

REDLISTR: Tools for the IUCN Red Lists of Ecosystems and Threatened Species in R

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Abstract

The International Union for the Conservation of Nature (IUCN) Red List of Ecosystems and Red List of Threatened Species are global standards for assessing risks of ecosystem collapse and species extinction. However, misconceptions of the Red List assessment process, along with its technically demanding nature, can result in the misapplication of their criteria, leading to inconsistent and potentially unreliable assessments. To address this problem, we developed *redlistr*, an R package aiding in the production of consistent species and ecosystem Red List assessments. *Redlistr*'s features include methods to calculate (i) area from spatial data, (ii) range size metrics, (iii) rates of change of distributions or populations, and (iv) distribution or population at another time from these rates. A key feature of the package is the systematic approach used to eliminate geometric uncertainty when estimating Area of Occupancy. Here, we develop two case studies to demonstrate the functionalities of *redlistr* with typical workflows for both species and ecosystems. *Redlistr* was developed to be accessible to users with a broad range of experience in programming for spatial and temporal data analysis, and sufficiently flexible to allow users to parameterise functions and select equations to fit their purposes. The package specifically aims to assist researchers and conservation practitioners to conduct robust and transparent risk assessments of ecosystems and species under the IUCN Red List criteria but is also useful for other studies requiring analyses of range size, area change and calculations of rates of change.

Keywords: Geometric uncertainty; IUCN Red Lists; Open-source tools; Range size metrics; Risk assessment;

Introduction

The International Union for Conservation of Nature (IUCN) Red List of Threatened Species (RLTS) and Red List of Ecosystems (RLE) are widely used tools for conservation. They are based on transparent and quantitative criteria and can be used as a foundation for evidence-based management decisions across a range of spatial, temporal, and administrative scales (Keith et al. 2015, IUCN 2017). In particular, they enable the comparison of different ecosystems (RLE), and plants, animals, and fungi (RLTS) based on their relative risk of collapse or extinction (Nicholson et al. 2015). A widely recognised issue of the Red Lists is the considerable number of assessments that apply the criteria incorrectly (Collen et al. 2016), introducing inconsistencies into the Red List and potentially limiting their ability to objectively inform conservation decisions (Nicholson et al. 2015). The technically demanding nature of the criteria can also lead to their incorrect application, which is particularly pervasive in the quantification of spatial metrics used in the risk assessment processes (Keith et al. 2018). The Area of Occupancy (AOO) and the Extent of Occurrence (EOO) are two such metrics representing geographic range size (Gaston 1991) that are integral components of criterion B in both protocols, and can be used in criterion A (change in distribution) for species (Bland et al. 2017, IUCN 2017). The main misapplications of these criteria include the use of different grid sizes for estimating AOO, unspecified geometric placement of the grids used to estimate AOO, which can lead to varying AOO estimates (Moat et al. 2018), and the use of different methods to calculate EOO (such as using other types of convex hulls rather than a minimum convex polygon as specified by the IUCN guidelines). These issues have led to the potential misclassification of 13% of all species on the Red List of Threatened Species (Joppa et al. 2016).

One means of reducing misapplications of the Red List criteria is to provide tools that standardise the assessment process and comply with red listing guidelines. Such tools can also support iterative analysis of large datasets, streamline the reapplication of the criteria in subsequent assessments, and promote reproducible workflows in the red listing process. Currently, a range of tools for supporting red listing exist, each developed to meet different needs, including the Geospatial Conservation Assessment Tool (GeoCAT, Bachman et al. 2011), RAMAS Red List (Akçakaya and Root 2007), and the Remote Ecosystem Monitoring & Assessment Pipeline (REMAP, Murray et al. 2018). However, as interactive software, these tools are limited in their ability to be applied iteratively, making repeat assessments difficult, and typically requiring specific input data formats. Freely available R packages, mostly

delivered as open-source and highly accessible software, can allow reproducible workflows to be developed for consistent application of the Red List protocols. Three R packages are currently available for species red listing, *ConR* (Dauby et al. 2017), *rCAT* (Moat 2017), and *red* (Cardoso 2017), but they lack functions for ecosystems and a systematic method of dealing with geometric uncertainty.

Here we introduce *redlistr*, an open-source R package developed to support the systematic, robust application of the Red List criteria. To demonstrate its use, we provide two detailed working examples using freely available data that showcase the functions of *redlistr*. Key features of *redlistr* include functions that: (i) operate on the two most common types of spatial data (vector and raster), (ii) enable standardised measurements of range sizes metrics, including a systematic method minimising geometric uncertainty, (iii) calculate rates of change of species populations and ecosystem area, and (iv) extrapolate these estimates across a given timeframe. In addition to Red List assessments, these functions will help conservation practitioners perform ecological assessments by estimating trends when data is scarce, and to calculate range size consistently from vector or raster data.

Features of the package

Redlistr was developed in R 3.3.3 (R Core Team 2013) and depends on ‘raster’ (Hijmans 2017), ‘sp’ (Pebesma and Bivand 2005), and ‘rgeos’ (Bivand and Rundel 2018). It is available on the Comprehensive R Archive Network (CRAN, <https://cran.r-project.org/package=redlistr>) and GitHub (<https://github.com/red-list-ecosystem/redlistr>). It currently consists of four families of functions, each developed to achieve specific components of the Red List criteria (Table 1).

Rate of change

The ‘rate of change’ family of functions in *redlistr* was developed to estimate rates of change with two data points based on recommendations by the Red List guidelines (Bland et al. 2017, IUCN 2017). These functions allow the estimation of population and distribution changes (Criterion A of RLTS and RLE; Bland et al. 2017, IUCN 2017), and of reductions in the extent of key ecological processes (Criteria C and D of RLE; Bland et al. 2017). As area is often required for ecosystem assessments, we have also included functions to estimate area for both raster (using a pixel count method) and vector data (using the *rgeos* package; Bivand and Rundel 2018). Using estimates at two time points, *redlistr* computes three rate of change statistics to enable users to extrapolate estimates from limited data to the time frames required by Red List guidelines (three generations/ten years for the RLTS and fifty years for the RLE). The rates are Absolute Rate of Decline (ARD), Proportional Rate of Decline (PRD), and Annual Rate of Change (ARC) (Puyravaud 2003, Keith et al. 2009). ARD assumes additive (linear) decline with a constant absolute loss (equation 1), while PRD assumes exponential decline with a constant fractional loss (equation 2), enabling assessments under pessimistic and optimistic scenarios (Fig. 1, Bland et al. 2017). ARC, derived from the compound interest law, also calculates exponential rates of change and is considered a more realistic estimation of annual loss than PRD when rates of decline are high (equation 3, Puyravaud 2003). Note that the trajectories estimated by the PRD and ARC are identical, as they differ only on their definition of rate. Importantly, ARC can be clearly interpreted as percentage change per year and can vary from negative infinity to infinity, while PRD is limited to between $\pm 100\%$ (Puyravaud 2003).

$$ARD = \frac{A_2 - A_1}{t_2 - t_1}$$

(eqn 1)

$$PRD = \left(1 - \left(\frac{A_2}{A_1}\right)^{\frac{1}{t_2 - t_1}}\right) \times 100\%$$

(eqn 2)

$$ARC = \frac{1}{t_2 - t_1} \times \ln \frac{A_2}{A_1} \times 100\%$$

(eqn 3)

All three equations require four variables, A_1 is area or abundance at time t_1 and A_2 is area or abundance at time t_2 . Other variables for which rates of change are calculated, such as abundance, can be substituted for A in these equations.

These approaches for estimating rates of change are based on extrapolations assuming a constant rate of change and, therefore, users should choose a suitable method by considering factors likely to influence the rate of change in the variable they are measuring. These include whether the rate is likely to be accelerating, stable, or decelerating. Users should also be aware that extrapolations are more uncertain over longer time frames (forwards or backwards; Bland et al. 2017, IUCN 2017). The functions included in this package are statistical methods for estimating decline using data at only two time points. If more data is available over a time series, more complex models (e.g. regression) will be more suitable to estimate both the trajectory and the uncertainty around the best estimate as suggested by the Red List guidelines (Bland et al. 2017, IUCN 2017). Statistical packages for fitting such models are widely available (R Core Team 2013), and thus beyond the scope of this package.

Range size metrics (EOO and AOO)

The EOO function calculates EOO using a minimum convex polygon (MCP) that encompasses all known, inferred or projected occurrence locations, excluding cases of vagrancy (IUCN 2017). *Redlistr* achieves this by first finding the points at the outermost edge of the distribution. For raster data, the centroid of each raster cell is used. The points are connected with straight lines to create the MCP, and the area for this polygon is calculated.

AOO is estimated by applying an empty grid with specified cell sizes to the inferred or projected occurrence locations or a raster or vector of species or ecosystem distribution, with the grid origin based on the upper left extent of the original data. The cells that intersect the distribution are found, returning the grid as a spatial object and the number of cells that are occupied by the species or ecosystem (Fig. 2). Users can parameterise the size of the cells used and decide whether to apply a minimum threshold before a cell is deemed occupied. For the purposes of red listing, ecosystem cells are 100km^2 and species cells are 4km^2 (Bland et al. 2017, IUCN 2017).

Geometric uncertainty function

AOO estimates can differ depending on the location of the grid origin, which can vary depending on the software used, potentially leading to overestimation of AOO and misclassification of risk category (Fig. 2; Keith et al. 2018, Moat et al. 2018). *Redlistr* minimises this issue by iteratively implementing different grid locations to systematically determine the minimum number of occupied cells possible. *gridUncertainty* begins by using a larger grid extent than that used by *getAOO*, moving the origin over multiple iterations following a geometric sequence of successively smaller shifts in each of the x- and y- dimensions with the distance of one-half cell length, then one-third, one-fourth and so on until no smaller AOOs are returned. We recommend a minimum of five iterations, though this can depend on the shape of the distribution (Keith et al. 2018). In accordance with the Red List guidelines, the function returns the minimum estimate of AOO (number of occupied cells) and the spatial data frame (vector) of the first grid that produced it (Bland et al. 2017, IUCN 2017).

Case study 1: Estimating trends in distributions

We developed a case study of the Aral Sea, Uzbekistan and Kazakhstan (Fig. S1), to demonstrate a typical workflow for applying the rate of change family of functions in *redlistr* to conduct an assessment of Criterion A (reduction in geographic distribution) of the Red List of Ecosystems (Bland et al. 2017). The Aral Sea wetland ecosystem has been severely impacted by water extraction, which led to a 74% decline in inundated area and eventual ecosystem collapse (Keith et al. 2013). We mapped the distribution of the Aral Sea in 2001 and 2016 using REMAP (Fig. S1; Murray et al. 2018), imported the mapped distribution as a raster file into R, reprojected it to a suitable projected coordinate system (UTM40), and used the *getArea* function to determine its area in 2001 and 2016.

Our results indicated that the area of the Aral Sea was 22,721 km² in 2001, subsequently declining to 8,725 km² in 2016. Additional estimates of area were calculated for the Aral Sea in 2001 and 2016 using a CART method implemented in Google Earth Engine as a way of representing uncertain estimates at each time point (Supplementary methods; Gorelick et al. 2017), returning estimates of 23,662 km² in 2001, and 8,871 km² in 2016. The rates of change calculated using *getDeclineStats* revealed an ARD of 933 to 986 km²/year, PRD of 6.18 to 6.33%/year, and ARC of -6.38 to -6.54%/year. The RLE protocol requires assessments over a 50-year period, so we used these rates of change to extrapolate and estimate the area of the Aral Sea in 1966 using

extrapolateEstimate, which assumes that the rate of change was the same in the proceeding 50 years as in the period between the observations. The results suggest that the Aral Sea has lost between 84.0 to 84.2% (ARD) to 95.9 to 96.2% (ARC) of its area since 1966 (Fig. 1). When assessed under the RLE criteria, the hindcasted decline in area returns a status of Critically Endangered under criterion A1, regardless of which method was used, because more than 80% of its area has been lost in the past 50 years (Bland et al. 2017; see Keith et al. 2013 for further information on this case study).

Case study 2: Estimating range size

To demonstrate the use of *redlistr* for calculating AOO and EOO, we acquired freely available spatial data for all species of Ursidae (bears). Spatial data of the occurrences of all seven extant species were obtained from the Global Biodiversity Information Facility (GBIF; accessed via 'rgbif'; Chamberlain 2017; Fig. S4). In accordance with guidelines and to exclude areas where they may no longer occur, we excluded data from before 1972 (~3 generations).

We estimated range sizes using the following workflow. *makeEOO* was used to create spatial polygons representing the EOO for each of the species and *getAreaEOO* was used to calculate the area of these polygons, measured in km² (table 2). The resulting vector file was used to create a map of range sizes (Fig. S5). *getAOO* was used to estimate the AOO (measured using the number of occupied cells) for each species, with grid sizes specified as 2x2 kilometres, in accordance to the RLTS guidelines (Table 2, IUCN 2017). Finally, *gridUncertainty* ensured the calculated AOO accounts for geometric uncertainty associated with unspecified grid origins, returning the minimum AOO for the given data (Keith et al. 2018).

Discussion

Redlistr allows consistent calculation of spatial metrics required for the IUCN Red Lists. It supports the use of common spatial data formats and can be incorporated into a reproducible or automated pipeline, enabling the processing of large amounts of input data and the iterative assessment of all species or ecosystems for which spatial data is available. *Redlistr* is compliant with the IUCN guidelines, which will serve to minimise inconsistencies that may arise from applying different methods or analysis routines while assessing the Red

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List criteria. *Redlistr* does not include any of the alternative metrics suggested in the literature for red listing because they are not endorsed by the IUCN, do not comply with the guidelines, and can introduce inconsistencies into the Red List of Ecosystems and Red List of Threatened Species (IUCN 2017, Bland et al. 2017). For example, although alpha hulls may be more accurate for estimating range size (Burgman and Fox 2003), they have been shown to not be suitable for assessing criterion B of the Red Lists because the criterion and thresholds were developed specifically for MCPs (IUCN 2017). MCPs are straightforward to compute, relatively robust to variations in spatial resolution, have no arbitrary parameters required, and thus provide the consistent results necessary for reliable global lists that include tens of thousands of independently produced assessments (Joppa et al. 2016).

Various types of uncertainties exist in estimates of Red List parameters and must be considered when conducting Red List assessments, even when they cannot be calculated statistically or directly from the data. For instance, the rate of change family of functions (*getDeclineStats* and *extrapolateEstimate*) provide a way of estimating and extrapolating change using only two time points without uncertainty, even though uncertainties due to measurement or observation error at each time point will influence the reliability of extrapolated results. Therefore, if additional information is available (e.g. more than one estimate at each time point), it should be used to estimate plausible bounds representing uncertainty for each time point, as a basis for estimating plausible minimum and maximum rates of change (e.g. Fig. 1). Similarly, the *gridUncertainty* function was designed specifically to account for geometric uncertainty in grid location. Although *redlistr* assumes that users have eliminated erroneous records (overestimation) and ensured no omissions of reliable records (underestimation), the efficacy of some records may remain uncertain. Plausible bounds for spatial metrics should thus be estimated by calculating separate results that include and exclude the uncertain records, returning the upper and lower estimates respectively.

Conducting Red List assessments requires assessors to understand their target species or ecosystem and to be aware of their obligation to implement the strict rules specified in the Red List guidelines. Using *redlistr* in the same way is recommended; we assume that assessors apply informed ecological judgments and have a detailed understanding of the red listing process. The data used for assessments should be proofed and verified by specialists to ensure their reliability, users should understand the assumptions associated with the shape of the decline trajectory when assessing for Criterion A, and they should be aware of biases in data

availability and survey effort and how these can influence the assessment outcomes (IUCN 2017). The methods provided in *Redlistr* can be implemented on only two time points (as suggested by the IUCN), and therefore assume that the processes driving decline remain unchanged. Users should consider carefully whether their variable of interest fit this assumption. It should be noted that the outputs from *redlistr* are not necessarily indicative of a final classification of extinction risk or the risk of ecosystem collapse because most criteria also require additional subcriteria to be met before a status is assigned. These subcriteria often require an informed interpretation of qualitative concepts (e.g. locations), and therefore *redlistr* does not return the final assessment outcome. Assessors should take the results produced by *redlistr* and refer to the Red List guidelines before making a decision on the final assessment outcome.

Redlistr aims to support the global effort to list all species and ecosystems on Earth under the IUCN Red List criteria. Providing tools that are free is particularly important for researchers and assessors working in places with limited access to proprietary software. To support these aims and to ensure transparency in the internal functions and methods, all source code is freely available. Lastly, the methods implemented in *redlistr* are not limited to Red List applications, and the functions can be parameterised to suit a range of objectives. As such, *redlistr* will also be useful in applications beyond red listing such as species distribution analyses (e.g. Grenyer et al. 2006) and studies reporting deforestation and ecosystem trajectories (e.g. Waycott et al. 2009, Brown and Zarin 2013).

Data accessibility

All data used in this article are freely available online. Detailed example scripts are available as supplementary.

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Authors' contribution:

DAK and NJM conceived the project; CKFL and NJM developed the methods; CKFL led the writing with help from NJM and EN; All co-authors assisted with edits and approve publication.

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Figure Legends

Figure 1. Hindcasted area of the Aral Sea extrapolated from four data points (two in 2001, two in 2016) using two methods included in *redlist* to estimate the rates of decline: Absolute Rate of Decline (ARD; dark grey) and Proportional Rate of Decline (PRD; light grey). Crosses represent the area of the Aral Sea obtained from remote sensing classifications, and are used to estimate rates of decline. Open circles are independent known areas obtained from the literature (Keith et al. 2013).

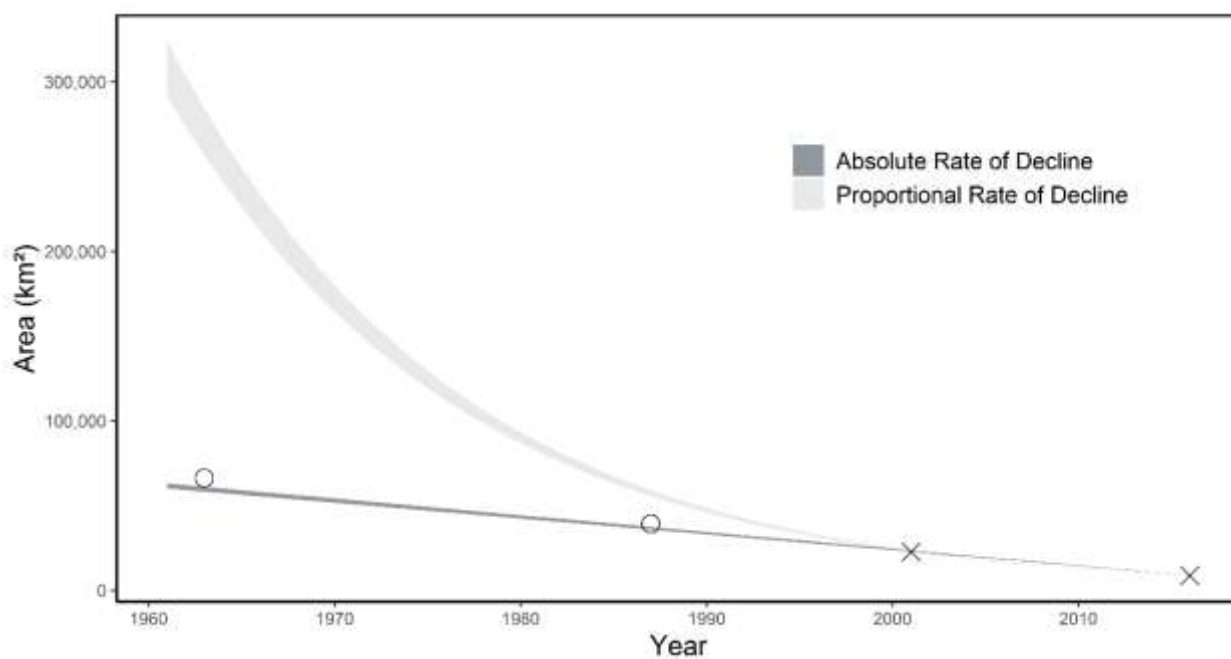


Figure 2. Comparison between the AOO of mangroves in northern Western Port Bay, Australia (black) using (a) *makeAOOGrid* (AOO = 11) and (b) *gridUncertainty* (AOO = 9) with a cell size of 100 kilometres². Filled grey grid cells denote occupied cells. Grid b was identified by *redlistr* after shifting the grid origin 2,463 metres west and 2,584 metres north. The diamonds denote the initial grid origin.

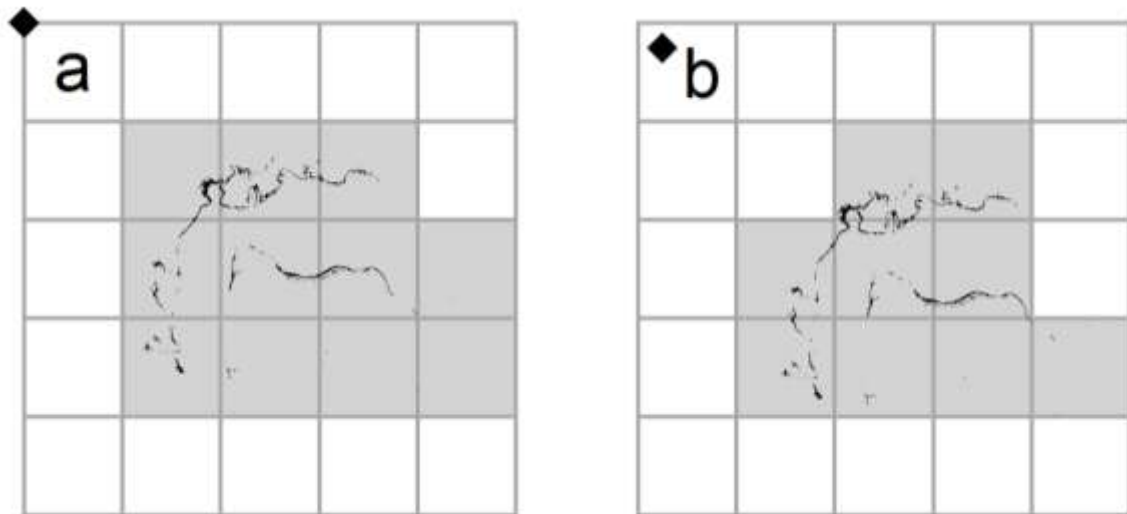


Table Legends

Table 1. Description of the groups of functions in *redlistr* and their application within the Red Listing protocols.

Function family	Brief description	Relevant criteria	Input data	Output	Key functions
Rate of Change	Measures and/or estimates rates of changes over specified timeframes	A in both RLE and RLTS; Criteria C and D for the RLE	Numeric values	Data frame containing chosen decline statistics or extrapolated values	<i>getDeclineStats</i> <i>extrapolateEstimate</i> <i>sequentialExtrapolate</i>
Extent of Occurrence	Calculates the Extent of Occurrence (EOO) using a minimum convex polygon, returning the polygon produced and its associated area	B1 in both RLE and RLTS	Raster or Vector	EOO polygon or area of EOO	<i>makeEOO</i> <i>getAreaEOO</i>
Area of Occupancy	Calculates Area of Occupancy (AOO) using grids of a specified size, returning the grid produced and the number of occupied cells	B2 in both RLE and RLTS	Raster or Vector	AOO grid or AOO based on grid size specified	<i>makeAOOGrid</i> <i>getAOO</i>
Geometric uncertainty	Extension of AOO function, systematically varies the grid origin of the AOO grid used, ensuring the minimum AOO is calculated	B2 in both RLE and RLTS	Raster or Vector	AOO grid with smallest AOO and minimum AOO based on grid size specified	<i>gridUncertainty</i>

Table 2. Results from *getAreaEEO*, *getAOO*, and *gridUncertainty* for each Ursidae species.

Species	Extent of Occurrence (km²)	Area of Occupancy Estimate	Minimum Area of Occupancy
<i>Helarctos malayanus</i>	3,177,677	7	7
<i>Melursus ursinus</i>	1,668,052	15	15
<i>Tremarctos ornatus</i>	1,677,691	20	19
<i>Ursus americanus</i>	25,873,680	1,313	1,294
<i>Ursus arctos</i>	52,688,650	4,100	4,056
<i>Ursus maritimus</i>	22,606,197	445	443
<i>Ursus thibetanus</i>	12,545,802	9	9