Binned Relative Environmental Change Indicator (BRECI): A tool to communicate the nature of differences between environmental niche model outputs

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Abstract

Niche models are now widely used in many branches of the biological sciences and are often used to contrast the distribution of favouroble environments between regionsa or under changes in environmental conditions such as anthropogenic climate change. Model performance and quality assessment are accepted as best-practice when using these models. One aspect that has received far less attention is developing methods to communicate the degree and nature of changes between model outputs (typically as raster maps). The method described in this paper, Binned Environmental Change Index (BRECI), seeks to address this shortfall in communicating model results.

Models of the realised niche of organisms are now routinely used to relate species occurrence to environment in fields as diverse as ecology, population genetics, biogeography and comparative studies. Just as diverse is the terminology which includes ecological or environmental niche model (ENM, a term used in this paper), species distribution model (SDM, resource selection models (RSMs) and habitat suitability model (HSM).

Many methods are available to fit ENMs and, when strict assumptions are met (Fithian and Hastie 2013, Hastie and Fithian 2013, Guisan et al. 2017) an ENM can produce a map indicating the probability of occurrence of the target organisms. However, these conditions are rarely met in practice (Guisan et al. 2017). In all circumstances a well-fitted ENM can provide a map showing the degree of environmental suitability.

A frequent use of ENMs is to contrast environmental suitability between two time periods to assess the potential impact of changed environmental conditions, typically related to climate change. Comparison of ENM output maps for the two times may provide insight into the degree of change, and its spatial distribution, and thus inform management responses. However, few studies have provided a way of communication the nature of differences between ENM ouputs.

In this note we introduce a new graphical tool, the Binned Relative Environmental Change Indicator (BRECI) to assist in understanding and communicating the nature of differences between pairs of ENM output maps. I define the method for computing BRECI, illustrate its application, briefly discuss its use in relation to evaluating model performance and statistical map comparison, and provide *R*-code for its computation.

A recipe for BRECI

When two rasters are available for comparison and both have the same raster geometry (grid origin, grid cell size, map projection and coordinate system) and the same environmental suitability scale, proportional change values may be computed for an arbitrary set of environmental suitability bins which partition the suitability scale into values from "low" to "high". Both the number of bins used and the suitability values defining bin widths are arbitrary parameters which may be adjusted to suit the task at hand. When these parameters are set, computing a suite of BRECI values proceeds as follows:

1. For each of two ENM output rasters to be compared, *Map1* and *Map2*, replace cell values with the index of the bin into which they fall;
2. For each bin, compute the proportional or relative change in the number of grid cells between the two maps relative to the number cells in that bin on *Map1*:

$$BRECI_i = (Map2\_Count_i - Map1\_Count_i)/Map1\_Count_i$$

The sign of the *BRECI* value in each bin indicates gain (positive values) or loss (negative values) of environmental suitability. The most frequently applied ENM tool, MaxEnt (Phillips and Dudík 2008), by default produces suitability scores transformed to a 0 (no suitability) to 1 (maximum suitability) scale. A reasonable but arbitrary number of bins is five equal-sized bins producing bin cut-points at 0.2, 0.4, 0.6, 0.8. The bins can be loosely but reasonably interpreted as shown in Table 1. A similar scheme can be applied to maps based on any suitability scale.

The *R*-script in supplementary material represents a workable first approximation to applying the BRECI method to the logistic- or cloglog-scaled output of the MaxEnt method. Possible refinements include making the colour palette user-definable (and thus allowing the selection of colour-blind friendly palettes), and allowing the user to select the number of bins and the value of cut-points. These enhancements and more should be accessible to users with modest *R*-scripting skills.

Application of the method

The application and interpretation of BRECI plots is illustrated by applying it to three plant taxa occurring in south-east Australia: *Wilkiea hugeliana* (Tul.) A.DC. (Tul.) A.DC. (Family Monimiaceae), *Pittosporum undulatum* Vent. (Family Pittosporaceae), and *Acacia linifolia* (Vent.) Willd. (Family Fabaceae).

For each taxon, herbarium occurrence records were obtained from the Atlas of Living Australia (ALA, www.ala.org.au) and cleaned to remove records of cultivated specimens, duplicate occurrences, missing spatial coordinates, and obvious geographical outliers. To reduce the possible impact of spatial sampling bias, occurrences were thinned using an adaptation of the method used in the function *ecospat.occ.desaggregation()* in the *R*-package ecospat (Di Cola et al. 2017). MaxEnt models were fitted using version 3.3.3k of the software (https://github.com/mrmaxent/Maxent/tree/master/ArchivedReleases/3.3.3k) with 10 cross-validation runs, default regularization setting, and hinge and threshold features turned off so that only linear, quadratic and product features were available. Background points were selected from a region restricted to be near existing occurrence records using an adaptation of the method of VanDerWal et al. (VanDerWal et al. 2009). Climate data for current conditions was supplied by the ANUClimate data set (http://dapds00.nci.org.au/thredds/catalog/rr9/ANUClimate/catalog.html) from which the basic 19 Bioclim variables were computed (Nix 1986, Busby 1991). Future climate conditions were downscaled from ESM/GCM models forming part of the data supporting the IPCC Fifth Assessment Report (IPCC 2014).

BRECI, model performance and map comparison

In contrast to the rich literature dealing with image comparison and map comparison generally, there are relatively few papers which consider raster map comparison with respect to ENM fitting. However, there is still a diversity of approaches in the literature which maybe grouped according to whether they used binary rasters, or directly compare the continuous-valued rasters output by ENM software.

Converting ENM output to binary form requires the application of a threshold value and selecting an appropriate threshold is a significant challenge (Liu et al. 2005, Freeman and Moisen 2008, Nenzén and Araújo 2011) and may mask important differences in the distribution of marginal environmental suitability. Even though it is problematic, thresholding is widely used and several methods are available to compare binary maps. Simple counts of pixels classed as "suitable" or counts of pixels considered suitable in both maps may be made (e.g. Mellick et al. 2014). Alternatively, more sophisticated statistical comparisons maybe made (Robertson et al. 2007).

Methods for the direct unthresholded comparison of raster maps such as ENM output maps include statistical tests of pixel (grid cell) differences (Levine et al. 2009) and other moments of pixel values (Wealands et al. 2005, Jones et al. 2016), measures of niche overlap and adaptations of the Hellinger distance between probability distributions (Warren et al. 2010, Wilson 2011), threshold-free measures of range shift and overlap (Kou et al. 2014), and simple correlation between rasters (Wealands et al. 2005, Syphard and Franklin 2009)

A range of model performance measures are used to determine the quality of ENMs including the Area Under the receiver operating characteristic Curve (AUC) and the True Skill Score (TSS) (Guisan et al. 2017). For presence-only models fitted with the MaxEnt program, Warren and Seifert (2011) also introduced an AIC-like measure. Application of any of these performance measures to model comparison or criticism is valuable, is strongly recommended as best practice, and is an active area of research and debate. However, no one measure can capture all aspects of model performance (Guisan et al. 2017). For example, the most widely applied measure, AUC, has been severely criticised for several short-comings (Lobo et al. 2008, Hand 2009).

One aspect of model comparison which has received less attention is the direct comparison of spatial outputs by some method of map comparison. One motivation for direct spatially-referenced comparison is that model fits for the same taxon may produce the same or very similar performance metrics (assessed against occurrence records) yet display different spatial distributions of suitability scores across the geographical extent of the model (Wilson 2011). An additional motivation for comparing spatial outputs is that it is frequently not valid to use statistical measures of model performance to compare models for different taxa (Guisan et al. 2017) but the projection of models into geographical space does permit similarities and differences to be examined across taxa. A further motivation is to convey objectively but simply the nature of differences between maps to guide decision making.

ENMs are used most frequently to provide insights into the likely impact of anthropogenic environmental change on species. Model performance metrics and statistical map comparison methods can help convey many aspects of difference between model fits and between their output (i.e. maps) but my own experience suggests that a simple, clear representation of the nature of differences between maps is useful. A motivation for considering the spatial distribution of changes in environmental suitability is that threat assessments and impact mitigation strategies are most likely to be effective if tailored to local conditions.

The Binned Relative Environmental Change Indicator (BRECI) is designed to provide a simple but objective representation of map differences. It allows two aspects of the difference between two maps of environmental suitability: (a) overall visualisation of the magnitude and direction of change, and (b) representation of the nature of that change. In addition, BRECI plots may be produced for the whole model extent or any arbitrary region within it. The most important feature of this method is that it avoids the use of thresholds which have the potential to give a misleading indication of the spatial extent of, and changes in, suitability.

Overall visualisatiuon of ENM map differences can be reduced to a statement about “gain” or “loss” of environmental suitability. Often such statements are made by applying a threshold to the continuous-valued maps produced by ENMs, turning them into binary maps. BRECI allows users to easily understand the degree of “gain” or “loss” without the need to use thresholds. It is possible to provide a ranking of species into categories such as “severe loss”, “moderate loss”, etc. In many instances this is acceptable for triage decisions or for indicating the way members of species ensembles or ecological assemblages may face disparate futures. As noted earlier, it is also possible to produce a BRECI plot for the entire extent of a fitted model, or arbitrarily defined spatial sub-sets, allowing assessments of range-wide change to be contrasted with, say, changes within a particular management region or jurisdiction.

The second aspect, visualising the nature of differences, is achieved by partitioning values in the map into a number of arbitrary bins or environmental suitability classes. The relative gain or loss in each bin allows users to see the way suitability changes across the spectrum of values present in the two maps. For example, it is possible to discriminate between pair-wise comparisons showing major changes in all bins with those showing large overall change but where change is dominated by differences in a particular environmental suitability class. These insights into the nature of changes in suitability could then be included in management decisions: Should greater weight be given to taxa suffer large losses of high suitability versus those predicted to face losses of areas of marginal suitability?

Conclusions

BRECI has a number of strengths including: ease of computation, an intuitive interpretation, the ability to convey aspects of difference not easily represented in statistically orientated measures, avoids the potential for errors introduced by applying a threshold to make binary maps, and it may be applied to the output of *any* modelling method which produces environmental suitability scores on raster maps. Naturally, there are some limitations which include: it is not a substitute for model performance measures such as AUC, it is non-spatial (i.e. it does not show on a map where changes occur), it uses an arbitrary sub-division into suitability classes or bins, and it can only compare maps with values on the same suitability scale (e.g MaxEnt logistic scale versus MaxEnt logistic scale) and the same raster geometry (e.g. matching grid cell size, grid origin, map projection and coordinate system). Experience has shown that placing a BRECI plot alongside the two maps being compared is a powerful heuristic tool for communicating the nature of differences between the maps.

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Figure 1: Results of fitted ENMs for (a) *Wilkiea hugeliana*, (b) *Pittosporum undulatum*, and (c) *Acacia linifolia* and associated BRECI plots. Maps on the left are output from an ENM fitted using current climate conditions, and maps to the right show each model projected onto predicted climate in 2050. Details of model fitting and climate data are provided in supplementary material. BRECI plots were computed only for grid cells falling within the border of New South Wales, Australia.

Table 1: Suggested default bin ranges and an heuristic interpretation of suitability values included within each bin.

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Figure 1

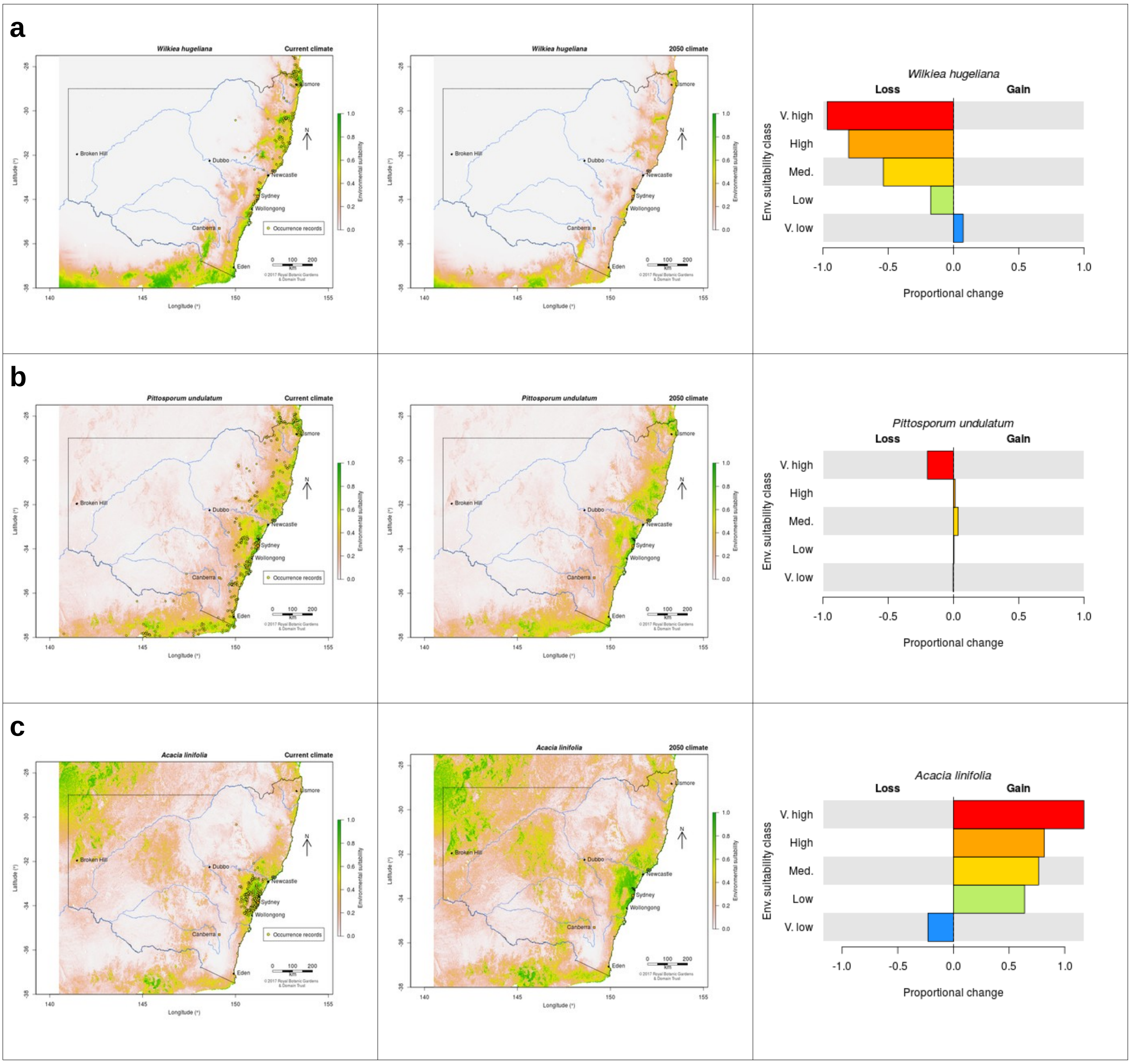

Table 1

Bin	**Range**	**Interpretation**
1	0 – 0.2	Very low suitability
2	0.2 – 0.4	Low suitability
3	0.4 – 0.6	Moderate suitability
4	0.6 – 0.8	High suitability
5	0.8 – 1.0	Very high suitability