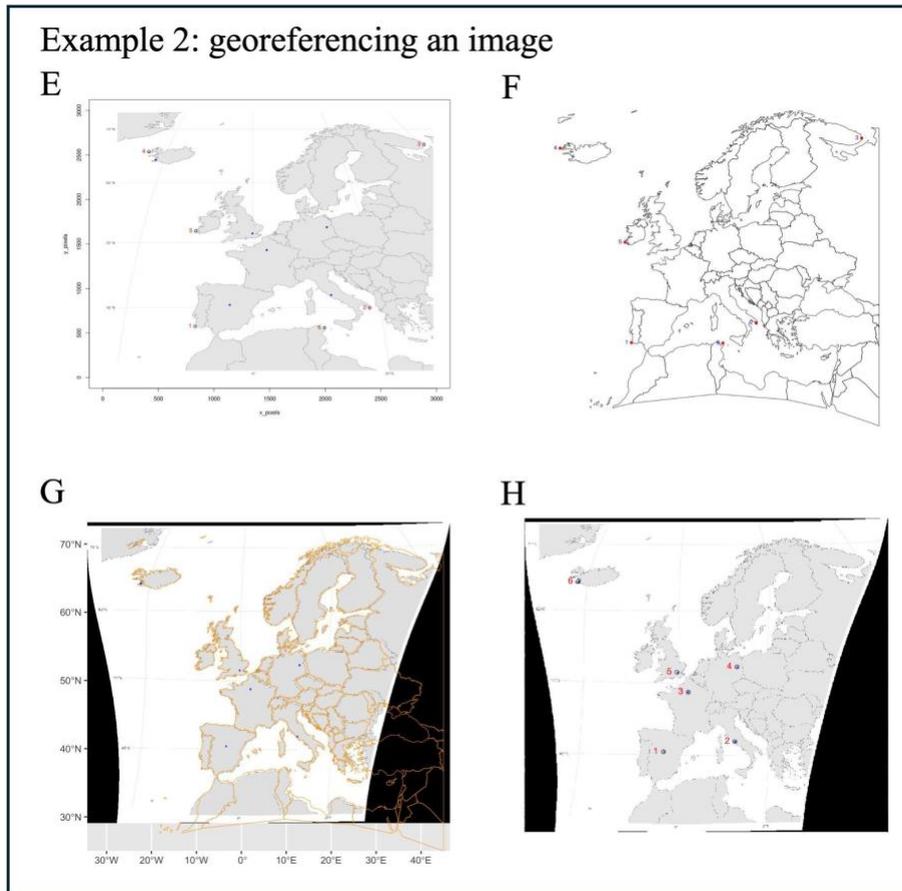
195 as a reference, and then using these points to warp the image into the geographic space. Here,

196 the input is a simple JPEG image of Europe showing major country outlines and a few capital  
197 cities represented by blue dots.

198

199 The first step involves manually selecting GCPs using the interactive “choose\_gcp()”  
200 function. To facilitate accurate georeferencing, GCPs should correspond to easily  
201 recognisable features, such as country corners or coastlines (Figure 2E). Once GCPs are  
202 defined, the next step is to assign them geographic coordinates. This is achieved using the  
203 “find\_gcp\_coords()” function, which matches the selected GCPs with their corresponding  
204 positions on a georeferenced map used as reference (Figure 2F). The image is then  
205 georeferenced using the “georeference\_img()” function, which applies a spatial  
206 transformation and outputs a new GeoTIFF file with embedded geographic information  
207 (Figure 2G). It may be necessary to repeat these first two steps multiple times, extending the  
208 number of GPCs to reduce misalignment biases and achieve the best result. Finally, once the  
209 image is correctly aligned, the “extract\_coords()” function can be used to retrieve the  
210 geographic coordinates of specific locations, here the blue dots representing European  
211 capitals (Figure 2H). This outputs a table of longitude and latitude values for each location.

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213

214 Figure 2. Outputs from the example 2: source image of Europe showing locations of interest  
215 (blue points) and selected Ground Control Points (GCPs; red points with numeric labels) (E);  
216 georeferenced reference map with corresponding GCPs (F); warped georeferenced image  
217 showing alignment between image and map (G); locations of interest selected via the  
218 function for coordinates extraction (H).

219

## 220 CONCLUSION

221 The increasing accessibility and complexity of spatial data require tools that not only  
222 facilitate accurate analyses and visualisations but also ensure methodological transparency  
223 and reproducibility. *crstools* provides an integrated and reproducible framework for  
224 addressing key challenges in spatial data analysis, including automatic projection selection,  
225 distortion visualisation, and image georeferencing. *crstools* provide all these functionalities

226 within a standardised R framework, thus avoiding the necessity of switching between  
227 software for any of the processes described above.

228 While *crstools* is unlikely to replace specialist software like ArcGIS or QGIS, which allow  
229 users to perform more detailed and comprehensive analyses, this package represents an  
230 accessible, easy-to-use, and reproducible tool for a wide variety of users.

231

## 232 **SOFTWARE AVAILABILITY**

233 The package and relative vignettes are free, open-source, and can be downloaded from the  
234 following GitHub repository: <https://github.com/EvolEcolGroup/crstools>.

235 The development version of the package can be installed in R via R-universe:

236 <https://evolecolgroup.r-universe.dev/crstools>.

237

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