SPARC

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Spatial Planning for Area Conservation in Response to Climate Change

Methods Documentation

Principal Investigators

Patrick R. Roehrdanz

Lee Hannah

Guy Midgley

Jon Lovett

Wendy Foden

Richard Corlett

Brian Enquist

Pablo Marquet

Contributing Authors

Yolanda Chirango

Caitlin Kelly

Benedictus Freeman

Alice Ruhweza

Ezequiel Fabiano

Sandra Zenda

Sofie McComb

Cristina Sparks

Eva Marrero

Robert Zomer

Derek Corcoran

Cory Merow

Brian Maitner

Xiao Feng

Simon Scheiter

Simon Ferrier

Tom Harwood

Javier Fajardo

Institutional Partners

Project Overview

Protected areas are the centerpiece of place-based conservation. The Convention on Biological Diversity (CBD) has supported protected areas as a conservation tool since its inception and has reaffirmed this commitment through the expansion of the global conservation estate under the Aichi targets 11. The GEF-recipient countries, GEF agencies, and co-financing partners are among the largest investors in protected area creation and management. However, these investments and their successful application are placed at risk by climate change.

The location of species' ranges will shift due to climate change as species track their unique climatic tolerances. These movements will cross protected area and national boundaries. As species shift, ecosystems will fragment, adjust and re-assemble, affecting habitat coverage and spatial representation across protected areas.

SPARC aims to increase the effectiveness of national protected area networks in the face of climate change by providing information on the movement of key species that reserve networks seek to conserve. This regional perspective is critical for efficient planning and management of protected areas, as it provides the basis for understanding what national actions can be taken independently, and what actions are contingent on the actions of neighboring countries.

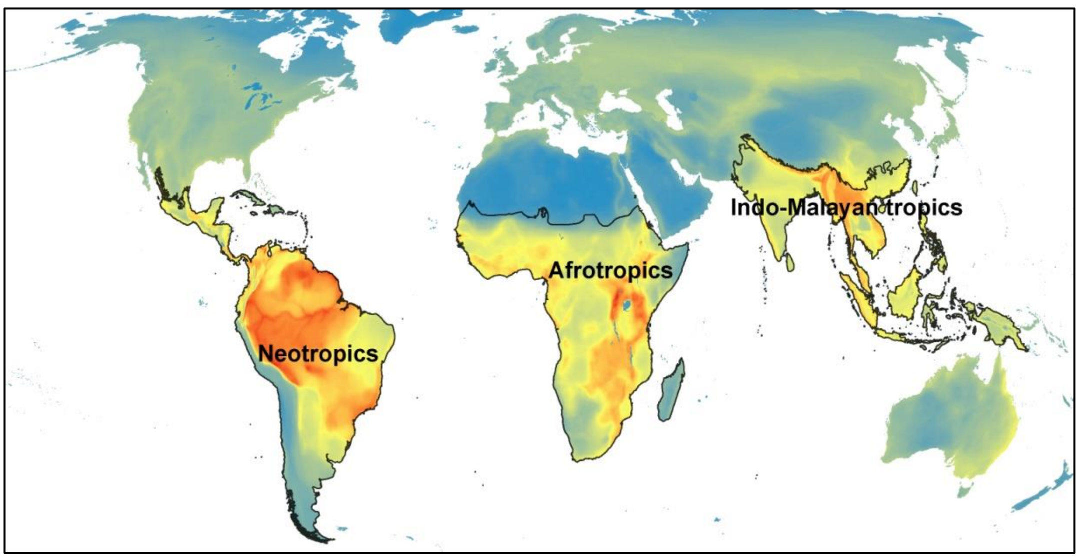


Figure 1. SPARC Project Domain - Three tropical bio-geographic realms (Neotropics; Afrotropics; Indo-Malayan tropics) Blue-Red color ramp shows richness of bird species (red=high; blue=low). Species richness map from www.biodiversitymapping.org.

SPARC brought a big data approach to this problem, modeling tens of thousands of species and using multiple climate change models and datasets. In doing so, the project constructed scenarios of change in the three highest diversity continental tropical regions (Neotropics, Afrotropics, Indo-Malayan tropics) to better understand threats from climate change and opportunities for adaptation of terrestrial protected area networks.

SPARC was implemented over the course of three years and consisted of three project phases: 1) global data compilation and methods evaluation; 2) detailed analysis of climate change impact on species and ecosystems as it pertains to protected areas conducted by top scientists in each region; 3) synthesis and communication of findings to protected areas managers and key stakeholder groups in each region. SPARC has applied state-of-the-science spatial planning tools to help identify candidate cross-border areas for new protection to respond to climate change, as well as zones in which species' movements and ecosystem changes will best be addressed by management of existing protected areas. Through the outputs of the completed project SPARC aims to continue to provide comprehensive analysis and decision support for terrestrial protected areas planning in the face of climate change for countries across the three biogeographic realms.

SPARC project implementation was led by a core team from Conservation International consisting of a Principal Investigator (Dr. Lee Hannah), Managing Scientist (Patrick Roehrdanz), with financial and administrative professionals. This core team was advised by a Science Advisory Panel comprised of leading climate-impact and protected area planning scientists with representation from the selected geographies.

Three lead regional scientists will aid in the global data compilation and were responsible for coordinating the detailed assessments in each region. The regional lead scientists for the SPARC project are: 1) Neoptropics -- Dr. Pablo Marquet (Catholic University of Chile); 2) Afrotropics – Dr. Guy Midgley (Stellenbosch University); 3) Indo-Malayan tropics – Dr. Richard Corlett (Xishuangbanna Tropical Botanical Gardens; Chinese Academy of Sciences). In addition, three representatives from international advisory institutions provided guidance for data compilation, methods selection and large scale implementation of the analytical methods. International data advisors that participated in SPARC are: 1) Dr. Jon Lovett (University of Leeds); 2) Dr. Brian Enquist (University of Arizona; BIEN); 3) Dr. Wendy Foden (Stellenbosch University; IUCN Species Survival Commission Climate Change Specialist Group).

Project Objectives and Structure

Global data compilation and methods recruitment

The first phase of the project was dedicated to assembling the best available datasets in each region, recruiting and evaluating analytical methods to be used in common across all regions and developing analytical workflow and data management protocols. Datasets that were gathered include species occurrence records, expert verified species ranges, species traits and phylogeny, land cover, protected areas layers, climate surfaces, dynamic global vegetation model outputs and many others.

Occurrence records for plant species are a particular focus for SPARC as plant species are underrepresented in other large-scale species modeling and conservation planning efforts. SPARC partnered with the Botanical Information and Ecology Network (BIEN) which has developed innovative techniques to produce a global database of plant occurrence records that have been taxonomically and geographically verified. The BIEN database served as a foundation for species modeling efforts. The SPARC has leveraged the existing informatics infrastructure to recruit additional occurrence records that were previously not within the BIEN database to further improve both geographic and taxonomic coverage.

The conservation planning tool Zonation software served as the primary method for spatial prioritization as it able to simultaneously prioritize 1) species current ranges; 2) species projected future ranges. Zonation prioritizations were conducted using all available species range data for all three continental regions and all identified multi-country focal regions. Zonation runs were conducted both with individual climate models but also through techniques that directly account for the uncertainty of model projections.

To identify priority areas for conservation under climate change, SPARC used two novel methods: 1) Conservation Prioritization using Network Flow (CPNF); 2) Marginal Benefit of Protection Index (MBPI). CPNF is an algorithm that optimizes protected areas through time for large numbers of species for a given set of conservation targets and land acquisition costs. A valuable aspect of CPNF is that conservation targets must be met at each modeled timestep and therefore captures the entire temporal trajectory of a suite of species responses to climate change.

As an alternative to a prioritization based on species models, MBPI is a novel method that has been developed by CSIRO that makes use of their global generalized dissimilarity model. MBPI evaluates the benefit of adding each 1-km grid cell to the protected area portfolio under climate change. Grid cells that are the likely destination comparatively greater numbers of species and/or relatively rarer climates will receive greater weight in the index. SPARC is the first large scale implementation of MBPI which offers a distinct prioritization metrics for vascular plants, vertebrates and invertebrates.

Regional Assessments

Detailed regional assessments began 2017 and brought expertise of regional scientists to bear on an analysis of protected areas and climate change. Regional assessments were conducted by the SPARC regional PI and an assembled team of top scientists throughout each region. Regional assessments each began with an inception meeting to launch the analysis and conclude with a synthesis meeting after roughly 1.5 years of regional work.

Within each regional assessment, loss of species and ecosystem representation was assessed for individual protected areas and opportunities to restore lost representation were identified using methods consistent with the other regions. Although the entire region was analyzed, each regional assessment will identify 2-3 multi-country focal areas that 1) are especially important for conservation under climate change based on region-wide analysis; 2) have scope for adding protected areas; 3) have ongoing or imminent real-world protected areas planning or implementation. Focal areas were modeled at finer resolution and employed additional analytical methods. Stakeholders from the region will be engaged early in the project in an effort to ensure maximum uptake of SPARC results in protected areas decision making.

Synthesis and Communication of Results

Following the regional analysis, SPARC engaged with stakeholders to create country and multi-country research briefs and action plans, enabling more effective and efficient planning processes informed by analyses of climate-induced changes in biodiversity, as well as changes in the major threats to biodiversity. Stakeholder groups were directly embedded into project planning in each region and took part in the production of research briefs so as to maximize the likelihood of national or regional uptake. Scientists as part of each regional assessment team interacted with a range of stakeholders drawn from GEF agencies, civil society, international organizations, government ministries and representatives of local communities that are directly affected by protected area management effectiveness.

Project outputs also included dynamic tools for visualizing and planning protected areas for climate change. System planners are able to see spatial plans that define areas in which new protection can maintain conservation targets even as climate changes. Protected areas managers will modeled outputs that identify species likely to decline and areas potentially in need of special management to cope with climate change. These SPARC contributions aim to support national protected areas systems that maximize representation of species and ecosystems as climate changes and hence bolster the resilience to climate change of tropical countries across the selected geographies.

Climate Data and Scenarios of Climate Change

Gridded surfaces of both baseline and projected future climates are fundamental inputs for virtually all SPARC analyses and outputs. This combined list of up to 10 GCMs from all three regions will be used to drive initial centralized calculations and modeling efforts including climate exposure metrics, species distribution models, and dynamic global vegetation models. All analysis will be conducted under RCP 2.6 and 8.5 to form low and high emissions scenarios respectively. Worldclim downscaled baseline and projected climate grids for CMIP5 (30 arc-second, 2.5 arc-minute, 5 arc-minute) will be used for pan-tropical analysis with the aim of using the finest resolution that is technically feasible.

Table 1 – Downscaled Global Climate Models used throughout SPARC

Model	Model Code	RCP2.6	RCP8.5	Source
access1.0	ac		x	Worldclim v1.4
bcc_csm1.1	bc	x	x	Worldclim v1.4
cnrm_cm5	cn	x	x	Worldclim v1.4
gfdl_cm3	gf	x	x	Worldclim v1.4
mohc_hadgem2_es	he	x	x	Worldclim v1.4
ncar_ccsm4	cc	x	x	Worldclim v1.4
lasg_fgoals_g2	la	x	x	CCAFS
ncc_noresm1_m	no	x	x	Worldclim v1.4
miroc-esm	mr	x	x	Worldclim v1.4
mpi-esm-lr	mp	x	x	Worldclim v1.4

A majority of SPARC analysis used downscaled 20-year climate normal available from Worldclim v1.4 for mid-century (2040-2060) and late century (2060-2080). However, decadal time slices were interpolated for use in analysis that required finer temporal scale representations of change – for example in the spatial prioritization method network flow.

Climate Exposure Metrics

As a primary means of assessing and communicating climate change impacts on protected areas and areas of potential protected areas expansion, the SPARC project will produce several metrics of exposure to climate change. In its most simple form, climate exposure can be expressed in terms of projected change in mean annual temperature, mean annual precipitation or other relevant bioclimatic variables for a given region across multiple scenarios of change. While this straightforward approach is instructive in conveying the magnitude, direction and uncertainty of projected change for a particular location, SPARC will also produce metrics that assess the climate more holistically (i.e. not using individual variables) and that incorporate topo-climatic processes that influence how a species or ecosystem may be able to respond to climate change. The additional metrics of climate exposure SPARC will produce can be broadly grouped into three categories: 1) velocity of climate change; 2) novel and disappearing climates; 3) climate stability.

Velocity of Climate Change

Originally described and implemented globally in Loarie et al. 2009, the velocity of climate change is a metric that combines the temporal rate of climate change with the spatial rate of climate change as one moves across the landscape. In other words, the velocity of climate change describes the rate at which an organism would need to disperse in order to keep pace with a suitable climate envelope. Under the same rate of climate change (e.g. projected temperature increase), organisms in areas with low topographic diversity would need to disperse much more rapidly to remain within suitable climates than organisms in areas of high topographic diversity. As such, the exposure to climate change a species or ecosystem experiences can be tied to the velocity of climate change as compared to its ability to disperse.

Velocity of climate change can be assessed primarily in two ways: 1) local neighborhood statistic (e.g. Loarie et al. 2009); 2) nearest analog climate search (e.g. Hamman et al. 2015; Carroll et al. 2015). The local neighborhood statistic is essentially the ratio of the temporal rate of projected change (e.g. °C/yr) to the spatial rate of change across the landscape (analogous to slope). The local neighborhood statistic has advantages in that is computationally feasible and clearly captures broad patterns of climate velocity. However, this method can underestimate the distance an organism would have to move to actually reach a region of similar climate (e.g. isolated mountain tops; climate dispersal dead ends near the coast or tip of continents).

The nearest analog search method does account for the absolute distance between climate analogs in current and future timesteps and therefore is perhaps a better representation of how a species or ecosystem would experience climate change vis a vis dispersal capacity. However, the metric is inherently sensitive to how climate analogs are defined.

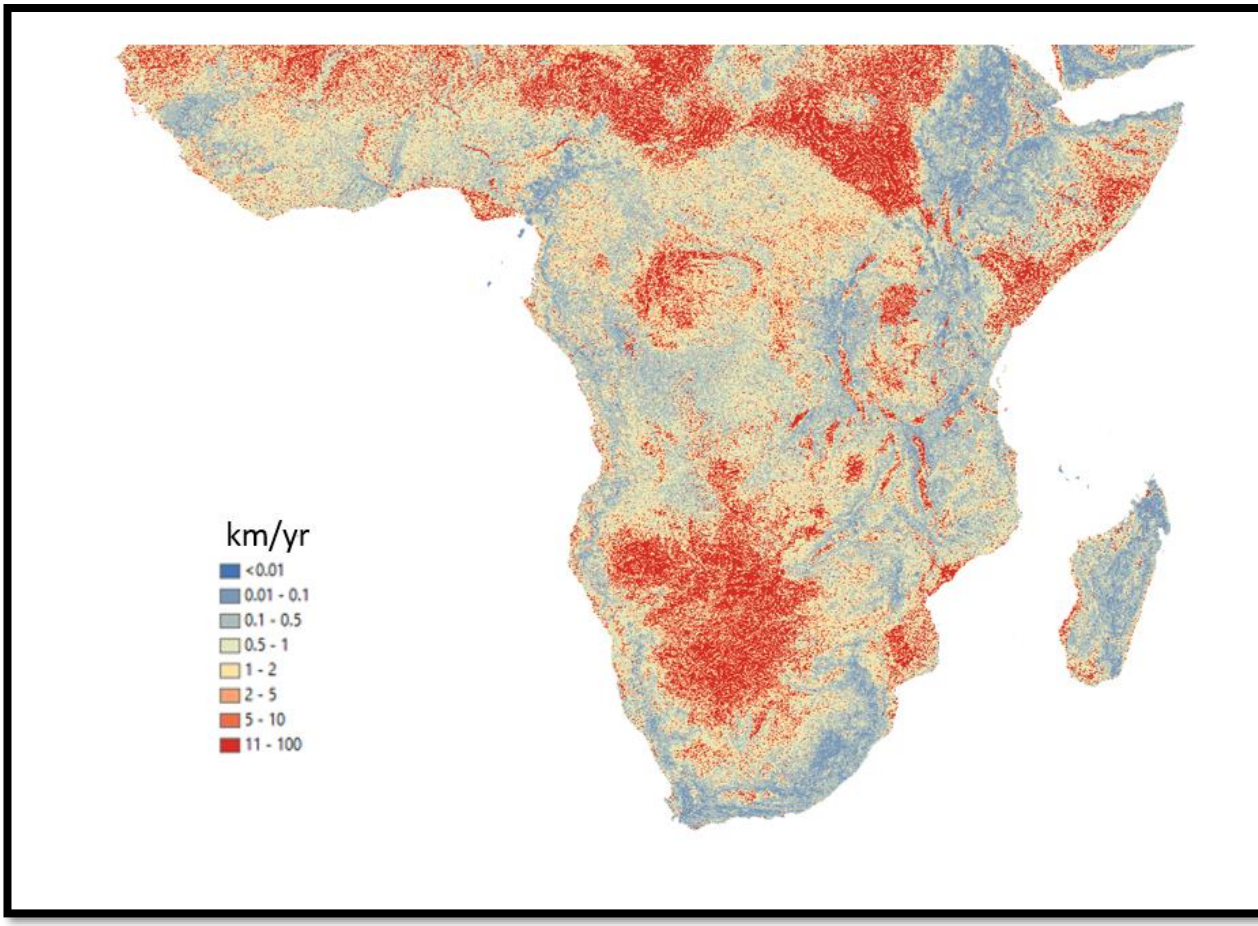


Figure 2. Velocity of mean annual temperature change for Africa using the neighborhood statistic method (Loarie et al. 2009). Areas in orange-red have velocities of temperature change that exceed 1km/year – meaning a species or ecosystem type would have to be able to disperse at that rate to track similar temperatures to current conditions. Areas in blue have much lower velocities and are there fore areas where species will not need to disperse as rapidly to keep pace with changing conditions. It should be noted that mean annual temperature is only one possible dimension of climate change and barriers to dispersal may exist even in areas of comparatively lower velocity of change.

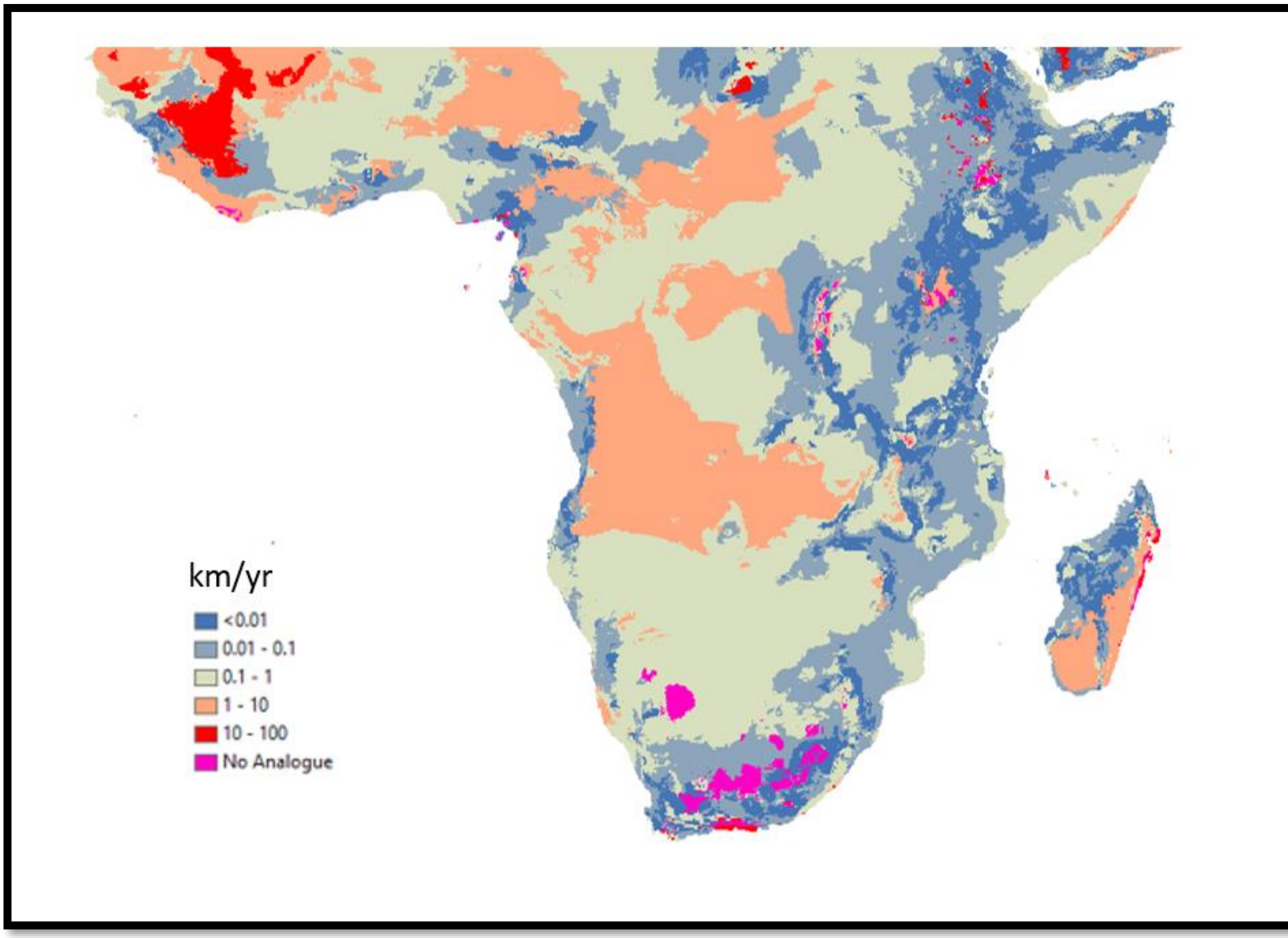


Figure 3. Velocity of multivariate climate change for Africa using the nearest forward analog method implemented as described in Hamann et al. 2014. As with Figure 1, areas in red have a more distant future analog (high velocity) whereas blue areas have a more proximate future analog (low velocity). Areas in bright pink have a nearest analog climate >10,000km distant and are therefore areas with no future analog.

Climate Stability Index

As a more continuous measure of climate change as experienced by ecoregion-level divisions of the landscape, SPARC will use a relative climate stability index as defined in Watson et al. 2013 and Iwamura et al. 2013. The method for estimates the overlap between present and future climate envelopes for each ecoregion. The procedure for the climate stability metric as described in Watson et al. 2013 is:

"The two-dimensional envelopes were determined on the basis of the six bioclimatic variables from the present and future climate data sets using principal component analysis. The distribution of the probability density was estimated for each climate using kernel density estimation, where each cell value of the density space represents a unique vector of climatic condition. The degree of overlap between present and future climate was estimated using a niche overlap measurement technique."

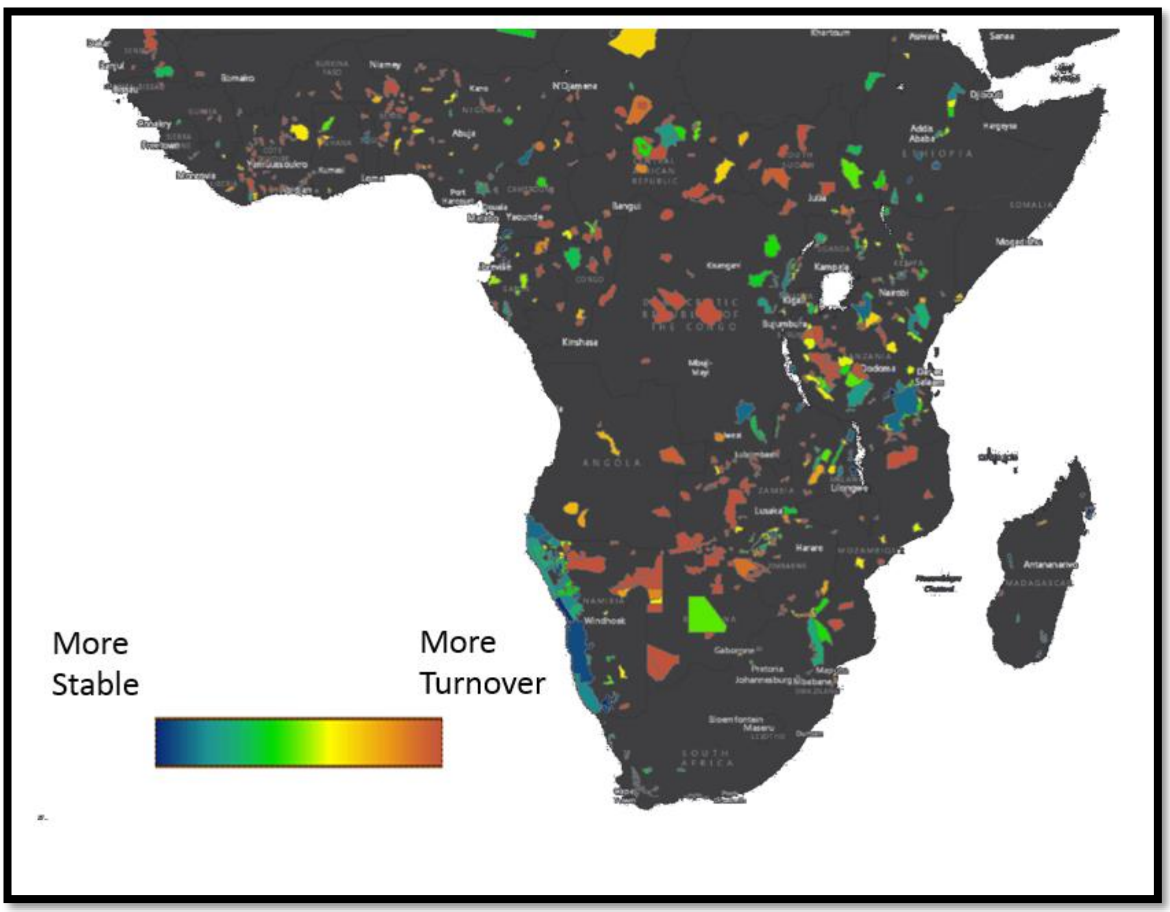


Figure 4. Velocity of multivariate climate change for Africa using the nearest forward analog method implemented as described in Hamann et al. 2014. As with Figure 1, areas in red have a more distant future analog (high velocity) whereas blue areas have a more proximate future analog (low velocity). Areas in bright pink have a nearest analog climate >10,000km distant and are therefore areas with no future analog.

GDM Based Exposure Metrics

SPARC has partnered with CSIRO to make use of their unique method of assessing how climate and other physical characteristics of the landscape relate to overall patterns in biodiversity. Termed Generalized Dissimilarity Modelling (GDM) the approach creates response functions for a series of climate and topographic variables vs. the observed community dissimilarity based on occurrence records for a given taxonomic group. The result is a metric of how climatically similar a given cell is to all other cells in the region of interest.

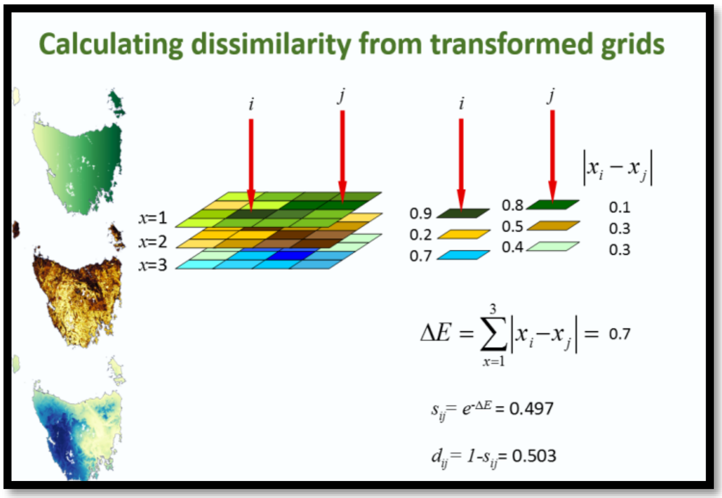


Figure 5. Illustration of dissimilarity calculation from a series of environmental surfaces that have been transformed to represent the relationship to community dissimilarity. Figure provide by Tom Harwood and Simon Ferrier at CSIRO.

GDM is applied at 30 arc-second (~1km) resolution and large scale analysis involves trillions of pairwise comparisons conducted through high performance computing resources. CSIRO will be running models pan-tropically to produce three distinct metrics of climate change through the lens of GDM for vascular plants, vertebrates and in vertebrates.

1) Point change in climate for each grid cell -- this metric simply compares each cell to its future self through the method illustrated in Figure 5. This can be thought of as the exposure to climate change in the variables that are most relevant for biological community turnover.
2) Novel and disappearing climates – this metric compares each cell in baseline climate to all other cells in future climate to produce a continuous metric of 'disappearing climate'. Cells with greater total dissimilarity to all future cells in the domain will have a greater 'disappearing' score. 'Novel' climate scores are calculated in reverse – comparing a cell in a future climate state to all cells in baseline climate.

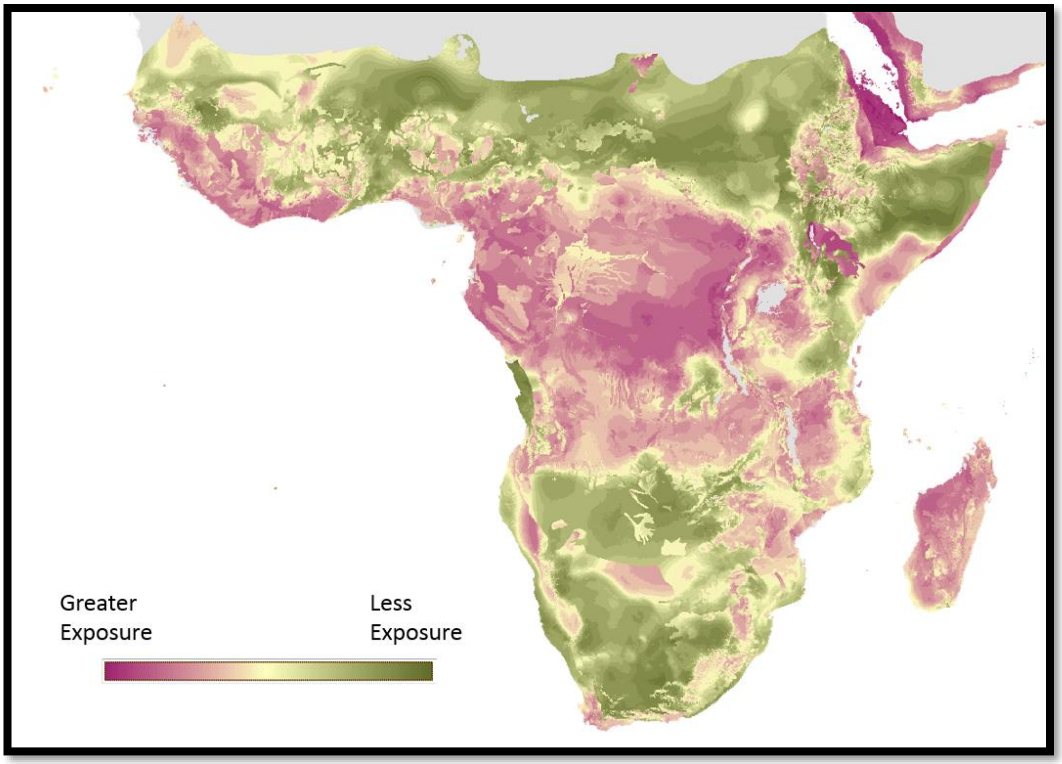


Figure 6. GDM based climate exposure for vascular plants under RCP8.5

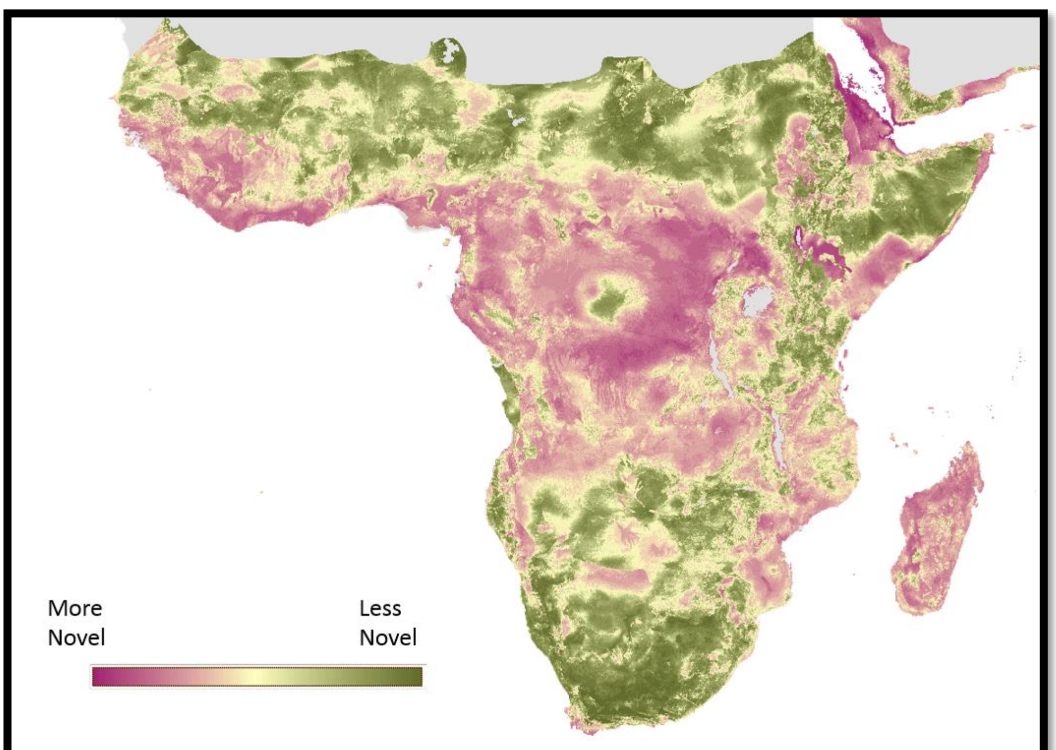


Figure 7. GDM based novel climates for vascular plant under RCP8.5

Ecosytem-Level Change

Environmental Stratification

Continental scale patterns in biome or ecosystem types can be broadly represented by differences in climate. Mapping these differences in climate and how they may change under projections of climate change can therefore provide insight as to how biomes may shift and which biomes may be losing the climate types that support them. Metzger et al. 2013 classified the earth's climate into 125 discrete strata ranging from dry arctic to the hot and wet tropics using a suite of 40 bioclimatic variables. Those 40 variables were screened for correlation globally. The environmental strata were then defined through unsupervised classification on the first three principal components of the remaining variables.

For the SPARC project, Dr. Robert Zomer led an analysis that applied the global strata definitions to projected future climates under two RCPs (2.6 and 8.5), two time steps (2040-2060 and 2060-2080) and the 10 GCMs used throughout SPARC. The resulting maps represent a purely physical proxy for potential biome/ecosystem level shifts under climate change. They also serve to provide a representation of how particular climate types – that are often associated with particular biomes/ecosystems – may expand, contract or redistribute under projections of change. This can communicate the spatial component of climate change in a way a map of projected temperature or precipitation change do not.

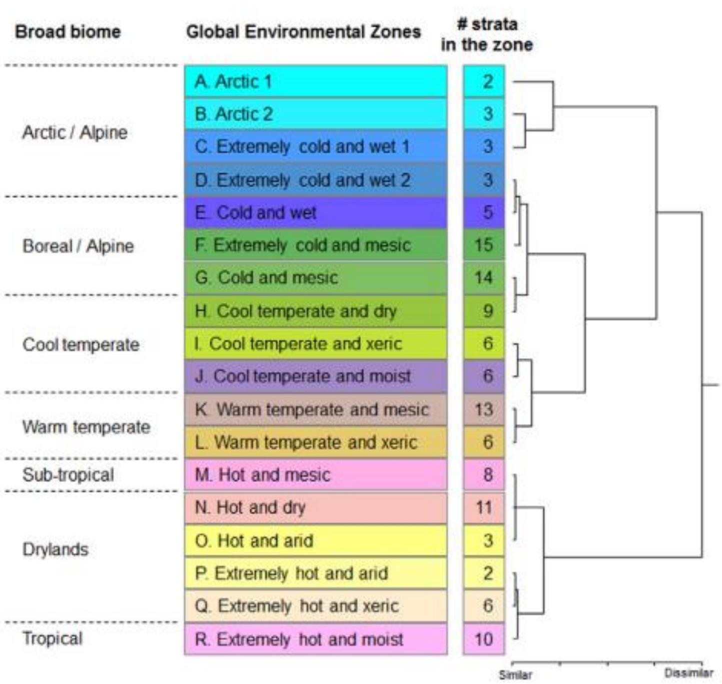


Figure 8. Original grouping and naming of global environmental zones and the number of strata within each zone (from Metzger *et al*. 2013).

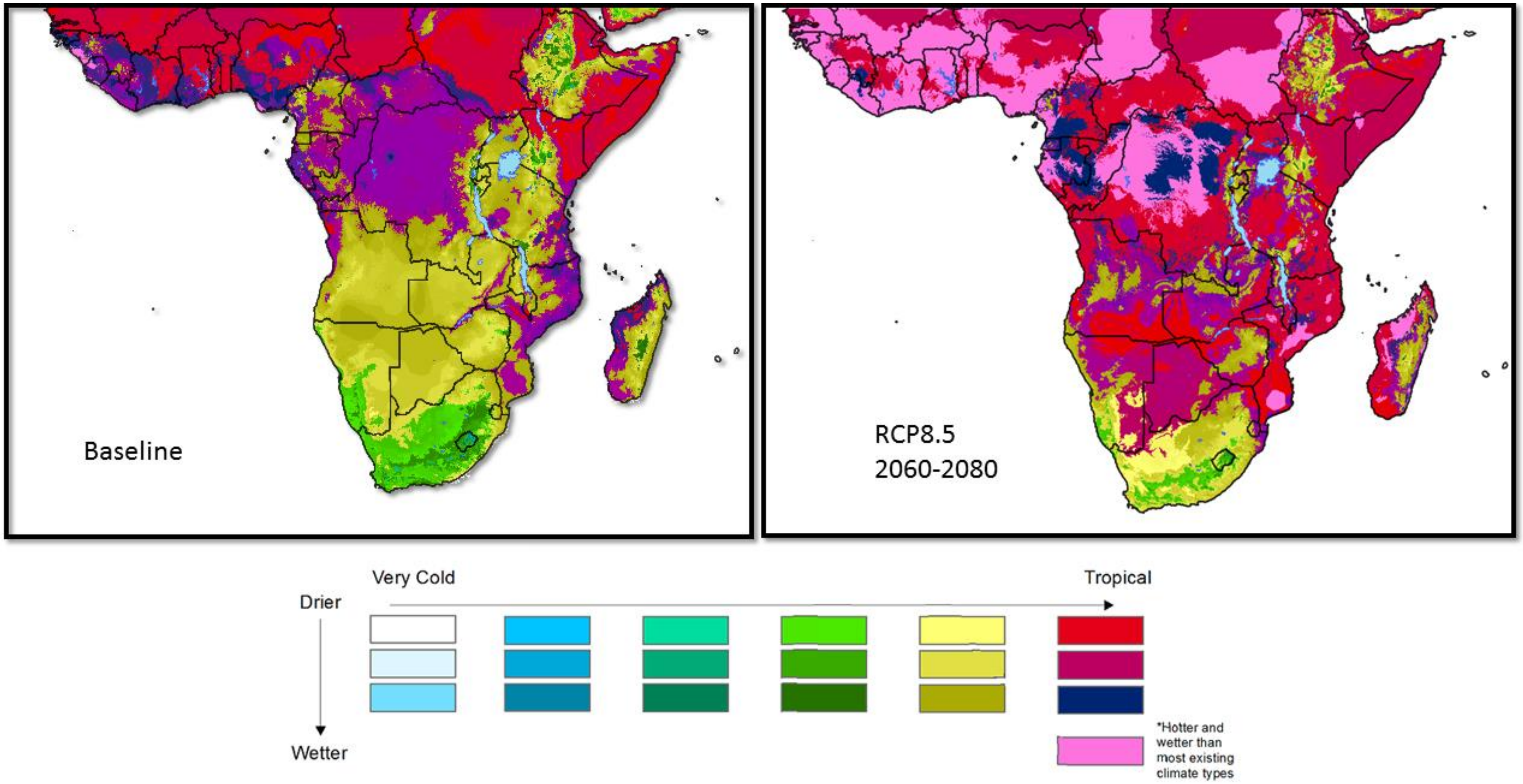


Figure 9. Distribution of environmental strata in the Afrotropoics region for baseline climate (left) and projected future climate for 2060-2080 under RCP8.5 (right). Notable patters are the emergence of a climate strata in the equatorial regions that is tropical but hotter than most existing climates on earth (pink) and the appreciable reduction of comparatively cooler climates (yellows and greens) in montane regions and the southern interior of the continent. Areas with greater turnover in climate types can be considered more exposed to climate change and may see greater impacts on existing ecosystems particularly where adaptive capacity is low.

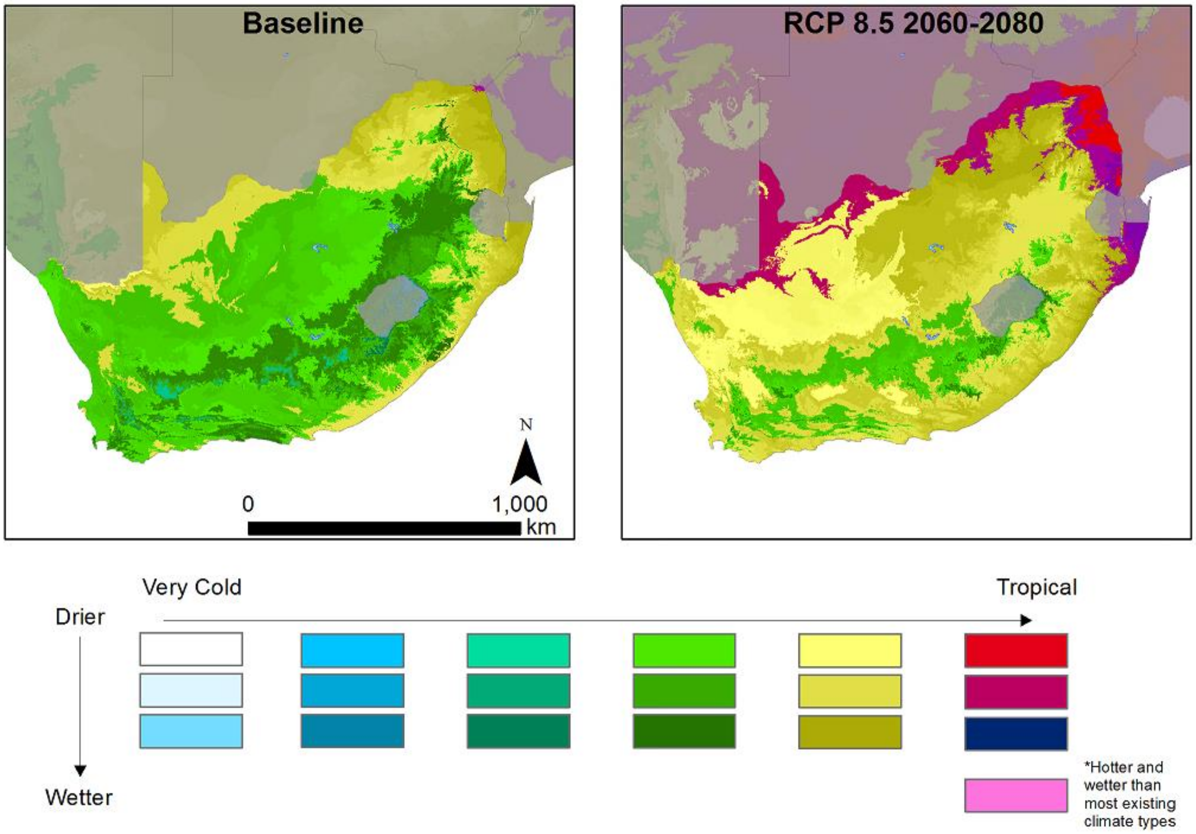


Figure 10. Environmental strata in South Africa for baseline climate (left) and projected future climate for 2060-2080 under RCP8.5 (right). Note that many of the comparatively cooler climates represented in shades of green are dramatically reduced in favor of hotter climate strata represented by shades of yellow. Very hot climate strata (reds and purples) which are quite rare for the country in baseline climate begin to become more common in the northern regions of the country.

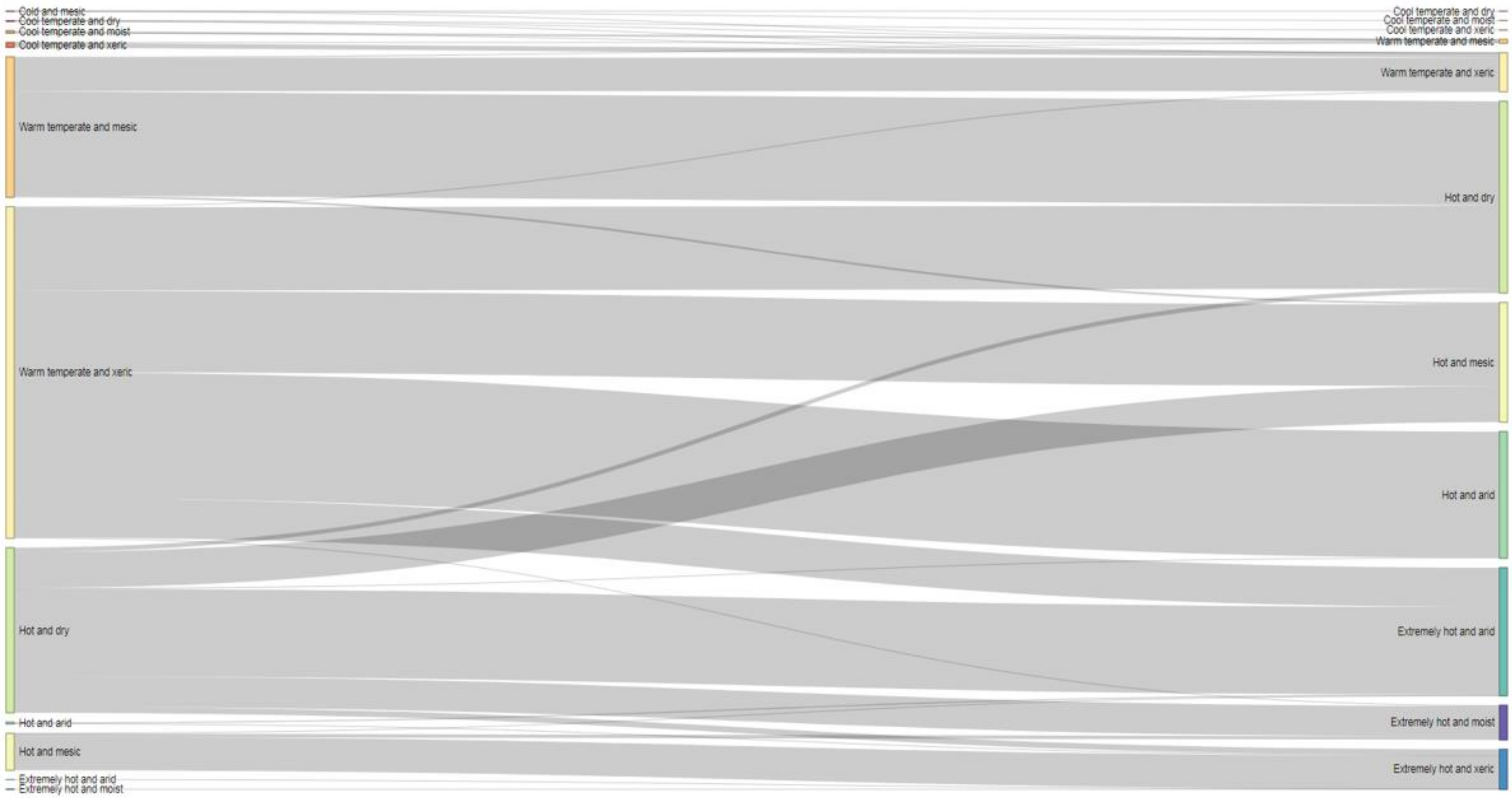


Figure 11. Transition plot of environmental strata in South Africa. Each band depicts the shift of one climate zone (and assemblage strata) in baseline climate on the left to the projected future climate zone (RCP8.5 2060-2080) on the right. In South Africa, many of the 'warm' climate types are almost completely replaces by 'hot' climate types by late century.

Dynamic Global Vegetation Models

As a means of understanding ecosystem-level responses to climate change and to provide important context for individual species model results, SPARC will assemble dynamic global vegetation model (DGVM) outputs for each of the three tropical realms. DGVM model vegetation community responses to climate, nutrient input, disturbance and other variable at daily time intervals or finer. Therefore, DGVM will more completely represent many processes that a strictly correlative models using 20-year climate normals (that will form the basis of our individual species modeling) would miss. Incorporating DGVM into the portfolio of methods that will be used by SPARC is therefore vital to ensure a range of possible outcomes is considered and to provide point of comparison against a species-centric modeling approach.

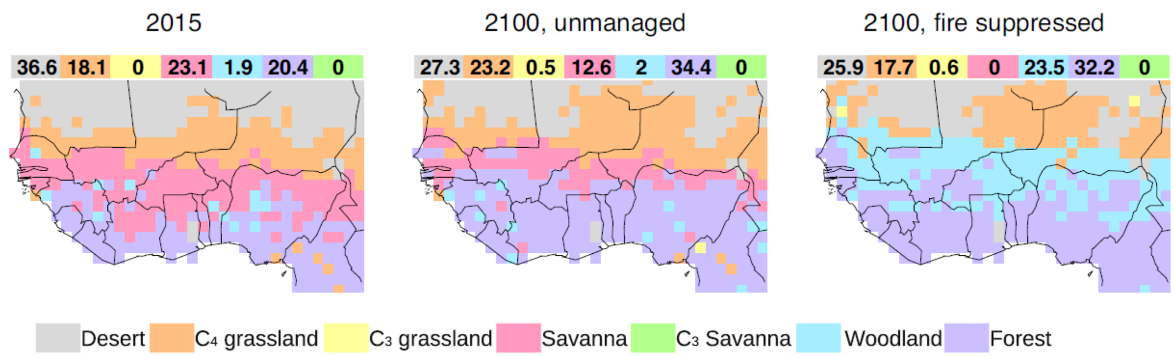
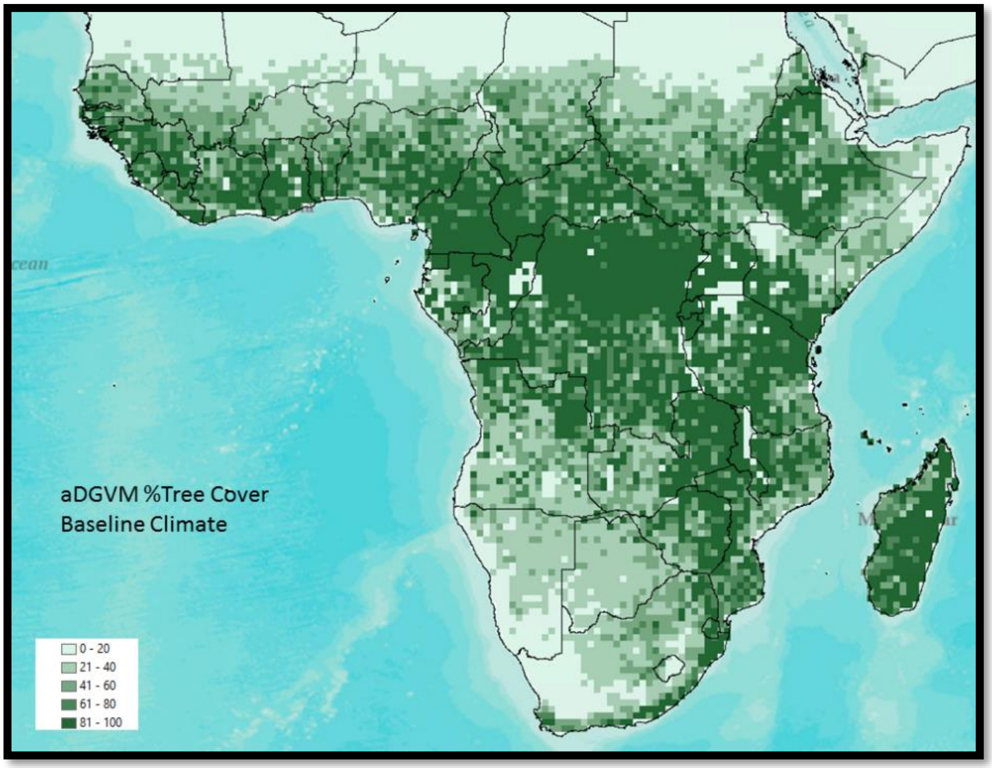


Figure 12. Example aDGVM output that explores ecosystem change in West Africa under alternative fire management regimes. Figure from Scheiter et al. 2016.

SPARC has cultivated a collaborative relationship with the aDGVM team based Frankfurt who have agreed to run both aDGVM1 and aDGVM2 over SPARC regions of interest in the upcoming months. The aDGVM1 model is well parameterized for Africa and is therefore relatively quick to run a model -- at 0.5 degree resolution for Africa it will run overnight generating monthly output for 1950-2100. However, aDGVM2 is likely to do much better over tropical and subtropical South America as it has been well parameterized for the growth forms and particular soil depth and hydrological conditions to allow it to capture well the transition between Forest to Savanna, for example. The aDGVM2 model has a number of innovations relative to the original model, but may involve appreciable customization for application in Asia, where the modeling team hasn't yet done detailed work.



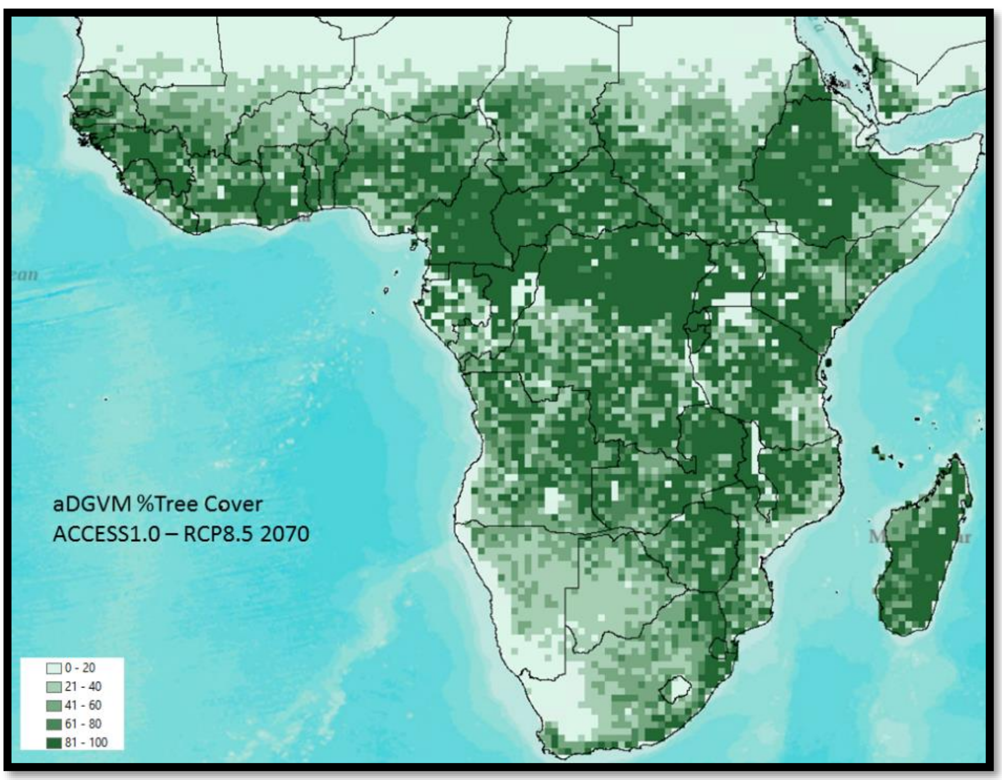
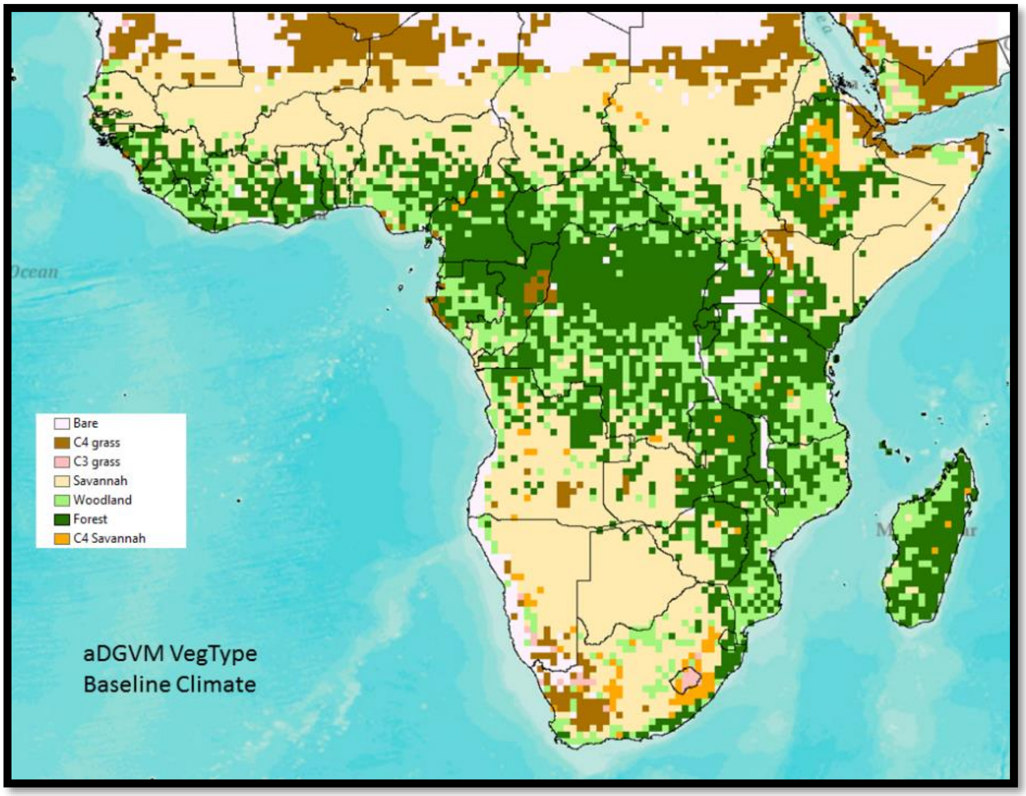


Figure 13. Baseline and projected future % Tree Cover derived from aDGVM (ACCESS1.0 model; RCP8.5)



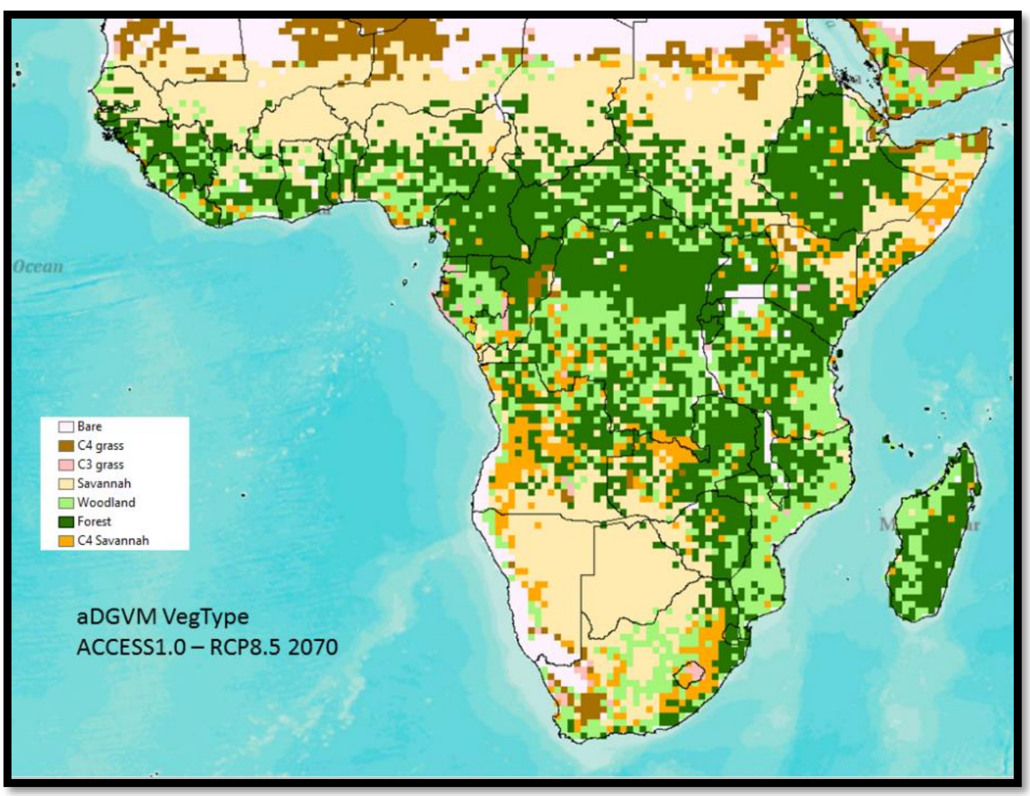
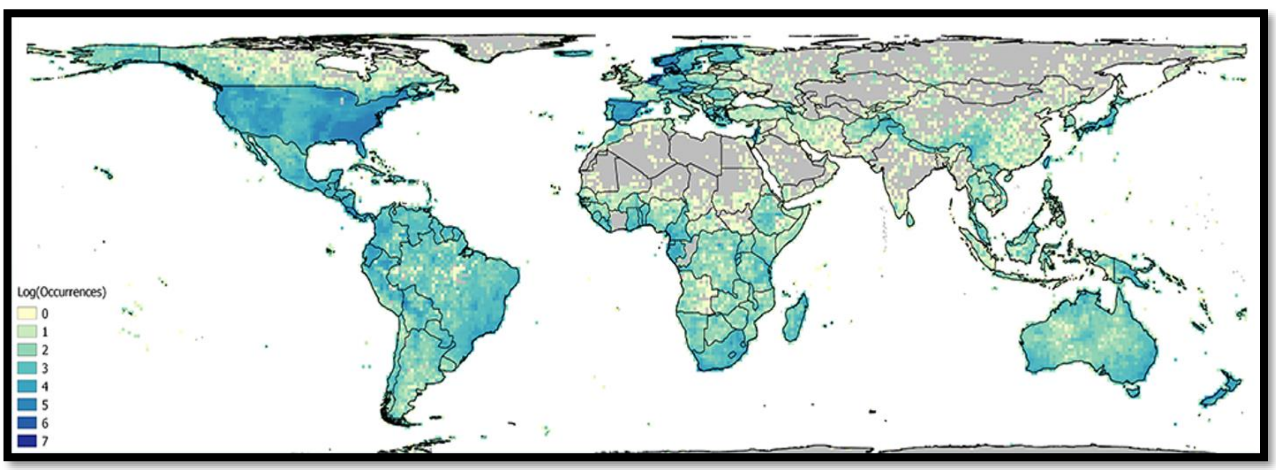


Figure 14. Baseline and projected future vegetation type modeled by aDGVM (ACCESS1.0 mode; RCP8.5)

Species Level Change

A major objective of the SPARC project was to make effective use of advances in ecological informatics and computational efficiency to produce species distribution models for many thousands of plant and animal species across the tropics. Models of species distribution serve as important inputs into assessments of species and ecosystem vulnerability under climate change as well as spatial conservation prioritization algorithms that can help inform protected areas planning decisions.

SPARC has leveraged many years of work undertaken by the Botanical Information and Ecology Network (BIEN) to produce a taxonomically and geographically clean database of plant species occurrences with focus on New World species. Similar efforts that have focused on Africa and tropical Asia were recruited for SPARC analysis and that information was incorporated into the BIEN database and species modelling workflow to the extent possible. The BIEN group also has expertise in working with high performance computing resources which are necessary for modeling this many species within the project timeframe. The SPARC species modelling effort built upon the previous methods the BIEN group has used to produce species range maps with important modifications to ensure optimal performance in producing distribution models under climate change.



Total observations:	100538252
Specimens:	52019375
Plot observations:	17450920
Plots:	114462
Species:	445229

Figure 15. Summary of occurrence records within the BIEN v4.1 database.

Species Distribution Model Methods

Species distribution models were produced using three variant modelling approaches: 1) 1km resolution models that were optimized for computational feasibility to produce models usable for fine scale representation and planning; 2) 10km resolution models optimized for model performance and per-species variable selection; 3) models that incorporate outputs from aDGVM (dynamic global vegetation model described in previous section). All models were fit in baseline climate and projected to future climates across two emissions pathways (RCP 2.6 and RCP 8.5) and 10 GCMs. In summary models were produced for over 110,000 individual species across the three tropical domains.

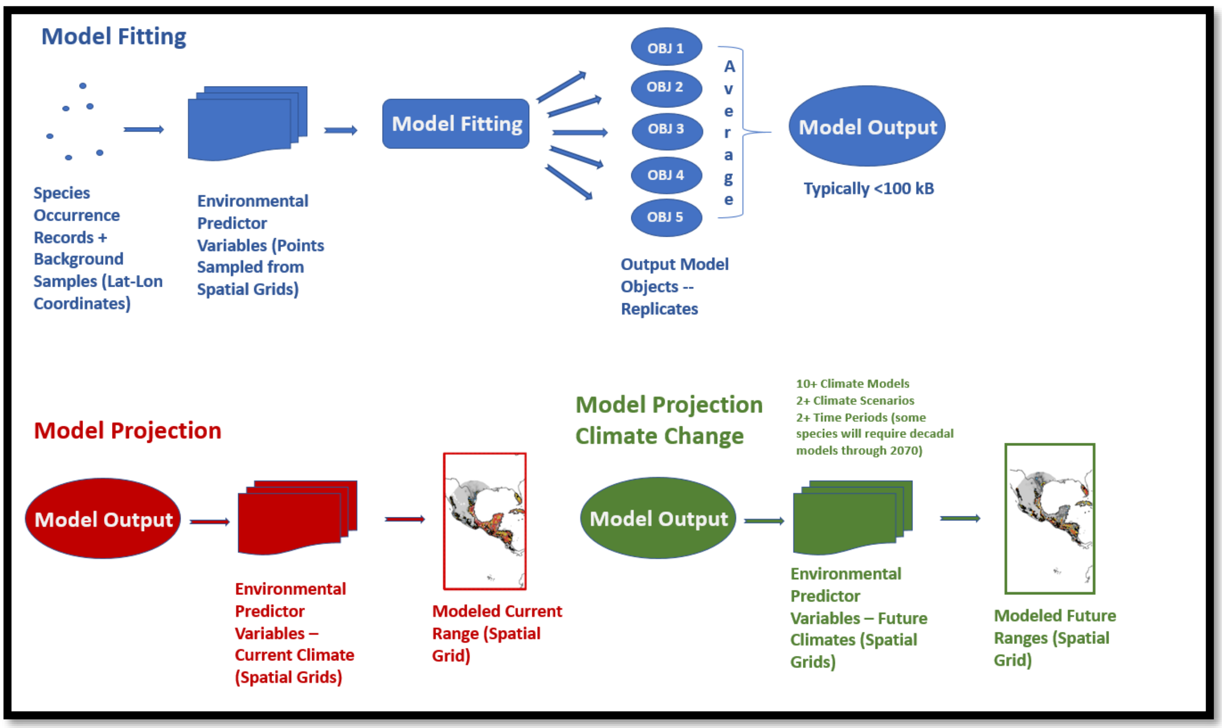


Figure 16. Schematic of Species distribution modeling workflow.

Species Model Method 1: 1km Maxent models

To maximize the number of species that could be represented across two emissions scenarios and 10 GCMs at 1km resolution modelling choices for speed and efficiency without sacrificing accuracy/predictive capacity were used to drive this bulk species modelling effort. Model methods for this variant are summarized below.

Model Settings

- Species data screened for standard taxonomy and geovalid records
- Species distribution models were produced with Maxent (Phillips et al. 2006) for species with >10 unique occurrence records (i.e. unique 1km grid cells in the modelling domain)

- Maxent settings followed the recommendations of Merow *et al*. 2013 and Merow *et al*. 2014 to produce relatively less complex models (e.g. limiting features to linear, quadratic, and product functions) to minimize overfitting.
- Modeling domains were limited to a spatial buffer of 500km within any geovalid occurrence record
- Background sampling for pseudoabsence point was a random sample of 50,000 points
- Five model replicates were used in fitting the model
- Average of five replicates was used for final species model in baseline climate – and those fitted parameters were used for all projections into future climates
- 30% of occurrence records were reserved to assess model performance
- For outputs that used binary models, maximum test sensitivity + specificity cloglog logistic threshold determined the cutoff for presence vs. absence in mapped distributions

Environmental Predictor Variables

Climate Variables

The following bioclimatic variables from downscaled 20-year normals based on pan-tropical correlation analysis and ability to describe the climate for a given location. When presented with the choice of two variables that were otherwise closely correlated, we selected the variable that were not combinations of temperature and precipitation or relied on monthly segmentation of the yearly climate (e.g. precipitation in the warmest quarter).

- Mean annual temperature (BIO1)
- Mean diurnal temperature range (BIO2)
- Seasonality of temperature (BIO4)
- Minimum temperature of the coldest month (BIO6)
- Mean annual precipitation (BIO12)
- Seasonality of precipitation (BIO15)

Accumulated Aridity Index

To account for the effect of dry season length and the water deficit experienced by vegetation during dry periods we derived and accumulated aridity index that identifies the maximum duration and accumulated water deficit for consecutive months where potential evapotranspiration exceeds mean monthly precipitation. The accumulated aridity index was created through the following steps:

- Mean monthly potential evapotranspiration (PET) was calculated for each month in both baseline climate and in projected future climates. Calculation followed the methods of the CGIAR-CSI Global-Aridity and Global-PET Database (http://www.cgiar-csi.org)

- PET = 0.0023 * RA * (Tmean+17.8)* (TD^0.5)
- RA = monthly total extraterrestrial radiation (data from CGIAR)
- Tmean = mean monthly temperature
- TD = mean monthly diurnal temperature range

- Runs of consecutive months where PET > monthly precipitation were identified for each pixel
- The accumulated aridity index is the sum of the month aridity (precipitation – PET) for the maximum run of consecutive months where (PET > precipitation)

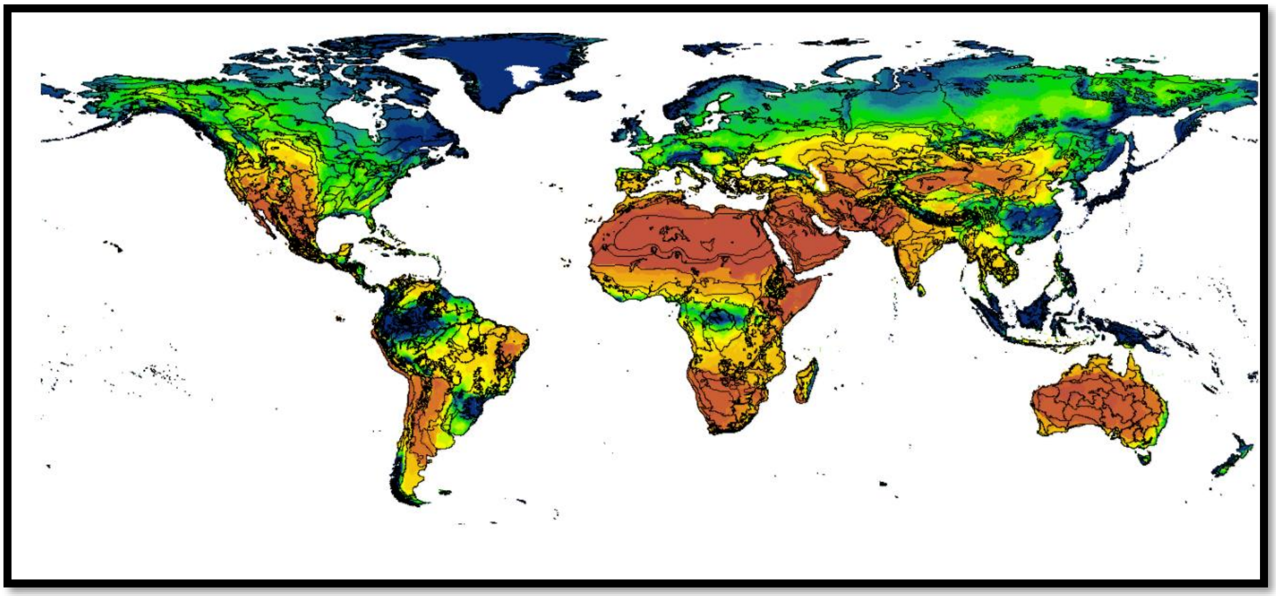
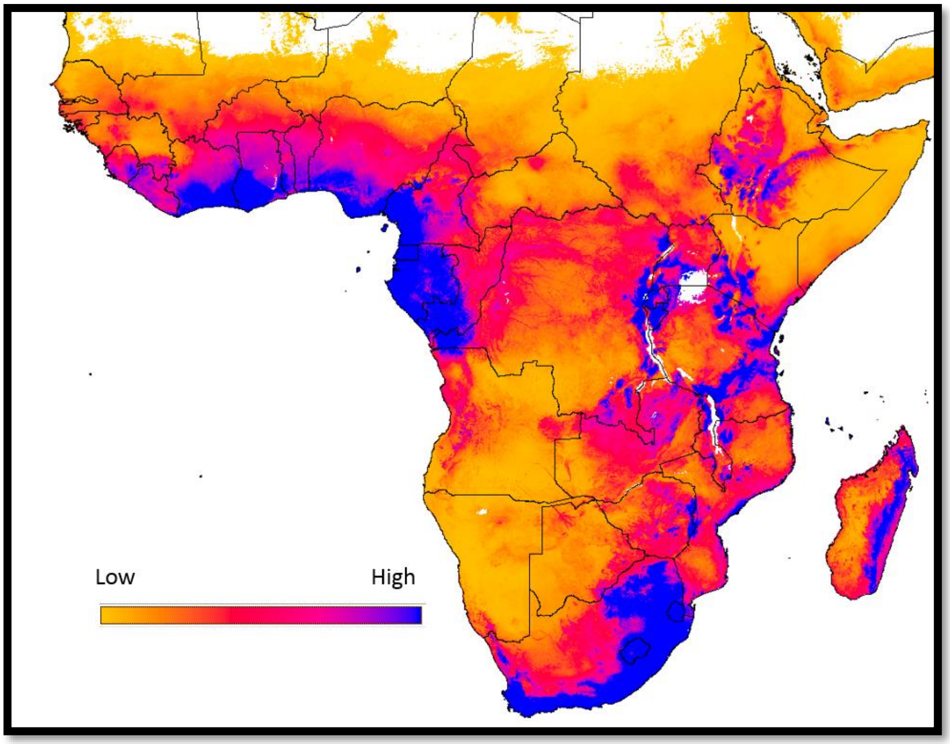


Figure 17. Accumulated aridity index for baseline climate. Color ramp shows Maximum accumulated aridity for consecutive months of PET > mean monthly precipitation. Red = highly arid; blue = no water limited months.

Soils Variables

The following soils variables were used in climate+soils species distribution models. All variables were obtained from Soilgrids (www.soilgrids.org). Variables with multiple strata available are the mean of the top 1m (strata 1-4).

- depth to bedrock
- pH
- clay proportion
- silt proportion
- bulk density



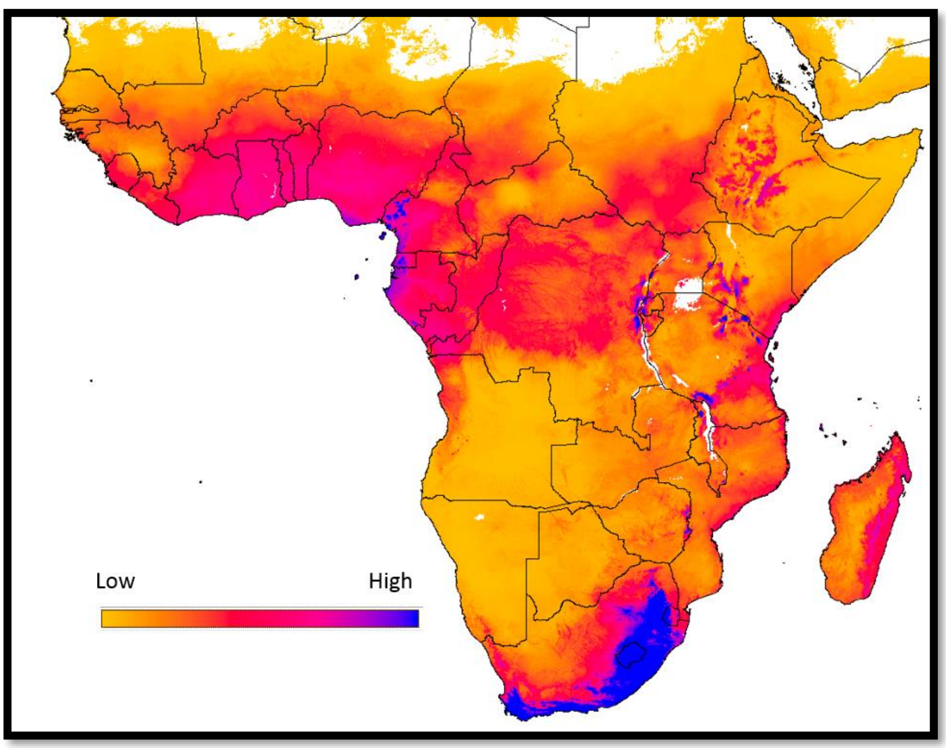


Figure 18. Modeled species richness for vascular plants in baseline climate (top) and RCP8.5 2070 climate (bottom)

Species Model Method 2: 10km Point Process Models

The second species modelling method used for SPARC builds upon previous large-scale species modelling efforts conducted by the BIEN group. This method employs more rigorous methods for cross validation, spatial stratification of model replicates, background sampling approaches and model evaluation. Due to the additional computational expense involved in implementing these features, this method was run at 10km resolution. As with the first modelling methods, models were fit in baseline climate and projected to all future climates for the 10 GCMs/2RCPs across all three continental domains. Due to the prior experience of the BIEN group in modelling plants in the new world, North American plants and vertebrates were all so included in the model batches. A full description of the modelling methods described briefly here is available in Merow et al. in prep and all model outputs will be accessible via the BIEN R package (Maitner *et al*. 2017).

Data Preparation

- Standard taxonomic and geographic validation through BIEN taxonomic name resolution and geographic name resolution services (Boyle et al. 2013)
- Spatially thinned by 20km to minimize spatial biases in sampling
- Spatially stratified for five-fold model replication

Domain and sampling

- Model fitting domain limited to ecoregions with at least one occurrence record retained after data preparation. Ecoregion boundaries were defined by the ecoregions of the world 2017 dataset (Dinerstein *et al*. 2017).
- Projections to future climate scenarios allowed for ecoregions spatially adjacent to the fitting domain.
- Background sampling was a random sample of 3e4

Model Algorithm

- Implemented with 'maxnet' package through custom workflow in R
- Optimal regularization used for each model replicate
- Linear, quadratic and product functions used
    - Simpler functions used if unable to converge on a solution within allotted time

Environmental Variables

- All climate and soils variables use for Species Modelling Method #1 were also used for this method
- Additionally, this method used a derived variable that determines if the majority of rainfall occurs during the coldest part of the year or the warmest. This variable is

particularly useful in discriminating Mediterranean type climate and their distinct flora/fauna

- Variable is calculated as: Precipitation of Warmest Quarter/ Precipitation of Warmest Quarter + Precipitation of Coldest Quarter
    - BIO18/(BIO18+BIO19) using Worldclim variable nomenclature

Binary and Trinary Maps

- Binary map produced with both 5th percentile training presence and the calculated maximum sensitivity + specificity thresholds
- Trinary maps (Merow et al. in prep) use the pAUC values to explore uncertainty in range driven by choice of threshold (see figure x for example trinary map)

Evaluation

- Model performance is evaluated through ten distinct metrics
- Where alternate sampling approaches are employed, these metrics can be used to automatically determine the 'better' performing model

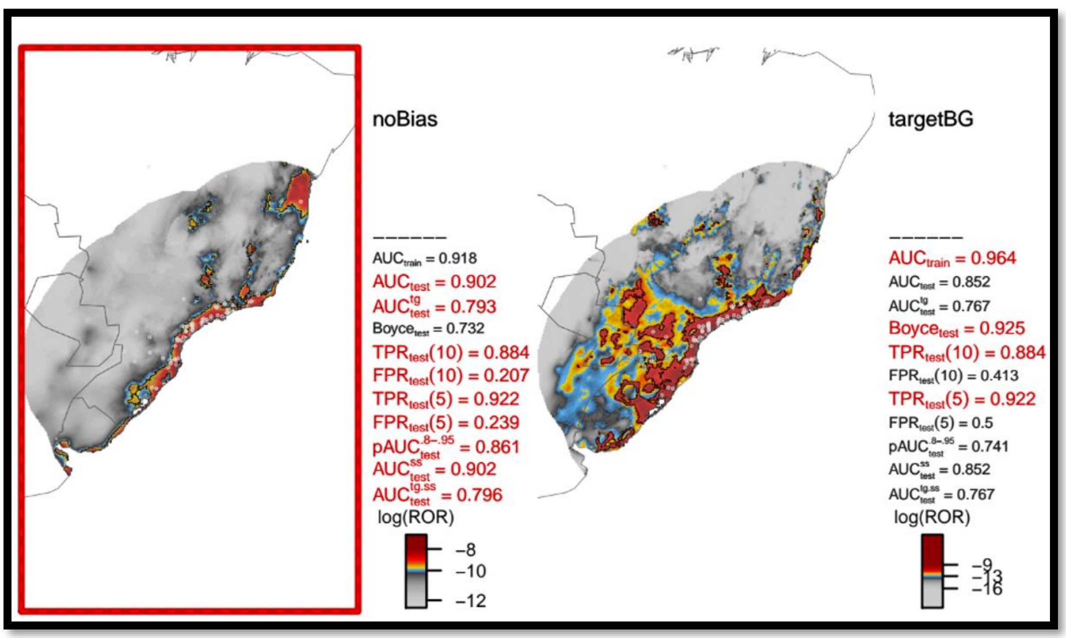


Figure 19. Example species distribution model output comparing random background sampling (left) and target background sampling as means of controlling for spatial sampling bias. Models are evaluated through 10 performance metrics and the better performing model is identified by the red box.

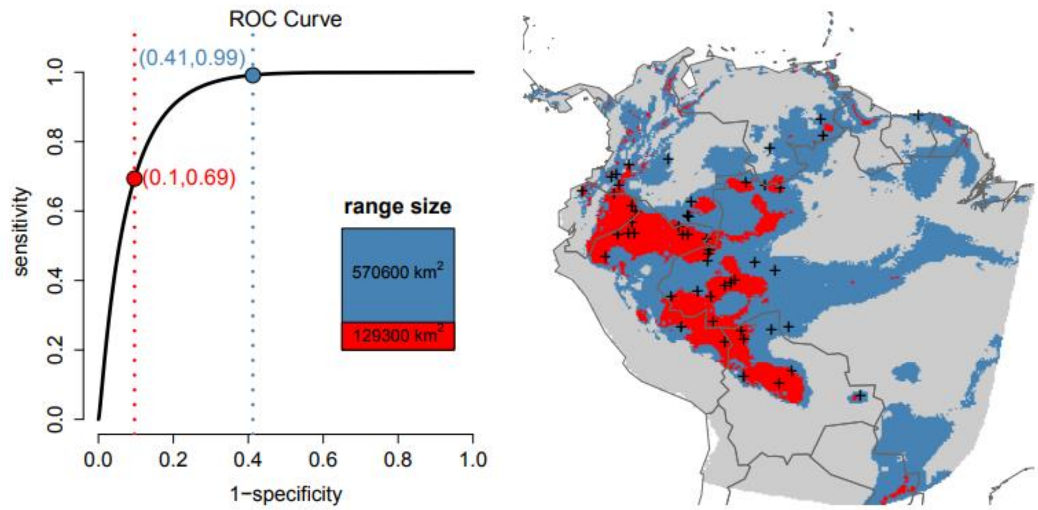


Figure 20. Example trinary map (Merow et al. in prep). Red and blue markers on the ROC indicate the range chosen to explore the effect of threshold choice on binary range map. Range in red indicates a conservative view whereas range in blue shows a less restrictive potential range.

Species Model Method 3: Maxent Models with Dynamic Global Vegetation Model Outputs Included as Predictor Variables

The final species distribution modelling method combined the general approach of SDM Method #1, but also incorporated outputs of vegetation characteristics from aDGVM runs for sub-Saharan Africa. Including the dynamic vegetation variables in the model parameterization in effect incorporates some mechanistic processes such at CO_2 enrichment or fire that a correlative model based on climate and soils variables would not. The DGVM-infused models differ from the climate + soils models primarily in that whereas many individual species may be experiencing declining suitability, if the dominant vegetation type (e.g. evergreen forest) associated with that species is not projected to change, there is a greater likelihood that species will retain suitability in the aDGVM infused model. Vegetation model outputs included in this modelling method were provided by Simon Scheiter and Steve Higgins for use in the SPARC project and are descried in Scheiter et al. 2016.

aDGVM Infused Species Distribution Model Summary

- Included all predictor variables, model settings and species occurrence data used in SDM Method #1 described above.
- Also included the following aDGVM outputs
  - Vegetation type (as a categorical variable)
  - Aboveground biomass
  - Percent tree cover
  - Mean tree height

- Data provided in yearly time steps was aggregated to match the baseline (1960-1990) and future time periods (2040-2060; 2060-2080) of the downscaled climate normal
- Projection data was available for six GCMs
- Baseline for aDGVM variables used was an average across all six GCMs in the 1960-1990 time period.

Source data for species distribution modelling

Plants

- All vascular plants occurrence records in BIEN v4.1 database
    - Data extracted from master database through BIEN R Package (Maitner *et al.* 2017)
    - Occurrence records that did not have the non-native or introduced flags
    - Occurrence records with geovalid coordinates
    - Occurrence records that were likely not a centroid of a political unit
- RAINBIO vascular plant occurrences for tropical Africa (Dauby *et al*. 2016)
- Newly georeferenced localities for Southeast Asia plants (SPARC funded project through Naturalis led by Dr. Niels Raes)

Vertebrates

- Point occurrences for global restricted range bird species (BirdLife International)
- Point occurrences for tropical vertebrates (GBIF, VertNet)
    - Occurrences with geovalid coordinates
    - Occurrences more recent than 1950
    - Human observations only (no fossil records or museum specimens)
    - Political centroids and locations with zeros removed
    - Spatial outliers – more than 500km from IUCN range polygon or >98th percentile of latitude + longitude
- Expert range maps polygons for all available mammals, birds, reptiles (IUCN, BirdLife) – were used as a means of model and occurrence record validation

Spatial Prioritization of Conservation Areas under Scenarios of Climate Change

To identify priority areas for potential new protected areas that will enhance the overall protected areas network effectiveness under climate change, SPARC will use two novel methods: 1) Conservation Prioritization using Network Flow (CPNF); 2) Marginal Benefit of Future Protection Index (MBFPI). CPNF is an algorithm that optimizes protected areas through time for large numbers of species for a given set of conservation targets, dispersal capacities and land acquisition costs. A valuable aspect of CPNF is that species or conservation targets must be met at each modeled timestep and therefore the optimization captures the entire temporal trajectory of a suite of species responses to climate change. MBPI is a novel method that has been developed by CSIRO and is derived from outputs of their global generalized dissimilarity model. MBPI evaluates the marginal benefit of adding each 1-km grid cell to the protected area portfolio under climate change in the context of climate representation in each tropical realm. SPARC will the first large scale implementation of MBPI and will provide distinct prioritization metrics for vascular plants, vertebrates and invertebrates. Each of these methods is described in detail below.

Zonation Prioritization under Climate Change

Zonation (https://github.com/cbig/zonation-core) is a widely used conservation planning tool that allows for simultaneous prioritization of hundreds to thousands of conservation features (i.e. species or ecosystem types) while also considering fundamental aspects of the landscape including habitat condition, connectivity, and opportunity cost of 'productive' use (Moilanen 2005; Moilanen 2007). As opposed to other conservation planning algorithms that identify optimal reserve networks given pre-determined conservation targets, Zonation outputs are hierarchical and therefore allow for the exploration as to effectiveness of conservation – terms of both representativeness of species and resource/cost efficiency -- at many different levels of protection.

Zonation is particularly suited for conservation prioritization under climate change as conservation features may be explicitly linked through interaction. This allows for simultaneous prioritization of a species current range, its modeled future range, and the connectivity between the two limited by a species' capacity to disperse. Additionally, conservation features may be weighted or discounted according to the uncertainty in 1) the species model methodology; 2) the climate projections. The resulting prioritization therefore is able to capture many different climate projections at one time – and can include projected ranges for thousands of species. The protocol for running Zonation under uncertain climate change projections is thoroughly described in Kujala et al. 2013 “Conservation Planning with Uncertain Climate Change Projections”

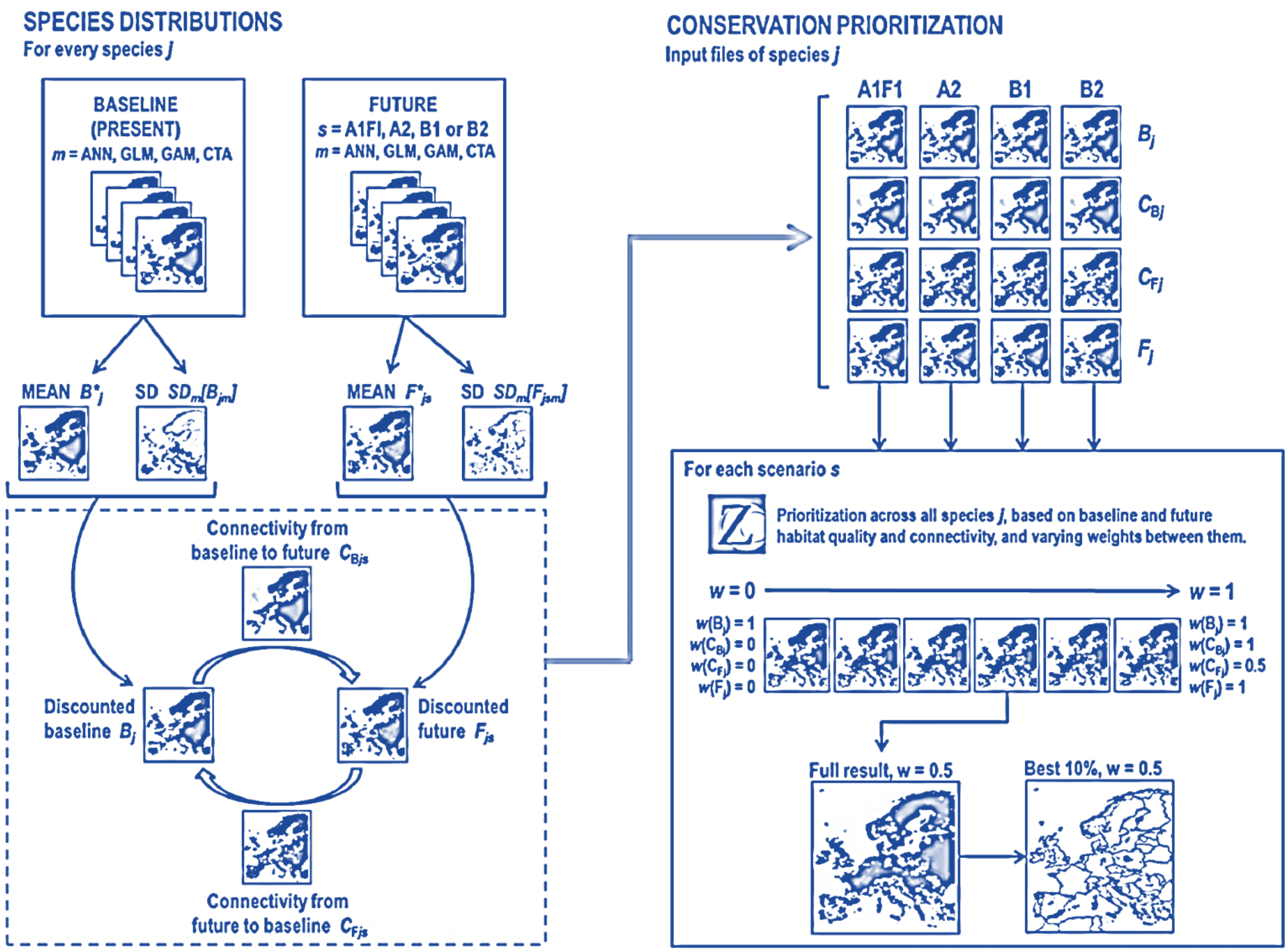


Figure 21. Schematic from Kujala *et al*. 2013 depicting the protocol for including climate projections with uncertainty in a Zonation prioritization.

Zonation Methods Summary

Conservation Features

- Prioritization used the continuous value of species distribution models for current climates and projected future climates. See species distribution modeling section above for more information.
- Models used 1km climatic variables from WorldClim v1.4 (www.worldclim.org) and 1km soils data from Soilgrids (www.soilgrids.org).
- Models were created using Maxent with background sampling conducted in a way to remove spatial bias

- Models were fit at 1km resolution – continental scale prioritizations used species ranges that were projected into 5km resolution environmental layers whereas regional scale prioritizations used the 1km resolution models
- All available species models (vascular plants and vertebrates) were used in continental scale prioritizations
- Species with too few occurrence records to produce a model were included as point locations (Zonation term = "Species of Special Interest")
- Equal weighting was used for all conservation features.

Prioritization Methods

- Zonation ranks all cells in a landscape according to their value -- and removes cells of lowest value at each processing step. Values are then recalculated for all remaining cells at each step.
- Core area zonation removal algorithm was used --- this assigns value to a cell from the highest values species present in that cell at each step of removal.
- Species with smaller ranges have few cells that are critical for their conservation -- these cells therefore tend to have high values
- By contrast, wide ranging species have more opportunities to be conserved -- so are typically lower value *until* only the core range remains
- Warp factor (number of cells removed at each step) for all analysis was set to 1.
- All prioritizations used edge removal

Climate Change Analysis

- Species current ranges were linked to projected future ranges through an interaction layer. This layer is transformed by a dispersal kernel with a parameter to limit the interaction to the species total capacity to disperse over the period of analysis.
- Total dispersal capacity was assumed to be 100km for vertebrates (roughly 1 km/yr) and 1km for vascular plants (roughly 100m/yr)
- The algorithm favors areas of the species range in baseline climate that are retained in the projected future climate.
- Prioritization were conducted using the mean projected future species ranges across 10 GCM that were discounted by the standard deviation the projected ranges.
- Prioritizations were also run for each GCM individually for both RCP2.6 and RCP8.5

Spatial resolution of analysis

- Africa-wide solutions used all available models for vascular plants and vertebrates and was conducted at 5km resolution.
- Focal region analysis used 1km species models and only included species whose present range is entirely within the focal region boundaries.

Land Cover and Land Use

- Areas of existing built up land or intensive agriculture were removed from the analysis and therefore those cells are not part of the prioritization solution. Built up and agricultural areas were defined as >50% of pixel coverage for 'urban' and 'agriculture' classes from the 1km global consensus land cover dataset produced by Tuanmu et al. 2011.
- Existing protected areas are solved first so that the priorities take existing protection into account.

Continental vs. Country-level planning

- Continental and Regional planning viewed each conservation feature as a common resource to be conserved
- For solutions that focused on country level planning, country boundaries from GADM were used as the administrative units
- Country-level planning analysis assumed each country was purely focused on conservation features within its border

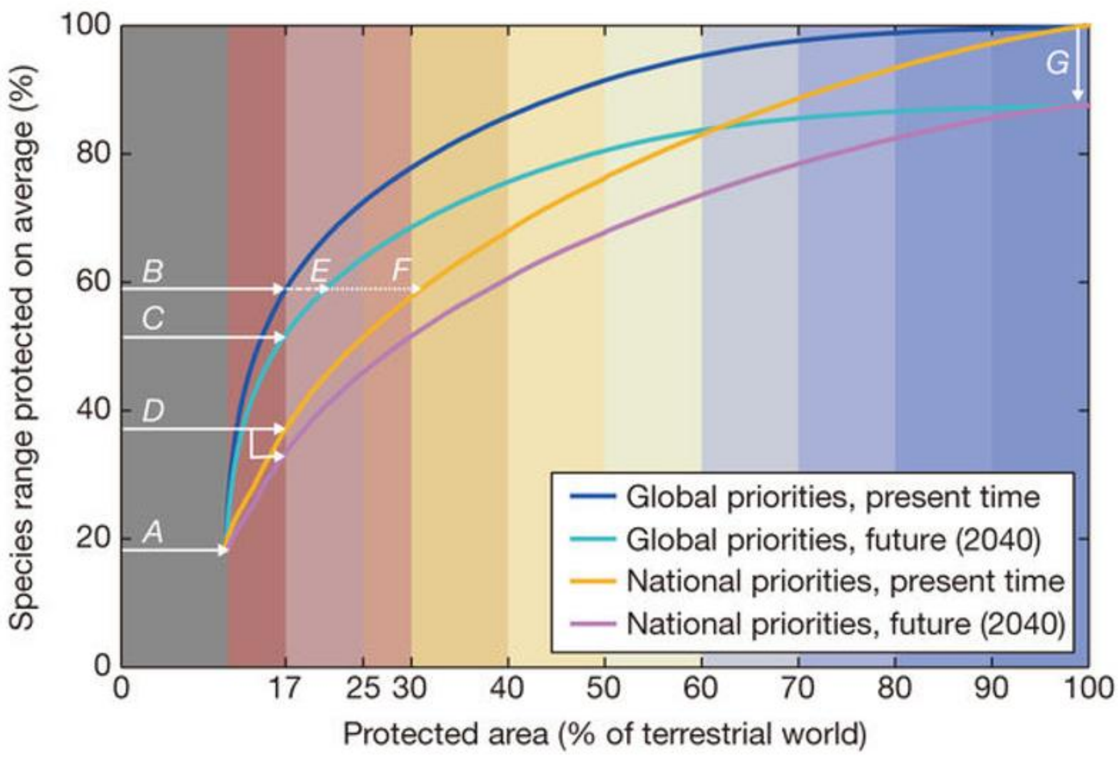


Figure 22. Figure from Pouzols *et al*. 2015 that illustrates the efficiency gained by planning from a global perspective (blue efficiency curves) and country by country (yellow and lavender efficiency curves). Although planning from a global perspective is more efficient in terms of species representation per area conserved, a majority of area-based conservation decisions are made at a national level. Zonation prioritization results produced for SPARC explore both continental scale priorities and country by country planning

Computation

- Large zonation solutions for continental scale prioritizations and 1km regional prioritizations were implemented with large memory instances on Amazon Web Services.
- Memory requirements were generally 20-50GB of RAM and often exceeded 150GB of RAM for larger domains and domains with a greater number of conservation features
- Run times were typically 1-4 days per prioritization

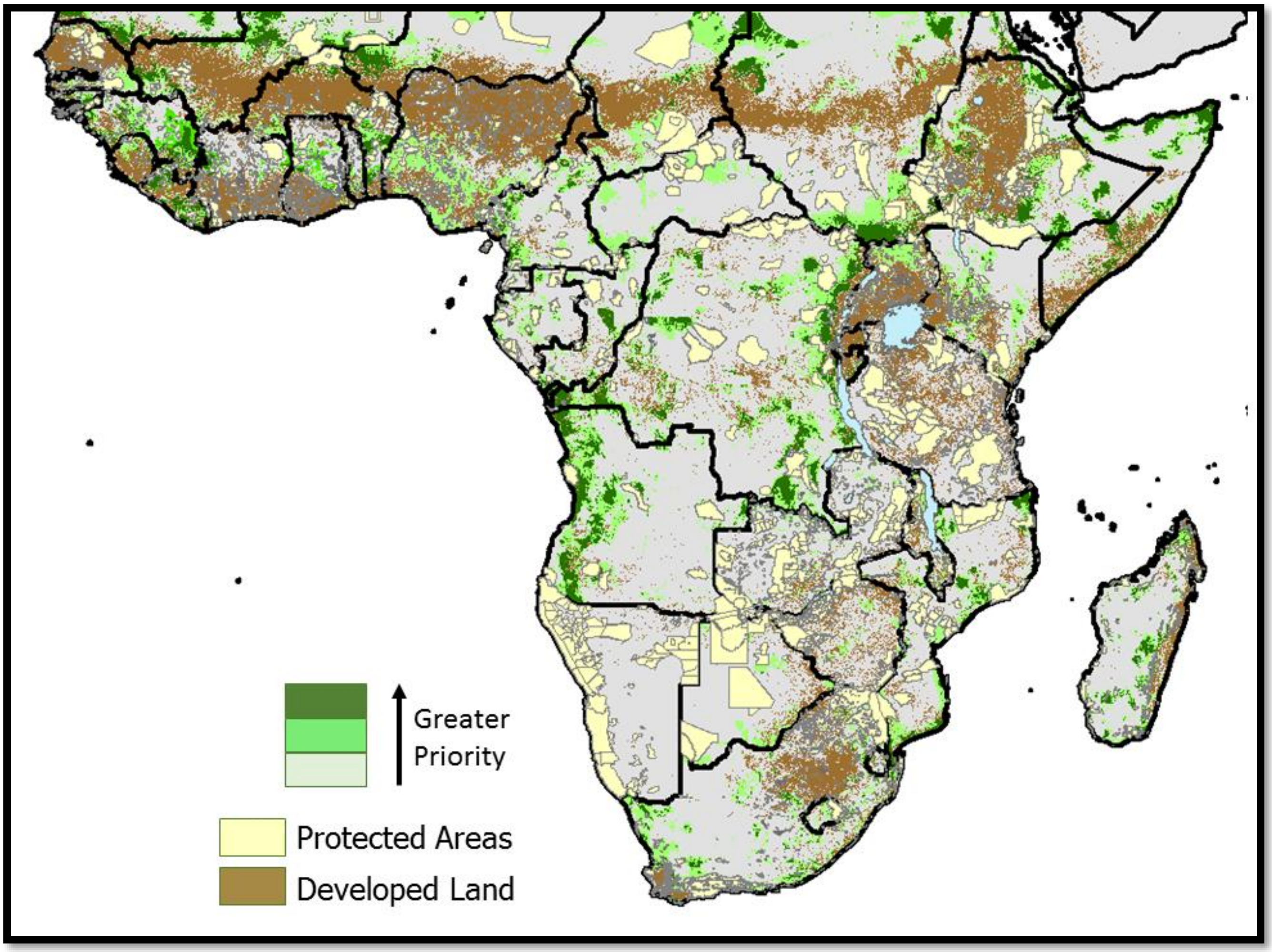


Figure 23. Zonation derived priorities for 25,000 plant and vertebrate species under climate change (RCP 8.5 2060-2080). Prioritization here is country-level planning with priorities re-scaled within each country so that areas in any shade of green represent priority areas for a country to achieve 30% coverage of conserved areas. Countries with >30% coverage (e.g. Namibia, Tanzania) will have no green visible in this map.

Conservation Prioritization using Network Flow: Target-based site prioritization under climate change

Many existing methods used to identify important areas for conservation are not optimized to dynamically respond to climate change impacts on species distribution or projections of economic development. Previous studies have employed species distribution models to project species ranges under climate change to generate optimal reserve designs in several time steps, and then identify areas that are either overlapping or contiguous across time (e.g Rayfield et al. 2008). Zonation software (Moilanen 2005) represents a refinement of this approach that prioritizes areas that will help facilitate the dispersal of species among reserves in successive time steps has been demonstrated across multiple taxa in Madagascar (Kremen et al. 2008), the Pacific Northwest (Carrol et al. 2010), and for offshore marine protected areas (Leathwick et al. 2008). Although Zonation is a powerful tool for conservation priority setting under climate change, its application thus far has not explicitly account for dispersal constrained protection in all intermediary time steps between the end points of 'current climate' and 'future climate'.

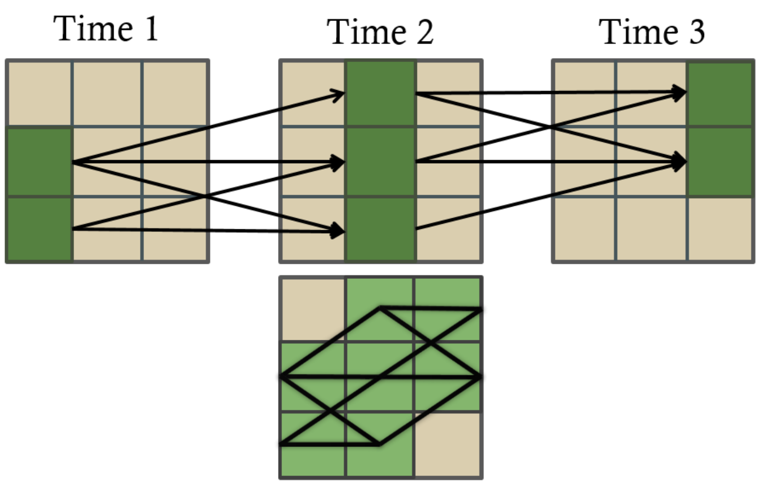


Figure 24. Schematic representation of a hypothetical species suitability in three timesteps (green) and the resulting chains of suitability

CPNF is means of identifying the optimal areas that are needed to ensure the continued protection of a suite of species (optimizations have been performed on 2000+ species) climate change. CPNF optimizes spatial sharing of connected conservation parcels required to meet a specified minimum cost for all species over the analytical time period. Cost surfaces are user defined and can simply represent total area of land needed to achieve conservation targets or could involve cost of land acquisition and/or a measure of habitat integrity. The resultant outputs represent the specific areas required to ensure spatial and temporal connectivity of suitable habitat through time, constrained by assumptions of a species ability to disperse. Essential connectivity chains identified by CPNF that are not currently within either protected areas or developed lands represent potential focal areas for conservation action to adapt a conservation portfolio to projected climate change. CPNF output can also be queried to establish species lists for any defined focal areas or to show the chains formed by individual species.

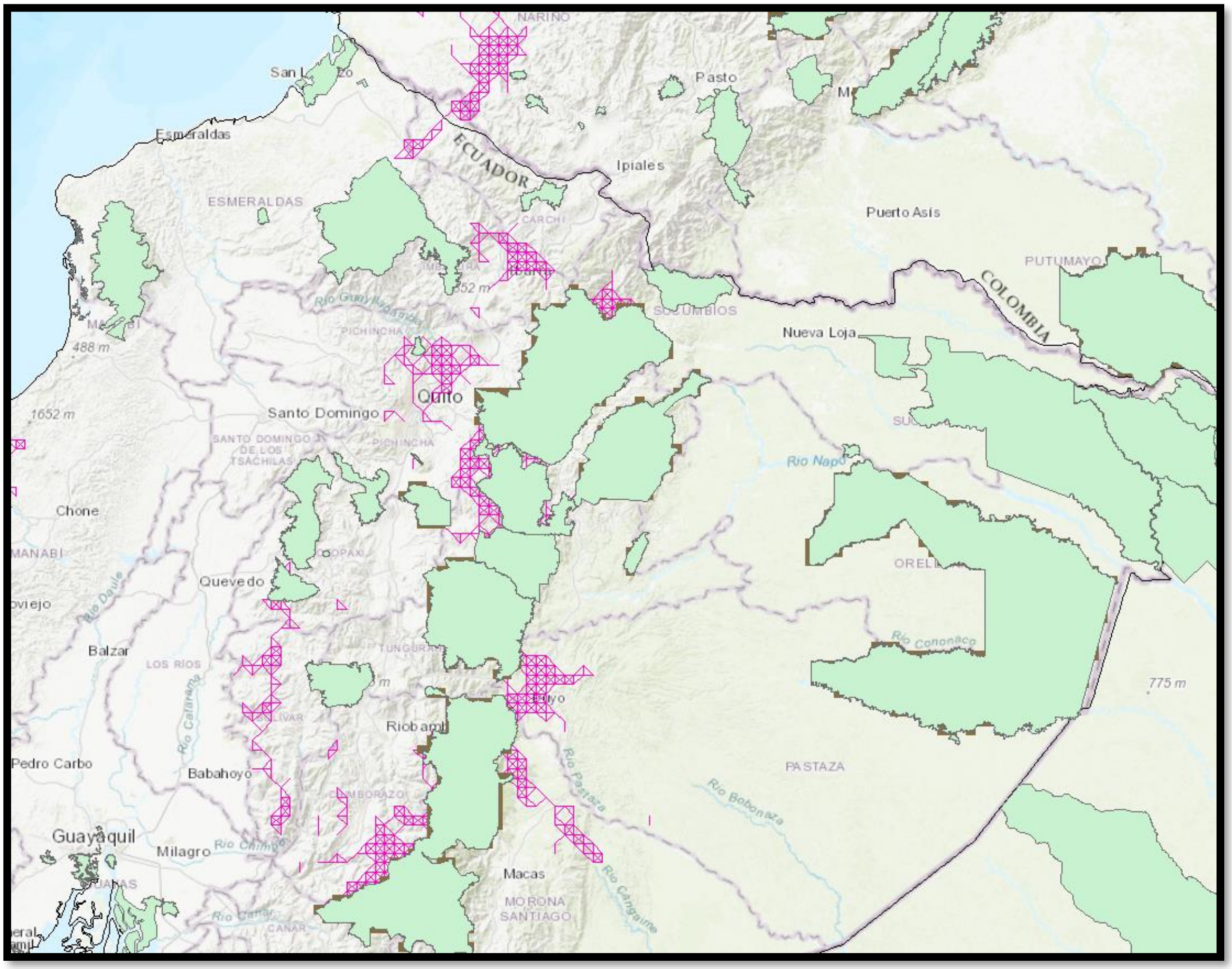


Figure 25.Example network flow optimization for plants native to Colombia, Ecuador and Peru. Pink chains represent dispersal-limited connected suitable habitat and are optimal (minimum area) areas to achieve the conservation target of ~1,250 km2 (50 pixels) for all species in all time steps. Existing protected area network shown as green polygons.

CPNF tools to be used in SPARC are constructed as originally described in Phillips et al. 2008, but implemented in a widely available optimization software package, Gurobi Optimizer version 6.5 (Gurobi 2016) and a customized R package that translates grids of species suitability and cost surfaces into a linear programming problem solved by Gurobi. CPNF for large problems (many species or large domains) is extremely computationally intensive. However, pre-screening species to exclude those that either cannot achieve conservation targets or those that can achieve targets entirely within existing protected areas can reduce the size of the problem and the computational burden.

Corridor Irreplaceability Index: Network Flow with Quadratic Cost

Network-flow methods can be used to model the survival and dispersal of species along dispersal chains" while their suitable environmental conditions shift across a landscape in response to climate change. This note describes how this network-flow framework can be combined with the notion of target-based site prioritization to derive an index of how important each site is to ensure a minimum number of non-overlapping dispersal chains per species.

A species' suitable environmental conditions shift geographically under climate change, so its survival over time may depend on repeated dispersal events from areas that are becoming unsuitable into areas that will become suitable. This process can be modeled using dispersal chains (Williams et al. 2005), which consist of a sequence of steps inter-leaving persistence inside a time slice and dispersal to nearby sites between time slices. Collections of dispersal chains can be represented as network flows in a suitably-defined network (Phillips et al. 2008).

Network flow has been combined with integer optimization (Phillips et al. 2008) to find a minimum number of cells whose protection would ensure that a collection of species would all have some minimum number of dispersal chains. The optimum solution represents only one way to conserve the collection of species, however, and gives little information about alternative solutions. Furthermore, the optimization process can be time-consuming, and therefore hard to use in a context where sites are protected incrementally and/or opportunistically, so that the conservation planning requirements are continually evolving.

In this method, rather than trying to optimize a conservation plan, we seek to do site prioritization in the context of dispersal chains and network flow. Specifically, we want to define an index of how important a given site is to ensure that a given species has at least a minimum “target" amount of flow (i.e., number of non-overlapping dispersal chains). This can be seen as a generalization of the notion of target-based site prioritization (Phillips et al. 2010) to the climate-change context.

We would like the index to satisfy some basic requirements:

1. It should equal zero if the site cannot be used in any flow that is feasible (i.e., the total flow is at least the target).
2. It should equal one if the site is essential in order to achieve the target number of non-overlapping dispersal chains, i.e., if every feasible flow uses the site. This would indicate that the cell is irreplaceable with regard to providing connected suitable habitat under climate change.
3. It should be smoothly graduated between these two extremes.
4. It should be reasonably fast to compute, so that it can be used in incremental or collaborative conservation planning, for example by embedding it in a decision-support system.

The index can be summed across species to achieve a composite index of the importance of a site. Species that are most at risk (i.e., with few possible dispersal chains) will contribute strongly to the composite index at some sites, while species with many dispersal chains will only contribute a small amount at any site.

To achieve the desired index, we added a quadratic cost function $c(f) = f^2$ to the within-time-slice connections and compute a minimum-cost flow of size equal to the target. The prioritization index I(s) at a site S is defined as the maximum across time slices t of the minimum-cost flow through site s in time t. The quadratic cost function (or any strictly convex increasing cost function) serves to split flow evenly across alternative paths. Therefore, the resulting flow across an edge is high only if there are few alternatives to using that edge in order to achieve the target flow.

The index is most easily computed using generic optimization software both CPLEX and GUROBI most likely have fast implementations of convex quadratic programs with linear constraints. Corridor irreplaceability index results developed for SPARC and presented here were implemented in AMPL and custom R code.

Summary of Network Flow Methods

Regions of Analysis

- Network flow was implemented over the multi-country focal regions in each of the three biogeographic realms
- Focal regions for Africa were: Liberia – West Africa, Kenya-Uganda-Tanzania, South Africa-Lesotho-Eswatini, Angola-Kaza
- Focal regions for Asia were: Thailand-Myanmar-Laos-Cambodia, Island of Borneo, Island of New Guinea, Nepal-India-Bangladesh
- Focal regions for South America were: Meso-america (Mexico+Central American Nations), Northern Andes (Colombia-Ecuador-Peru), Southern Andes (Ecuador-Peru-Bolivia), Guyana shield (Guyana-Venezuela-Suriname-French Guiana-Brazil)

Species Models

- Species distribution models for species 'endemic' to each multi-country focal region were used in the network flow prioritization. Species were included in the prioritization batch if either the entire expert range polygon or all validated occurrence records were within the regional boundary.
- Models were projected in decadal timesteps from baseline climate through 2070
- Due to the computational expense, four GCMs for each regions were used. GCM were chosen to represent maximum spread of within-region projections for temperature and precipitation using the GCMcompareR tool (see section X). GCMs were chose from the list of 10 GCMs used throughout SPARC.

- Species that took longer than 1 hour to achieve an optimal solution were not included in the final prioritization. This was typically species that demonstrated either significant range expansion or were already wide-ranging through out the domain. Number of species removed due to this constraint was less than ten for all focal areas.

Prioritization Assumptions

- Conservation targets for all species was 100 grid cells conserved in every time step. This equates to ~2500km^2.
- Existing protected areas were assumed to be zero-cost. This means if conservation targets can be attained within existing protection, those areas will be used first.
- Areas classified intensive agriculture or urban were excluded from the analysis (i.e. those cells were not available to meet conservation targets and may represent barriers to forming chains of connected suitable habitats).
- All other areas were given a per grid cell cost derived from the opportunity cost of agriculture dataset (Naidoo et al. 2007).
- Prioritization solutions achieve the conservation targets a minimum cost.

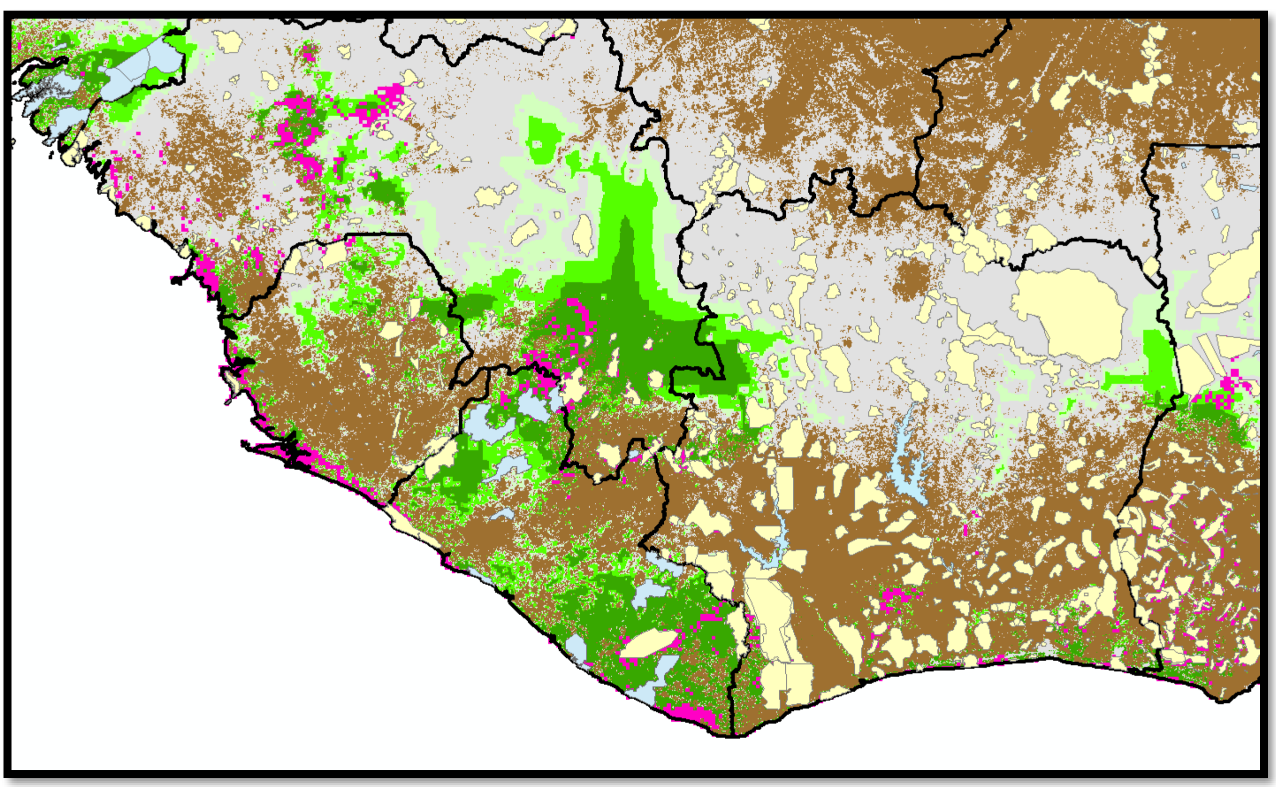


Figure 26. Spatial prioritization for species endemic to the Liberia/West Africa focal region. Green ramp is Zonation derived priorities. Pink overlay are optimal chains to conserve all species using Network Flow.

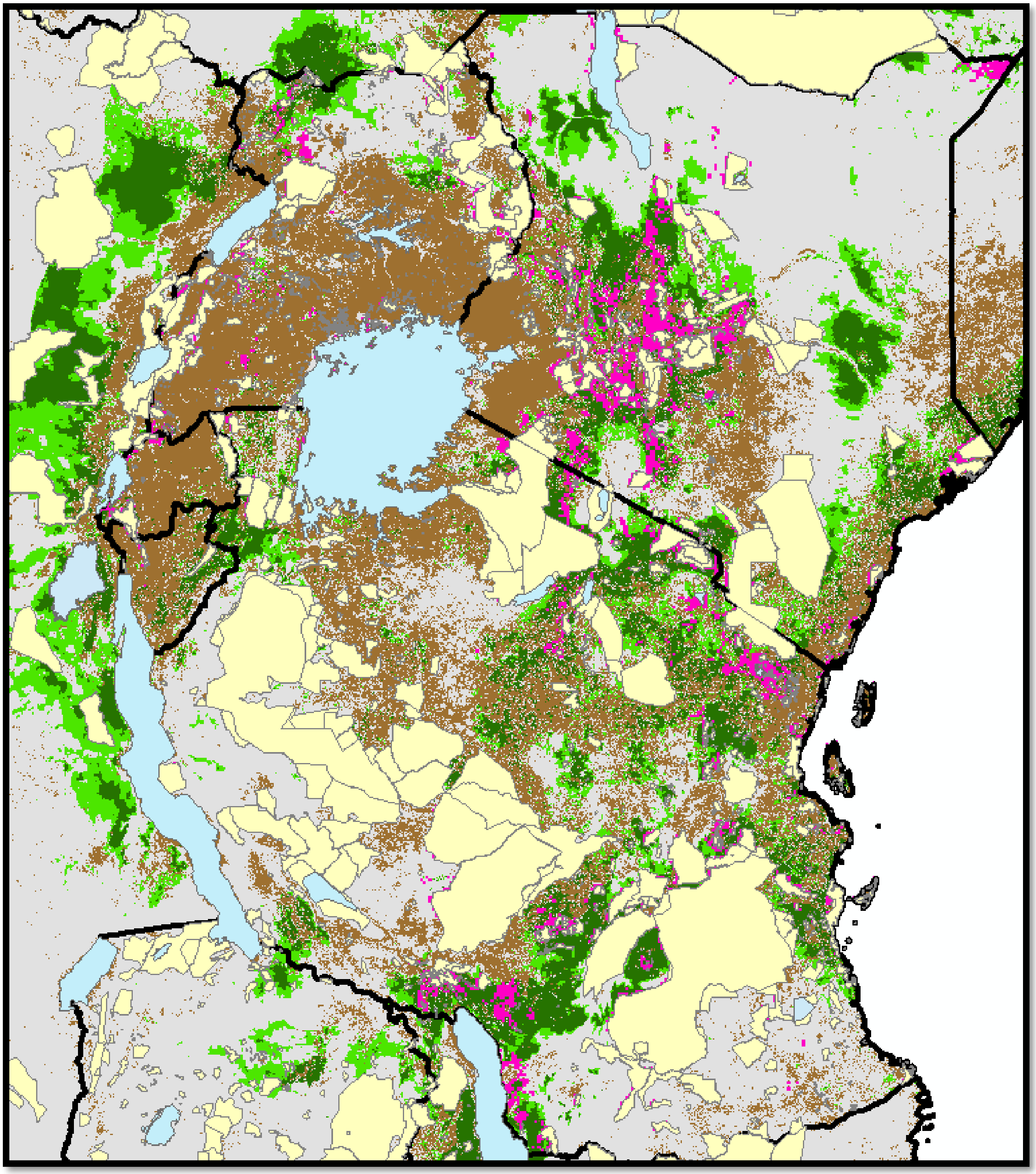


Figure 27. Spatial prioritization for species endemic to the Kenya-Tanzania-Uganda focal region. Green ramp is Zonation derived priorities. Pink overlay are optimal chains to conserve all species using Network Flow.

Marginal Benefit of Future Protection Index (GDM-based)

The Marginal Benefit of Future Protection Index is a novel application of Generalized Dissimilarity Model (GDM) results (Ferrier et al. 2007). In contrast to the other two methods of spatial prioritization, this index does not rely on species distribution model outputs to create the prioritization. Instead, MBFPI uses the relationships of the turnover species composition to the turnover of environmental variables determined by the GDM approach to identify which areas are most valuable for conserving climate-ecosystem types if they were added to the existing protected area network.

MBFPI is designed to assess the benefit of adding a given cell to the reserve system, to ensure effective representation of present-day biologically-scaled environments into the future, under climate change. Several factors determine the value of a new protected cell in the future. Firstly, the level of protection of future environments ecologically similar to that expected for the cell of interest needs to be considered. If the future environment of a grid cell is well represented within the future reserve system, then additional reservation will have less benefit than protection of a cell which is poorly protected by the future system. This component, representing the *numerator* of the MBFPI, can be calculated within a given future climate as the sum of similarities between the cell of interest and all protected cells, scaled by the areal coverage of protection within each protected cell.

The *denominator* of MBFPI is simply the total similarity of a given future cell as compared to the baseline climates within the region of analysis. For example, a mountaintop in the future under warming climate may have many cells of similar baseline climate in the surrounding plains. Conversely, an area of lowlands adjoining a mountain range in the future may have very few similar baseline climates if it has warmed beyond the range of current analogs.

If we treat the area of a given environment in the present (assuming an intact landscape) as the area which would currently support the full complement of species for that environment, then applying the species-area relationship to the fraction obtained above (by raising this fraction to an appropriate power, e.g. 0.25) we can estimate the proportion of these species expected to persist within the fraction of this environment protected under climate change.

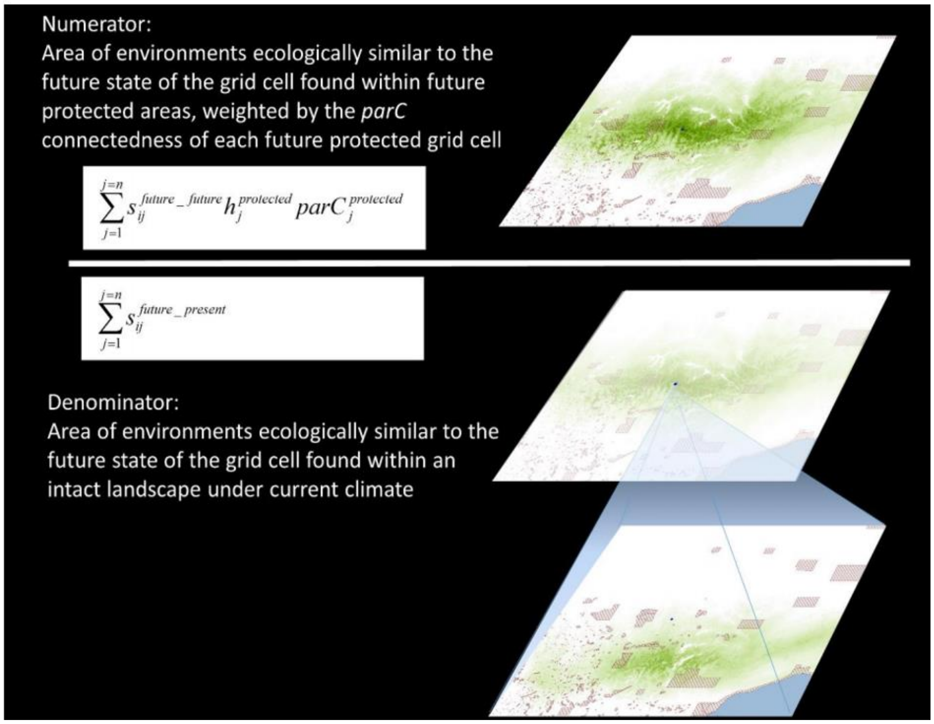


Figure 28. Illustration of MFBPI calculation. Figure provided by Tom Harwood and Simon Ferrier (CSIRO)

The MFBPI tends to prioritize areas that are:

- Comparatively rare climate-ecosystem types
- Not well represented in existing protected areas
- Areas that are 'destinations' for climate-ecosystem types in future climates.

These patterns are emphasized in Figure 29. below. For example, countries or regions with greater protected areas covers (Cote Ivoire, Botswana, Tanzania, trans-frontier conservation area of central-southern Africa) receive a lower marginal benefit score indicated by lighter colors. By contrast, areas with more unique ecosystem-climate type or lesser protected areas coverage (Horn of Africa, South Africa, Madagascar) receive higher marginal benefit scores indicated in darker blue.

The MBFPI was produced separately for vascular plants, vertebrates, and invertebrates over two GCM under RCP8.5. Exploration of additional GCMs or emissions scenarios was limited by the computational expense and queue times for supercomputers needed to run the analysis. All MBFPI outputs, as with the other GDM-based products for SPARC were produced at 1km resolution for the three continental domains.

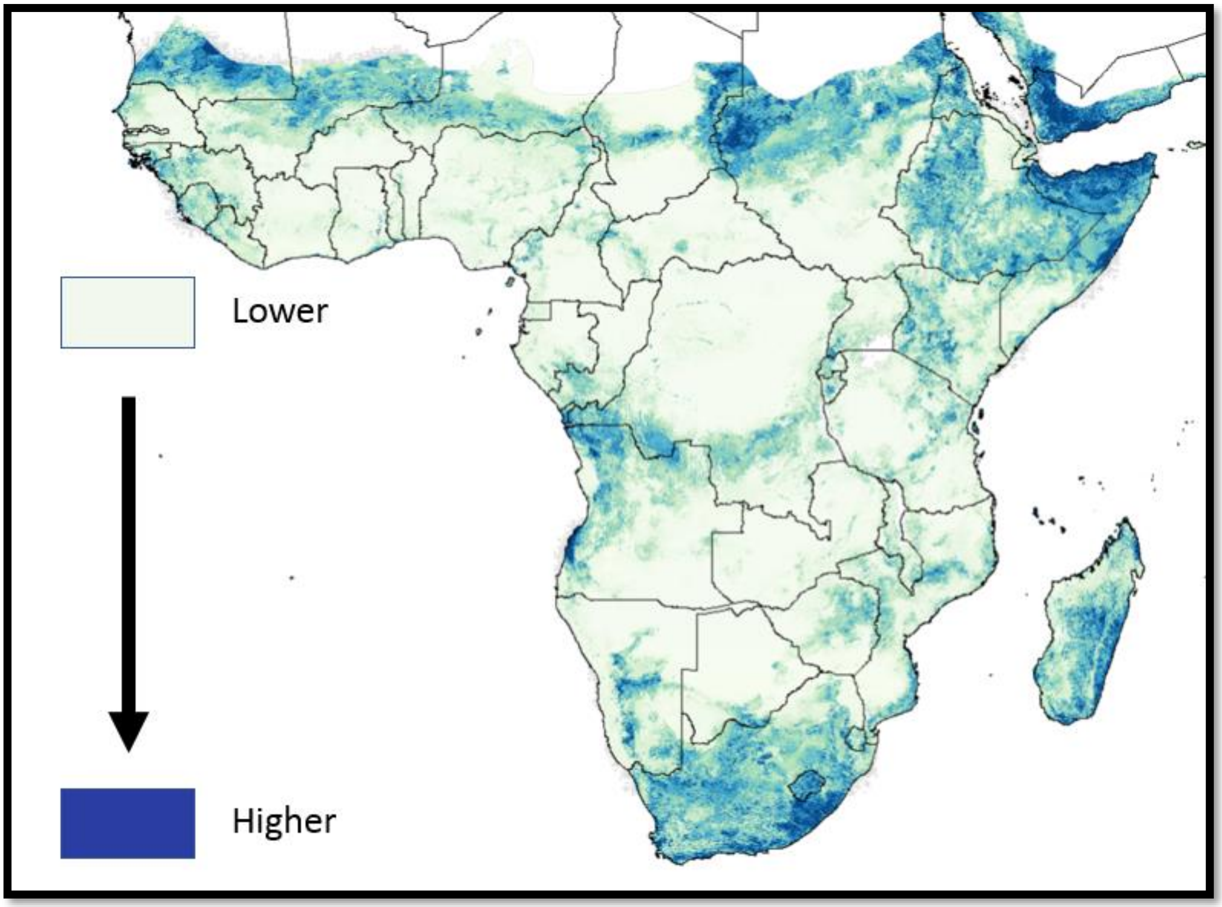


Figure 29. Marginal Benefit of Protection Index for vascular plants – RCP8.5 GFDL model. Darker blue indicated greater marginal benefit of adding each grid cell for representation of future climate-ecosystem types.

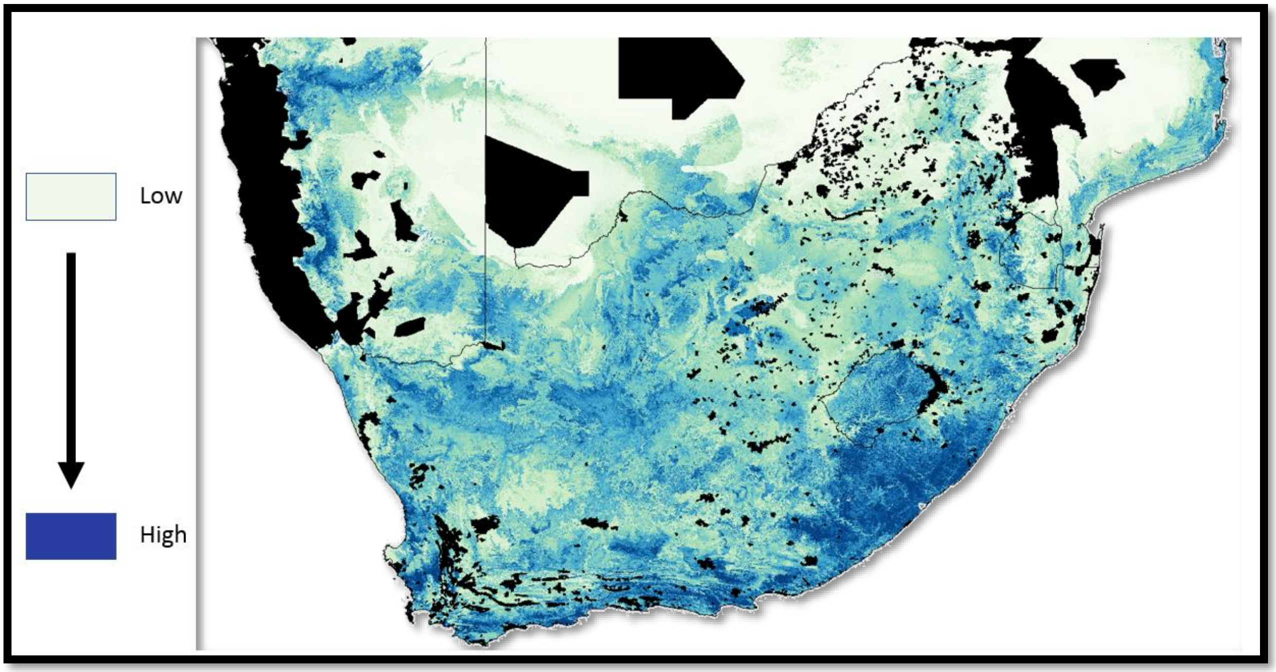


Figure 30. Marginal Benefit of Protection Index for vascular plants – RCP8.5 GFDL model. Zoom in on South Africa region. Darker blue indicated greater marginal benefit of adding each grid cell for representation of future climate-ecosystem types. Existing protected areas are overlaid in black. Areas of comparatively lower priority (lighter colors) surrounding large protected areas illustrates the effect of existing protection on the index.

Protected Areas Vulnerability Analysis

Identifying the protected areas across the tropics that will be most vulnerable to climate change is an important part of planning for climate change resilience of the protected network. Recognizing this, SPARC has included a vulnerability assessment of protected areas throughout the three tropical domains. Vulnerability of PAs will include exposure to the purely physical aspects of climate change, the biological responses to climate change and, most importantly, the potential human responses to climate change. The vulnerability analysis presented here is a reproducible methodology for assessing the relative vulnerability of protected areas to climate change. Methods and results presented here are the outputs from a study by Kevin Coldrey of Anchor Environmental Consultants funded by Conservation International, GEF and the SPARC project.

Scope of Analysis

This study considered protected areas in the three SPARC regions that:

- Fell within the IUCN Ia (strict nature reserves), Ib (wilderness areas) and II (national protected areas) categories
- Are greater than 10 000 ha in area
- Are not strict marine protected areas.

For Africa, the number of protected areas that meet these criteria is 373, for the Neotropics 465 and for the Indo-Malayan region 450. This yielded a total of 1288 protected areas across the three SPARC regions.

Vulnerability Assessment Framework

The vulnerability assessment framework used in this study is based on the methodology developed by Coldrey *et al*. (in prep.) but adapted to the global scale. The framework focuses on the potential climate impacts on the biodiversity conserved within a protected area, including resource pressure from neighboring communities which is likely to increase as climate change impacts livelihoods, as well as the capacity of protected area managers to adapt to these climate threats (Figure 1). The impacts of climate on biodiversity can be mitigated by enlarging and/ or shifting the areas under protection, as well as increasing the level of protection through more effective management. Therefore, the capacity to undertake these measures is linked to the financial situation and level of human pressure, where climate change will potentially increase the financing gap by increasing costs. These include effects of extreme weather events or sea level rise on infrastructure (necessitating more repairs), increasing management required to deal with more desperate neighboring communities, and reduced income from tourism as climate-related discomfort and biodiversity loss reduces demand.

The scoring of the potential impact components (species, habitats, and resource pressure) was on a scale of 0 – 100%, with 0% corresponding to zero impact and 100% representing the highest level of impact, while a score of 0% for the adaptive capacity components (finances and possibility of expansion) corresponds to zero capacity to mitigate the climate threats and 100% representing full capacity to deal with the climate threats. The models and indicators used for each of these components is explained below.

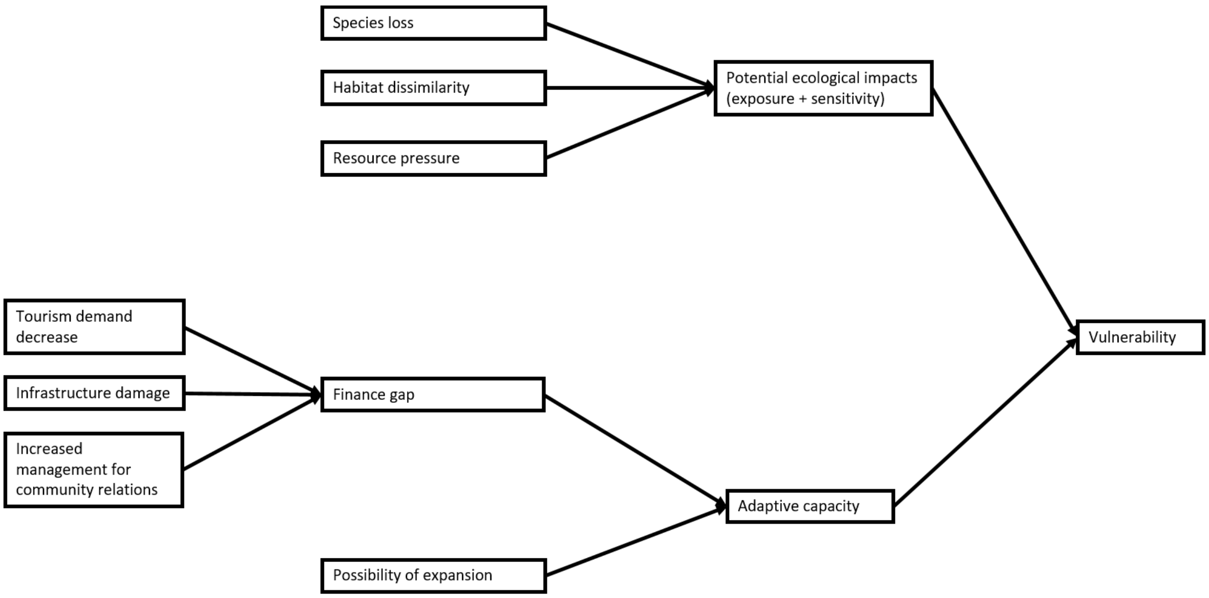


Figure 31. The vulnerability assessment framework applied in this study.

Potential impacts

For the purpose of this study, potential climate impacts on protected areas are defined as any climate change-related impact that hampers a protected area's ability to meet its conservation mandate, which includes the direct impact of climate change on species and habitats, as well as the impact of increased resource demand by neighboring communities. The indicators used for each of these components will be covered separately below.

Species

For the impact on species, species loss, using species distribution models developed for the SPARC project, were used. To compute species loss for each protected area, the modelled current and future distributions of reptiles (n = 1573), amphibians (n = 2500), birds (n = 6911), mammals (n = 2674) and plants (n = ~85000) were used. The modelled current distribution maps were not verified against protected area species lists as these were not available for all protected areas assessed.

Species impact score

The species impact score was computed by summing all species for which the protected area boundaries intersected with the current distributions and then calculating the proportion of those species for which the climate in a protected area becomes unsuitable in the future.

Habitats

In the absence of a global vegetation or biome change model to use as a proxy for ecosystem change, the modelled global environmental stratification (GEnS) data developed for the SPARC project was used instead. There are 125 GEnS in total globally (Metzger *et al.*, 2013) and the proportion of area belonging to each GEnS for both current and future periods was computed.

Habitats impact score

A dissimilarity measure, the complement of the Jaccard similarity index, was used to compute the change in GEnS classes represented for each protected area assessed:

$$\text{Dissimilarity} = 1 - \frac{\sum \min(\text{Present, Climate change})}{(\sum \text{present} + \sum \text{climate change})/2}$$

Resource pressure

For the resource pressure component, the population density within a 10 km buffer area around each protected area was computed. It is well established that higher human population densities bordering protected areas result in higher resource demand, increased illegal activities and higher degradation and destruction rates of protected area resources (de Marques *et al*., 2016; Harcourt *et al*., 2001; Kauano *et al*., 2017; Luck, 2007; Masanja, 2017). The population density data was sourced from the Centre for International Earth Science Information Network (CIESIN 2017).

Resource pressure impact score

For the resource pressure impact score, a relationship between population density and resource degradation, based loosely on the forest degradation rate and human population density relationship computed by de Marques *et al*. (2016), was estimated using the following equation:

$$\text{Degradation rate} = 6.1335 \ln(\text{human population density}) + 45.539$$

Adaptive capacity

The management effectiveness of parks is strongly affected by their level of financing in relation to financial requirements. Under climate change, this will also have an important bearing on the ability of parks to adapt, for example through more intensive protection measures or acquisition of more land. However, climate change will also potentially increase the financing gap by increasing costs. These include effects of extreme weather events or sea level rise on infrastructure (necessitating more repairs), increasing management required to deal with more desperate neighbouring communities, and reduced income from tourism as climate-related discomfort and biodiversity loss reduces demand.

The protected area's current capacity for management was taken as the average financial situation (actual budget as a percentage of ideal budget). This component of the score was then adjusted to take into account the way in which climate is expected to affect the situation, all other things equal.

The capacity for protected areas to adapt to climate change is also affected by the extent to which expansion is possible, since larger areas that encompass more altitude variation are likely to be better off. This depends on how much of the surrounding landscape remains untransformed. The indicators used for each of these components will be covered separately below.

Finances

For the finance gap component, country-level conservation expenditure data collated by Waldron *et al*. (2013) was used. The expenditure data was averaged over the period 2001 to 2008 and includes conservation expenditure from a number of sources such as domestic governments and international donors. The mean annual conservation spending estimate was transformed to reflect each country's conservation spend per 100 000 km^2 of protected area area in order to scale the data. An ideal conservation expenditure value was estimated using the same conservation expenditure data for 13 developed countries.

Finance score

For each country within the three SPARC regions, the proportion of the ideal conservation expenditure was computed.

The finance score was then adjusted to take into account the way in which climate is expected to affect the situation, all other things equal. These include effects of extreme weather events or sea level rise on infrastructure (necessitating more repairs), increasing management required to deal with more desperate neighbouring communities, and reduced income from tourism as climate-related discomfort and biodiversity loss reduces demand.

Infrastructure at risk

For the infrastructure impact component, both infrastructure at risk of flooding and storm surge were used. Point of interest (POI) data was sourced from OpenStreetMaps, a flood hazard map was sourced from Ward *et al*. (2013), and NASA's Shuttle Radar Topography Mission digital elevation model was used for the storm surge component (Daoudi, 2005).

For flood risk, the proportion of infrastructure (buildings) lying within the flood zone of the 1-in-100-year flood return period was computed. The flood hazard model used is based on current and historic flood events and has not been projected, potentially under-estimating the severity and magnitude of floods in the future.

For storm surge risk, the proportion of infrastructure (buildings) lying within the 5m contour line was computed. The current sea level was used and not projected sea level.

Infrastructure impact score

The infrastructure impact score was estimated by computing the proportion of all unique buildings at risk of flooding and storm surge out of the total number of buildings within each protected area.

Neighbouring communities

For the neighbouring community's component, the potential for increased conflict between communities and protected area management was estimated by using the proportion of the rural population in a 10 km buffer around each protected area at risk of flooding and drought as an indicator. We use rural communities as they are typically disproportionately affected by the negative impacts of climate change, as they are more dependent on climate-sensitive sectors and they have less capacity to adapt (Turpie and Visser, 2013), especially during periods of adverse weather, such as flooding and droughts. This results in increased reliance on protected area resources in the form of illegal harvesting which gives rise to conflict between managing authorities and neighbouring communities.

Rural extent and population density data was sourced from the Centre for International Earth Science Information Network (CIESIN, 2017), the drought hazard map was sourced from Carrão *et al*. (2016), and the flood hazard map was sourced from Ward *et al*. (2013).

Neighbouring communities impact score

The neighbouring communities impact score was estimated by computing the proportion of the rural population that resides within the drought and flood hazard regions of the 10 km buffer around each protected area.

Tourism demand

For the impact on tourism, the potential loss in tourism demand as a result of a loss of attractions (charismatic species turnover and reefs at risk of ocean acidification and bleaching), decreased tourist comfort levels and increased malaria risk, were used:

Loss of attractions

For the loss of attractions, the potential loss of reefs and charismatic species was estimated using the World Resources Institute's 'Reefs at Risk' map and the species distribution models developed for the SPARC project.

For the reefs component, a maximum threat score of more than 1000 was used to identify those reefs at considerable risk of vanishing or becoming non-functional.

For the charismatic species component, lists of charismatic species were sourced from the SPARC region offices and the same species loss methodology applied in the species component was used to determine the potential charismatic species loss for each protected area.

It is assumed that the loss of attractions would impact at most 20% of tourist demand, a more conservative assumption than the nearly 40% figure indicated by Di Minin *et al*. (2012). Therefore, for both species loss and the loss of reefs components, the score was multiplied by 20% to yield the potential change in tourism demand.

Change in comfort levels

For the potential change in tourist comfort levels, the Tourism Climate Index (TCI) was used, making use of seven climate variables (Table 1) that influence a tourist's comfort (Mieczkowski, 1985). The TCI can be used to calculate the comfort level for each month of the year based on the TCI rating system (Table 2).

Table X. The components of the tourism climatic index (TCI). Source: Mieczkowski (1985)

Subindex	Variable(s)
Daytime comfort index	Maximum daily temperature (°C)
	Minimum daily relative humidity (%)
Daily comfort index	Mean daily temperature (°C)
	Mean daily relative humidity (%)
Precipitation	Precipitation (mm)
Sunshine	Daily duration of sunshine (hours)
Wind speed	Wind speed (km/h)

Table X. The tourism climatic index (TCI) rating system. Source: Mieczkowski (1985)

Numeric value of index	Description of comfort level for tourism activity
90 - 100	Ideal
80 - 89	Excellent
70 - 79	Very good
60 - 69	Good
50 - 59	Acceptable
40 - 49	Marginal
30 - 39	Unfavourable
20 - 29	Very unfavourable

10 - 19	Extremely unfavourable
Below 9	Impossible

To calculate the change in TCI that may deter tourists from visiting a protected area, the proportion of months for which the TCI score changed from above 50 (‘Acceptable’ and better) to below 50 (‘Marginal’ and worse) was computed (Amelung *et al*., 2007). It was assumed that this change in comfort level would impact at most 50% of tourism demand so the proportion of months was multiplied by 50% to yield the potential impact on tourism demand (Coldrey and Turpie, in prep.).

Malaria risk

For the malaria risk component, the change in range of the malaria-carrying mosquito owing to climate change was assessed using the model developed by Caminade *et al*. (2014). This provided an indication of the protected areas projected to be climatically suitable for malaria in 2050.

It was assumed that malaria risk would impact at most 20% of tourism demand, a more conservative assumption than the nearly 50% indicated by Rossello *et al*.’s (2017) global study. Therefore, the score was multiplied by 20% to yield the potential change in tourism demand.

Tourism impact score

The tourism impact score was estimated by summing each component’s contribution to the loss in tourism demand.

Possibility of protected area expansion

For the possibility of expansion component, the proportion of untransformed (natural) land in a 10 km buffer zone around each protected area was computed using land cover data from the European Space Agency, which is at 300m resolution for the year 2015.

Possibility of protected area expansion score

For each protected area, the proportion of untransformed land was used.

Adaptive capacity score

In combining the two sub-components above (finances and the possibility of expansion), the possibility of expansion was given a smaller weight to account for the extent to which expansion might be expected to alleviate biodiversity loss through encompassing expected changes in range. The adaptive capacity score was estimated using the following equation:

Adaptive capacity = avg. (finance component** + possibility of expansion)

** Proportion of ideal budget * avg. (climate impact on infrastructure, tourism demand and neighbouring communities) %

Overall Vulnerability Score

The vulnerability score indicates a protected area's potential overall loss of biodiversity, taking both the potential impacts and the capacity to adapt into account. The potential impacts of climate on biodiversity can be mitigated by enlarging and/ or shifting the areas under protection, as well as increasing the level of protection through more effective management. The capacity to undertake these measures is linked to the financial situation and level of human pressure.

The vulnerability score, used for both ranking the protected areas in terms of vulnerability and to classify each protected area in terms of severity of vulnerability (Table 3), was computed by multiplying the potential impact score by the complement of the adaptive capacity score:

Vulnerability score = Potential Impact score * (100 – Adaptive Capacity score) %

Table 1. The classification of vulnerability scores into highly vulnerable, vulnerable or resilient. Source: This study.

Classification	Score range
Highly vulnerable	25 to 100%
Vulnerable	10 to 24%
Resilient	0 to 9%

The vulnerability scores were very high for all of the protected areas, with 96% of Africa's protected areas considered highly vulnerable, 95% of Asia's and 91% of the Neotropics (Figure 32).

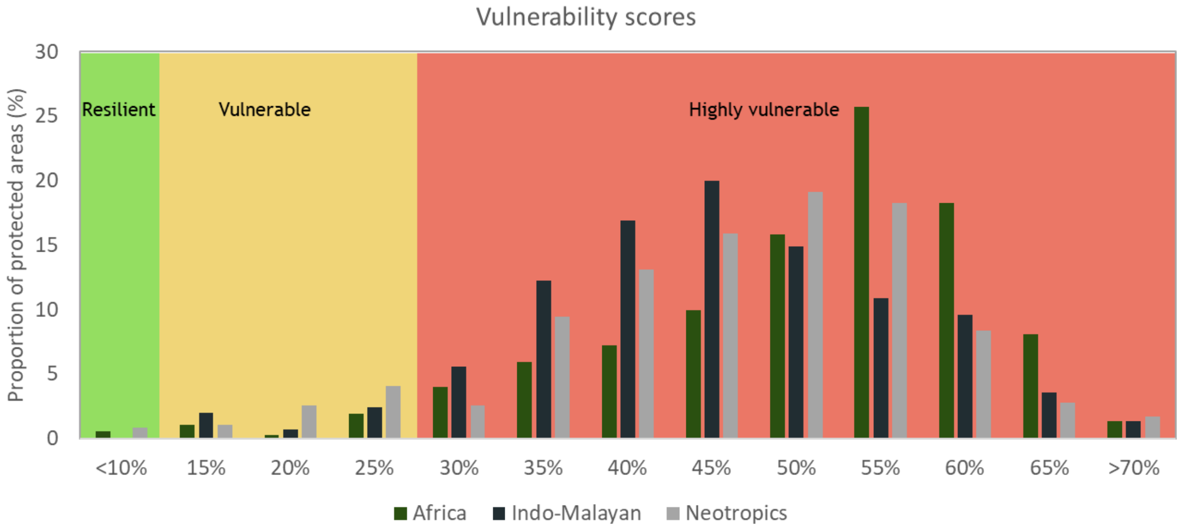


Figure 32. A histogram of the vulnerability scores for the protected areas assessed across the three SPARC regions. Source: this study.

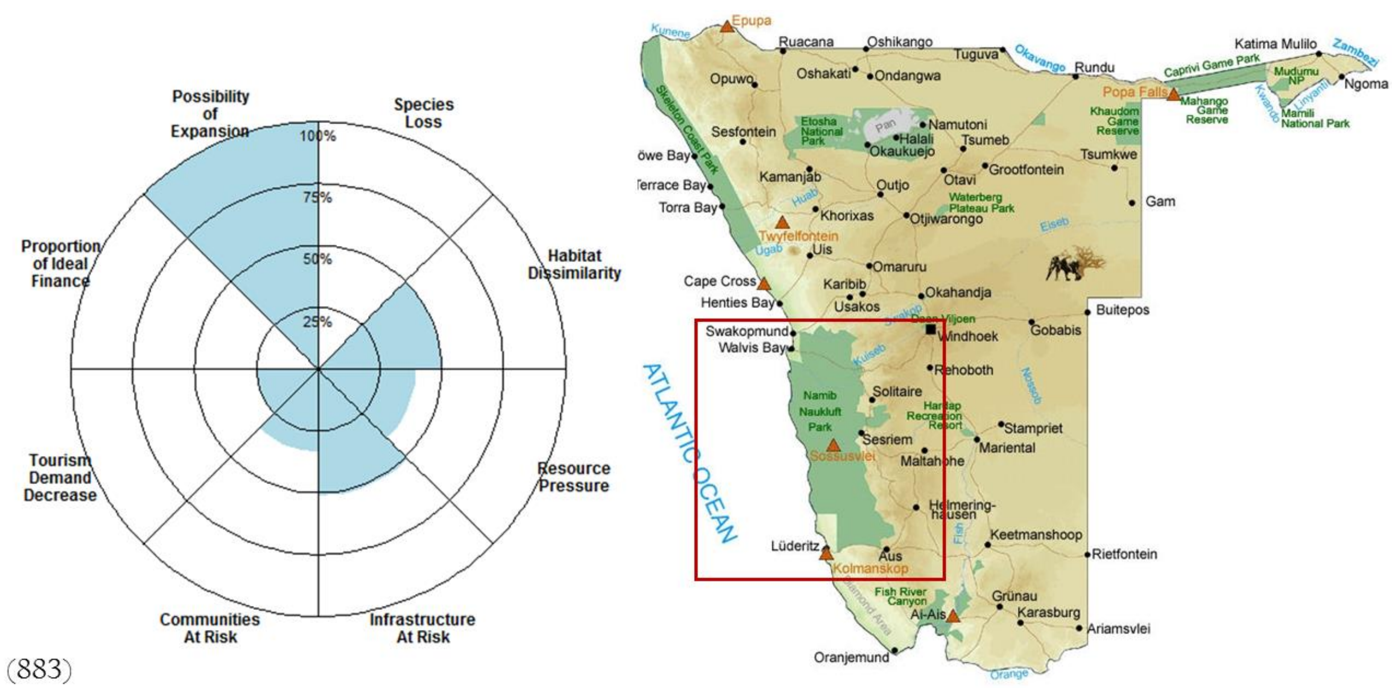


Figure 33. Example multidimensional vulnerability scores for Namib-Naukluft National Park in Namibia

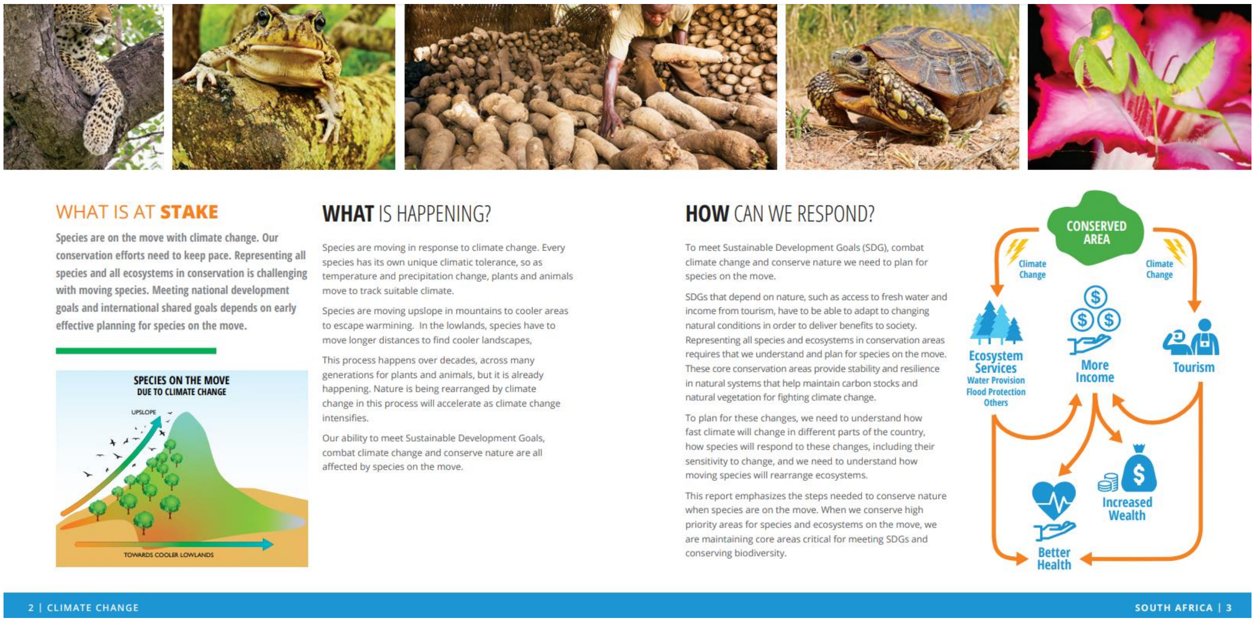
Resources, Tools and Data Availability

Research to Policy Briefs

A primary objective of the SPARC project was to synthesize project results into concise documents that provide an overview of types of outputs produced by SPARC, the methods used to produce them and how the results may be interpreted in the policy arena. As each country has a unique context for conserved areas planning – and differing scopes for area-based conservation – country- specific research to policy briefs were created in collaboration with experts and stakeholders within each country. In all 36 country-specific research to policy briefs were produced representing 10-14 countries in each continental domain. Additionally, six research to policy briefs were produced describing the outputs in a multi-national context for selected focal regions. Where possible, policy briefs were translated into the official language of the country. All research to policy briefs are available for download in PDF format at: http://www.sparc-website.org/policy-briefs-1

Table 2 – Research to Policy Briefs produced.

Country Briefs	Angola	Brazil	Ecuador	Malaysia	Papua New Guinea	Thailand
	Argentina	Cambodia	Guyana	Mexico	Paraguay	Uganda
	Bangladesh	Chile	Indonesia	Mozambique	Peru	Venezuela
	Bhutan	Tropical China	Kenya	Myanmar	South Africa	Vietnam
	Bolivia	Colombia	Laos	Namibia	Suriname	Zambia
	Botswana	Costa Rica	Liberia	Nepal	Tanzania	Zimbabwe
Multi-National Briefs	Liberia-West Africa	Kenya-Uganda-Tanzania	Thailand-Laos-Myanmar-Cambodia	Island of Borneo	Northern Andes	Southern Andes



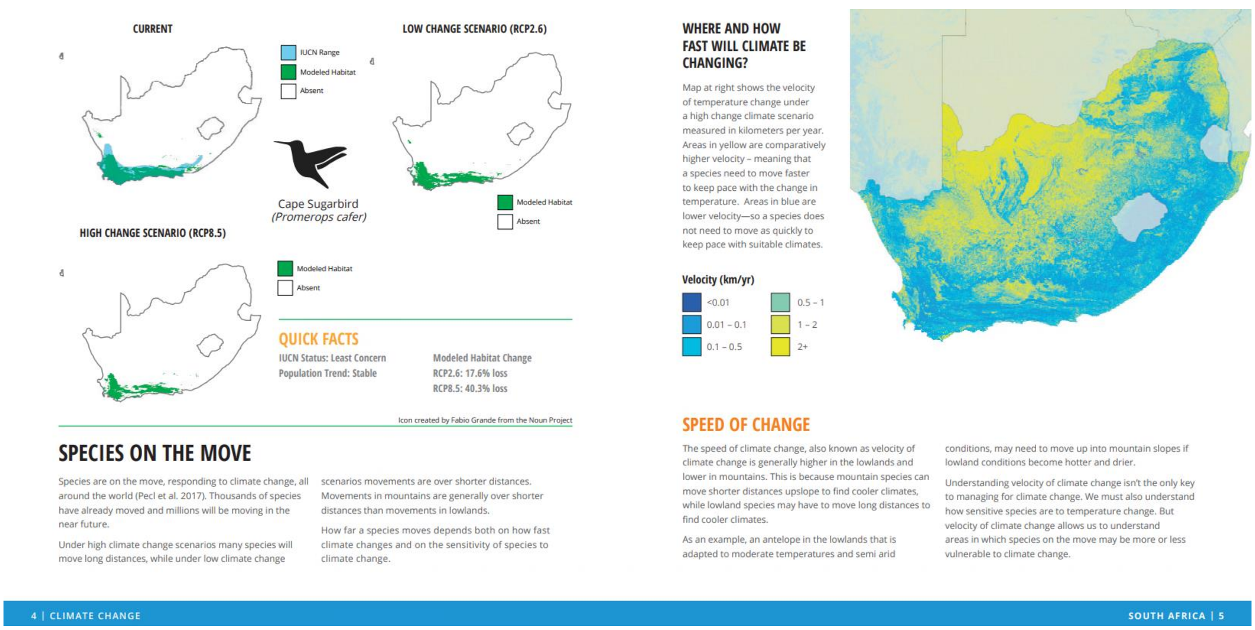


Figure 34. Excerpt from country research to policy brief.

Resilience Atlas and SPARC Visualizer

Tropical biodiversity, and the threats posed to that biodiversity, will be shifting as climate changes. This has an impact on the effectiveness and the context of success for conserved areas in protecting biodiversity. Many species' ranges will move to track suitable conditions with increasing likelihood that they fall outside of the conserved areas systems originally designed to protect such features. As species shift, ecosystems will fragment, adjust and re-assemble affecting habitat coverage and spatial representation across conserved areas – placing investments in area-based conservation and their successful application as a conservation instrument at risk by climate change.

Through synthesized global data as well as focused regional assessments to produce targeted recommendations, the GEF-funded SPARC project was designed to help countries in the Neotropics, Indo-Malayan tropics and Afrotropics to (1) understand the change and potential loss of species representation in national conservation areas; (2) understand the change and potential loss of ecosystem representation in conserved areas and (3) explore options that reverse or reduce the risk climate change presents to species and ecosystems representation in national and regional area-based conservation frameworks.

SPARC has developed a decision support platform to provide policymakers with integrated research products and tools to make informed decisions regarding conservation areas planning and management. The platform aims to provide an easily accessible summary of high-level results on spatial priorities for biodiversity conservation under climate change developed by SPARC.

The decision support platform is nested within Conservation International's Resilience Atlas (www.resilienceatlas.org) which serves as a both data portal an interactive spatial visualizer of Conservation International project results along with other frequently used data layers (e.g. protected areas, population density, land use, etc.). The newly developed features of the platform, termed 'SPARC Visualizer' provides a dynamically updated visualization that allows users to interactively explore the spatial prioritization results. As opposed to a static map, the visualizer lets the user decide what level of conservation coverage they are interested in – and can see where the priorities for meeting that area target fall within their region of interest. Additionally, the visualizer tool allows the user to compare how those priority areas overlap with potential trade-off or co-benefits. For example, a user can see how much of a country's above ground carbon stock would also be protected by conserving a given proportion of its territory. The visualizer allows the user to explore the full efficiency curve of priorities vs. co-benefits (or trade-offs). Finally the visualizer can produce summary statistics for user-defined regions of interest (country boundary, uploaded shapefile, free-hand drawn polygon) and produce a downloadable PDF report of the interactive session.

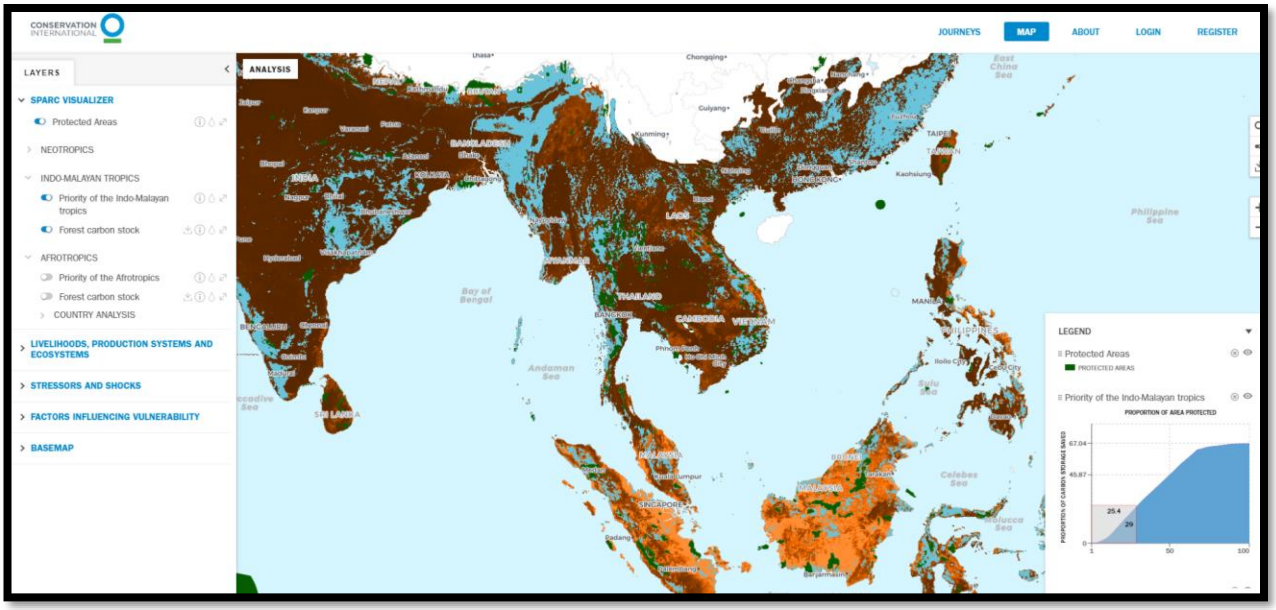


Figure 35. Screenshot of SPARC visualizer with Asia conservation priorities (blue) under climate change and total carbon stock (orange to brown color ramp) layers enabled. Protected areas from WDPA overlaid in green.

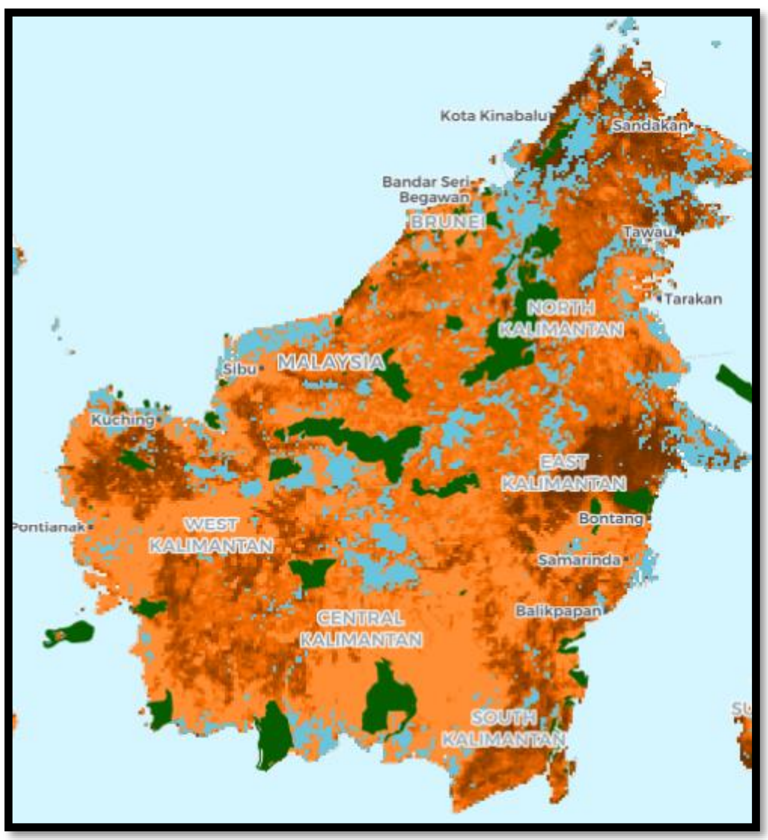


Figure 36. Screenshot of SPARC visualizer with Asia conservation priorities (blue) under climate change and total carbon stock (orange to brown color ramp) layers enabled. Zoom in on Island of Borneo.

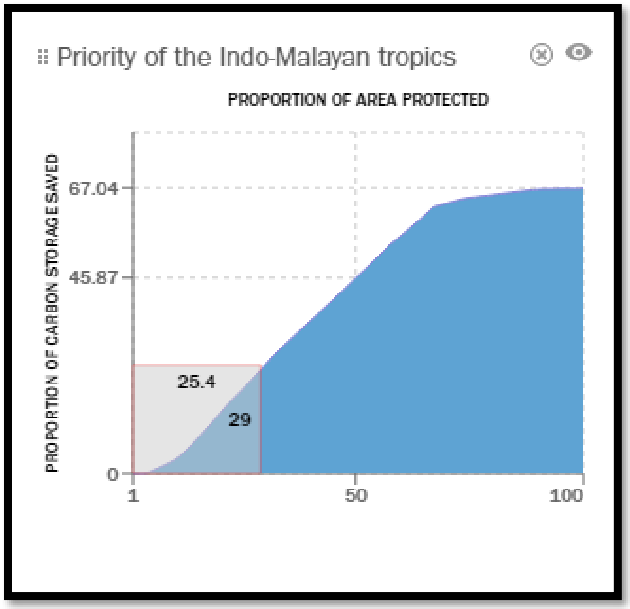


Figure 37. Example interactive efficiency curve for priority level (x-axis) vs. carbon stock (y-axis). Display of priorities is controlled by interacting with this graph.

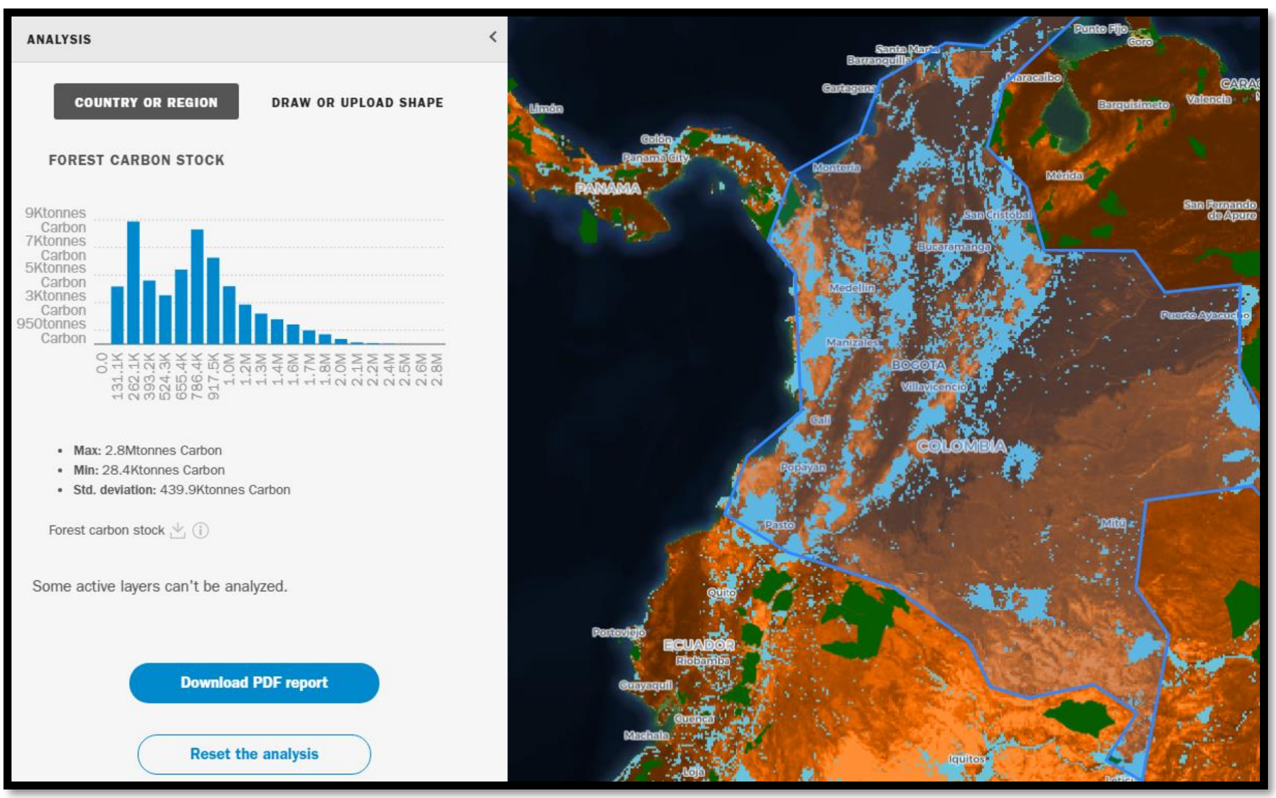


Figure 38. Example summary statistics using a Colombia-shaped region of interest polygon. CSV is statistic and PDF of maps are immediately available for download.

GCM compareR Web Application

GCMcompareR is a web application developed to assist ecologists, conservationists and policy makers at understanding climate change scenarios and differences between Global Circulation Models (GCMs), and at assisting the triage of subsets of models in an objective and informed manner. GCM compareR is written in R and uses the web app development package Shiny. The code of this app can be found in the project's github, https://github.com/marquetlab/GCM_compareR.

GCMs are key to climate change research. Currently, scientists can choose from a large number of GCMs, as meteorological research centers worldwide have contributed more than 35 different GCMs for four distinct climate change scenarios as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor, Stouffer, and Meehl 2012). Projections of future climate from all these models tell a common story, but the spread among them is also significant (Zappa and Shepherd 2017), which is an indicator of the irreducible uncertainty concerning any unverifiable future projection. For this reason, studies have shown that the choice of GCMs in modeling studies is an important source of variability in model outputs (Thuiller et al. 2019). The situation demands for workflows to help researchers exploring climate change scenarios to increase objectivity and repeatability in research and assure a well-judged treatment of uncertainty (T. G. Shepherd et al. 2018).

GCM compareR has been developed to play this role in helping researchers approaching GCMs in climate change studies and assist the selection of climate models. The app offers quick access to preloaded CMIP5 downscaled GCMs for the four RCPs (Vuuren et al. 2011) and allows users to compare their projections for future years. Comparison results are provided as scatterplots and maps where users may learn what makes different any GCM, identify groups of GCMs with similar characteristics (e.g. "colder" or "warmer" in their projection of temperature increase) and define storylines about the future climate (Zappa and Shepherd 2017).

GCMcompareR is currently accessible at: http://www.ecoinformatica.net/GCMcompareR.html and is described in Fajardo *et al*. 2019 (*submitted for review*).

Use of the App

GCM compareR contains tabs that might be used from left to right to define a comparison scenario, retrieve results and generate a report with them. The Intro tab includes all the information needed to use the app. Move to the Workflow section to find full details about how to use the app and go to About to find information about developers.

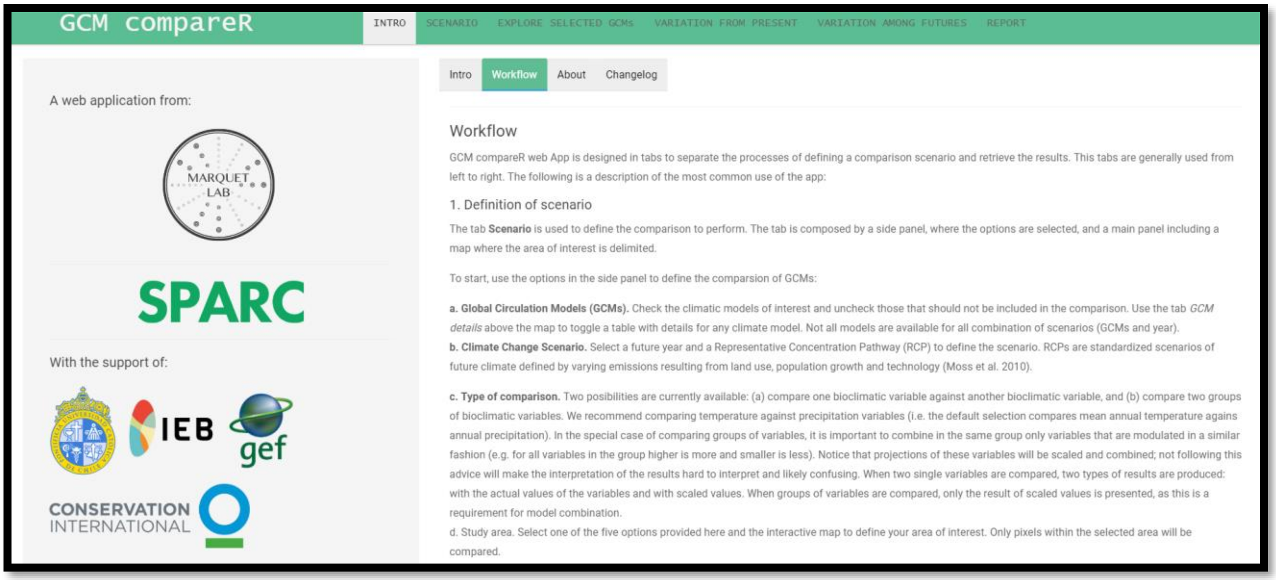


Figure 39. Landing page for GCMcompareR (http://www.ecoinformatica.net/GCMcompareR.html)

In the Scenario tab you will be able to set up a comparison scenario by making all choices: select the GCMs you would like to compare, pick a climate change scenario (year of projection, RCP, etc.) and set the geographic extent of your analysis. Use the 'Compare' button on this tab to trigger the start of the analyses.

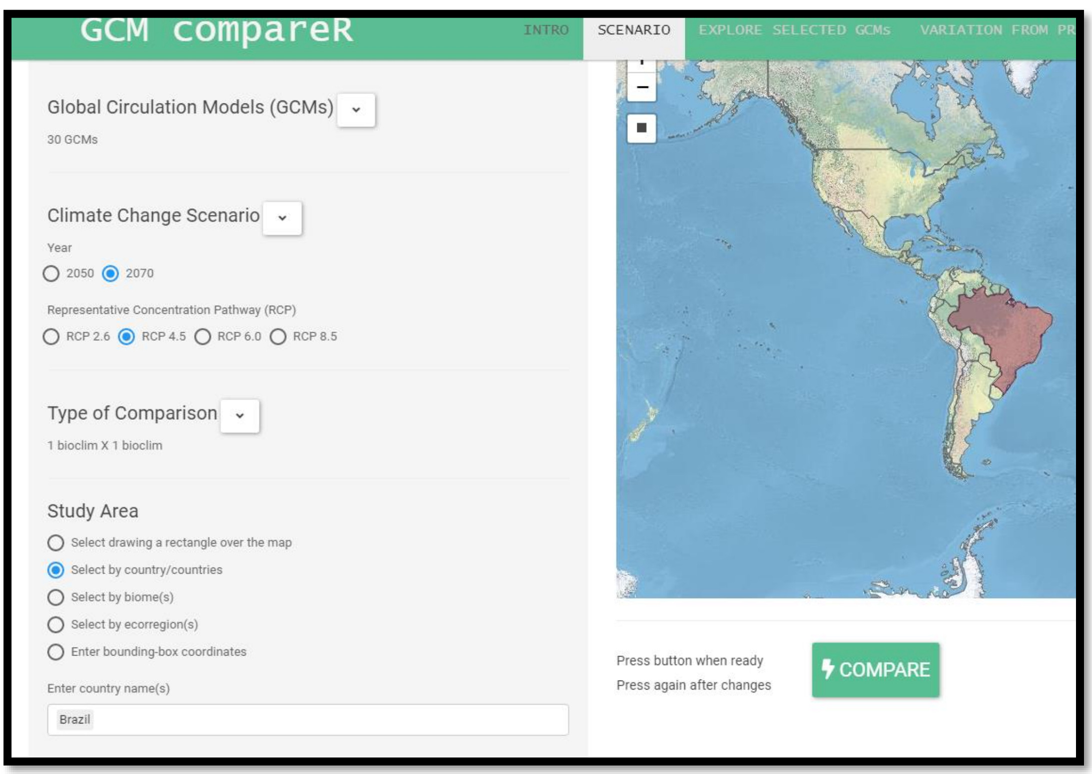


Figure 40. User interface to select 1) GCMs; 2) climate scenario; 3) variables to compare; 4) region of interest.

All subsequent tabs in the application explore the variance of the selected GCMs in the chose region of interest and for the chosen variables. Analytics that are produced include:

- Maps of the downscaled GCM projections for the selected variables
- Analysis of how each GCM projection compares to baseline climates for the chose variables
  - Summarized in map form and in table+scatterplot of change from baseline
  - Presented either in raw change or in scaled change
- Analysis of how all GCMs chosen for evaluation compare against one another
  - Summarized in map form and in table+scatterplot of inter-GCM differences (median of projections represented as center of scatterplot)
  - Presented either in raw differences or in scaled difference

When all tabs have been accessed and all analysis completed a report in PDF format including all figures accessed during the session is available for download.

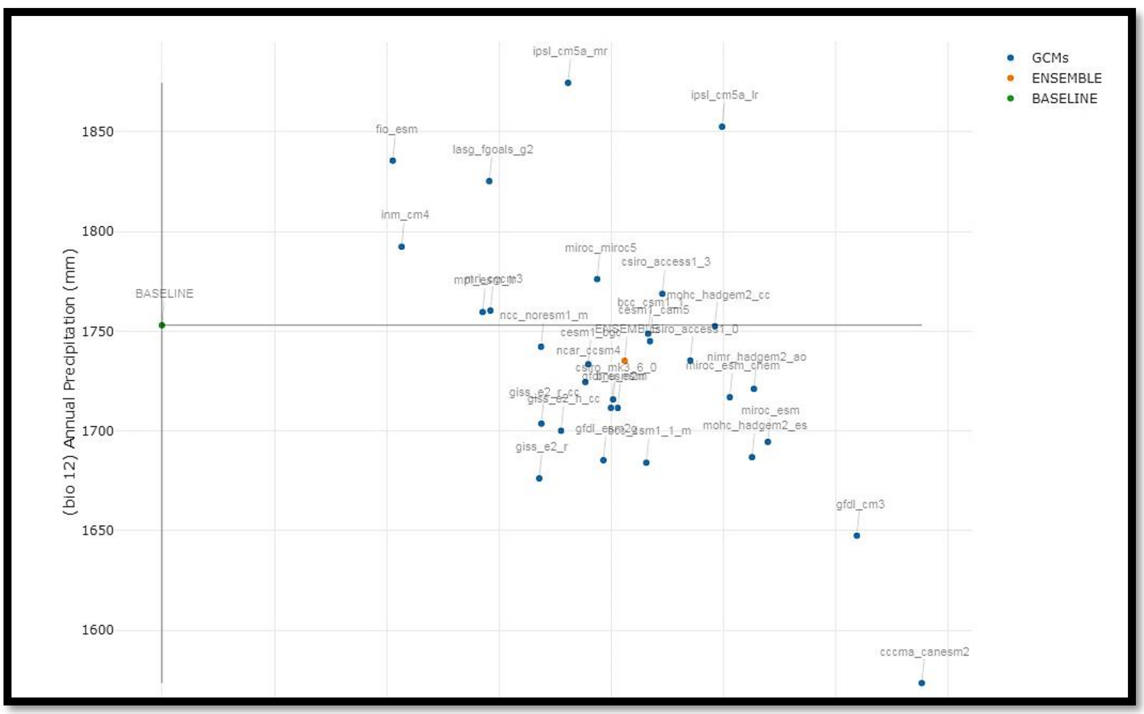
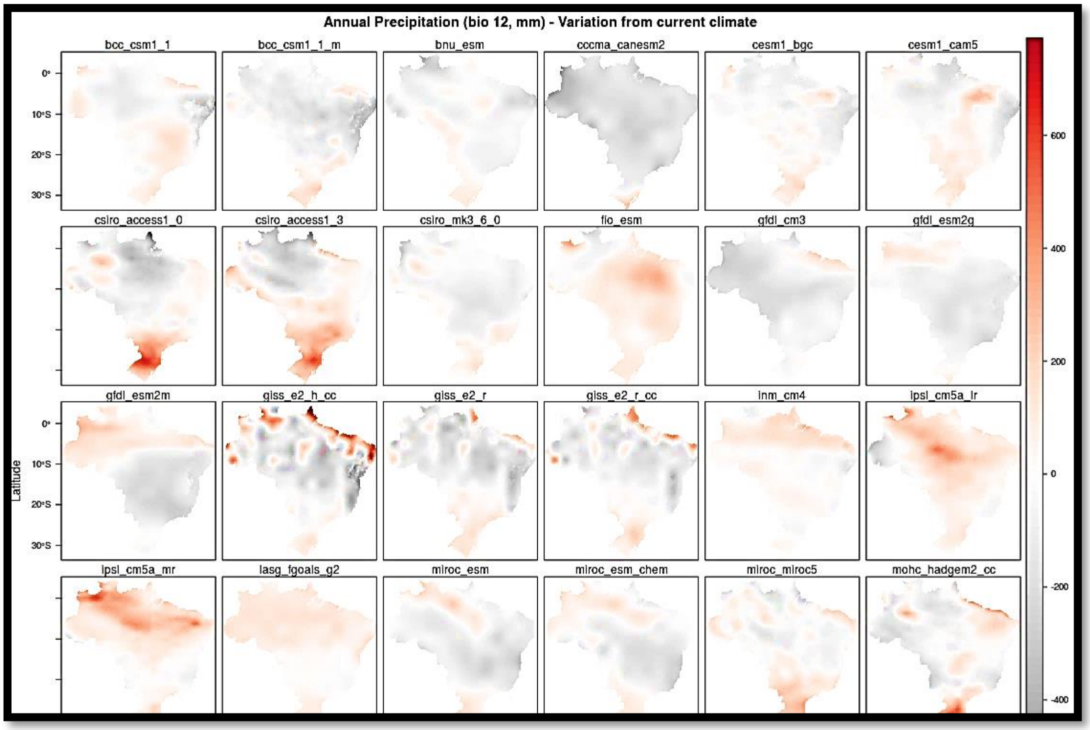


Figure 41. Example output scatterplot for variation from present. Baseline climate for temperature (x-axis) and precipitation (y-axis) indicated by green marker at left. Mean values for all projected GCMs in the region of interest are blue markers on the scatterplot (mean of all projections indicated by orange maker).



Annual Precipitation (bio 12, mm) - Variation from current climate
bcc_csm1_1
bcc_csm1_1_m
bnu_esm
cccma_canesm2
cesm1_bgc
cesm1_cam5
csiro_access1_0
csiro_access1_3
csiro_mk3_6_0
fio_esm
gfdl_cm3
gfdl_esm2g
gfdl_esm2m
giss_e2_h_cc
giss_e2_r
giss_e2_r_cc
inm_cm4
ipsl_cm5a_lr
ipsl_cm5a_mr
lasg_fgoals_g2
miroc_esm
miroc_esm_chem
miroc_miroc5
mohc_hadgem2_cc
Latitude
0°
10°S
20°S
30°S
600
400
200
0
-200
-400

Figure 42.

BIEN Data Portal and R Package

BIEN Interactive Data Portal

The BIEN group maintains an interactive data portal for browsing species data availability as well as range models produced by the group. The data portal allows for a simple text-based species name query and then displays the available occurrence records in the BIEN database and an interactive map of the modeled species range. The data portal has been updated to also include outputs of the modelling work conducted through the SPARC project. The data portal also allows the user to download: 1) the species occurrence records with citation information available in the database; 2) traits information associated with that species (if available); 3) the range model shapefile. The BEIN data portal can be accessed at www.biendata.org:

RBIEN – R package: Tools for Accessing the Botanical Information and Ecology Network Database

The BIEN R package allows users to access BIEN data and data products including geographic ranges, phylogenies, traits, species lists, and plot and occurrence data. Users are able to query the database by species name (or higher-level taxon), political region or even a GIS shapefile. The package is now available on CRAN and the development version is available on Github.

An RBIEN tutorial is outlined below and also available on Github at this link: https://github.com/bmaitner/RBIEN/blob/master/tutorials/RBIEN_tutorial.Rmd.

Read about RBIEN in Maitner *et al*. 2017 (open access publication).

1 Setup

```
#install_github("bmaitner/RBIEN/BIEN")
library(BIEN)
library(ape) #Package for working with phylogenies in R
library(maps) #Useful for making quick maps of occurrences
library(sp) # A package for spatial data
```

2 Overview

It is often easiest to start with our vignette. Particularly useful are the “Function Names” and “Function Directory” sections.

```
vignette("BRI")
```

The function names follow a consistent naming strategy, and mostly consist of 3 parts:

1. The prefix "BIEN_"
2. The type of data being accessed, e.g. "occurrence_"
3. How you'll be querying the data. For example, the suffix "state" refers to functions that return data for a specified state.

As a complete example, the function BIEN_occurrence_species returns occurrence records for a given species (or set of species).

3 Function Families

Currently we have 10 function families in RBIEN. These are sets of functions that access a given type of data.

1. occurrence records (BIEN_occurrence_...)
2. range maps (BIEN_ranges_...)
3. plot data (BIEN_plot_...)
4. trait data (BIEN_trait_...)
5. taxonomic information (BIEN_taxonomy_...)
6. phylogenies (BIEN_phylogeny_...)
7. stem data (BIEN_stem_...)
8. species lists (BIEN_list_...)
9. metadata (BIEN_metadata_...)
10. custom queries (BIEN_sql)

We'll walk through each of the function families and take a look at some the options available within each.

4 Occurrence records

These functions begin with the prefix "BIEN_occurrence_" and allow you to query occurrences by either taxonomy or geography. Functions include:

1. BIEN_occurrence_country Returns all occurrence records within a given country
2. BIEN_occurrence_state Returns all occurrences records within a given state/province
3. BIEN_occurrence_county Returns all occurrences records within a given state/province
4. BIEN_occurrence_family Returns all occurrence records for a specified family
5. BIEN_occurrence_genus Returns all occurrence records for a specified genus

6. BIEN_occurrence_species Returns all occurrence records for a specified species
7. BIEN_occurrence_state Returns all occurrences records within a given state/province

Each of these functions has a number of different arguments that modify your query, either refining your search criteria or returning more data for each record. These arguments include:

1. cultivated If TRUE, records known to be cultivated will be returned.
2. only.new.world If TRUE, records returned are limited to those in North and South America, where greater data cleaing and validation has been done.

- Note that the arguments cultivated and only.new.world may change the number of records returned.

3. all.taxonomy If TRUE, the query will return additional taxonomic data, including the uncorrected taxonomic information for those records.
4. native.status If TRUE, additional information will be returned regarding whether a species is native in a given region.
5. observation.type If TRUE, the query will return whether each record is from either a plot or a specimen. This may be useful if a user believes one type of information may be more accurate.
6. political.boundaries If TRUE, the query will return information on which country, state, etc. that an occurrence is found within.
7. print.query If TRUE, the function will print the SQL query that it used. This is mostly useful for users looking to create their own custom queries (which should be done with caution).

4.1 Example 1: Occurrence records for a species

Okay, enough reading. Let's get some data.

Let's say we're interested in the species *Xanthium strumarium* and we'd like some occurrence data.

```
Xanthium_strumarium <- BIEN_occurrence_species(species = "Xanthium strumarium")
```

```
#View(Xanthium_strumarium)
head(Xanthium_strumarium)
str(Xanthium_strumarium)
```

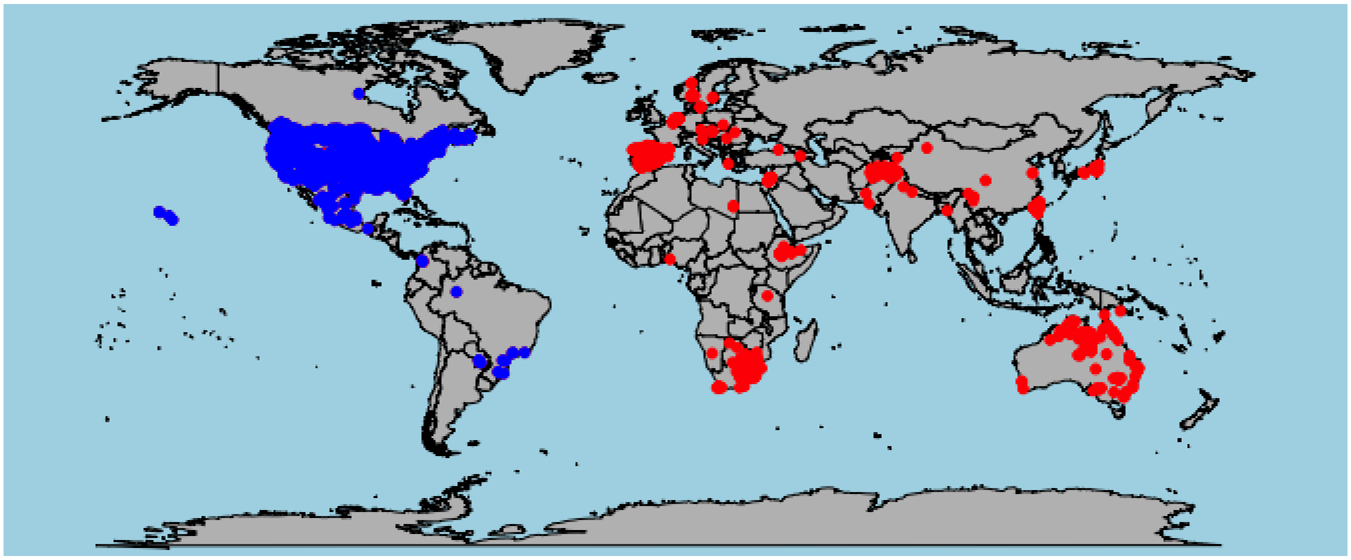
The default data that is returned consists of the latitude, longitude and date collected, along with a set of attribution data. If we want more information on these occurrences, we just need to change the arguments:

```
Xanthium_strumarium_full <- BIEN_occurrence_species(species = "Xanthium strumarium",cultivated = T,only.new.world = F,all.taxonomy = T,native.status = T,observation.type = T,political.boundaries = T)
```

We now have considerably more information, but the query took longer to run.

Let’s take a quick look at where those occurrences are.

```
# Make a quick map to plot our points on


map('world',fill=T , col= "grey", bg="light blue")


#Plot the points from the full query in red


points(cbind(Xanthium_strumarium_full$longitude,Xanthium_strumarium_full$latitude),col="red",pch=20,cex=1)


# Plot the points from the default query in blue


points(cbind(Xanthium_strumarium$longitude,Xanthium_strumarium$latitude),col="blue",pch=20,cex=1)
```



From the map, we can see that the points from the default query (in blue) all fall within the New World. The points from the full query (red + blue) additionally include occurrences from the Old World.

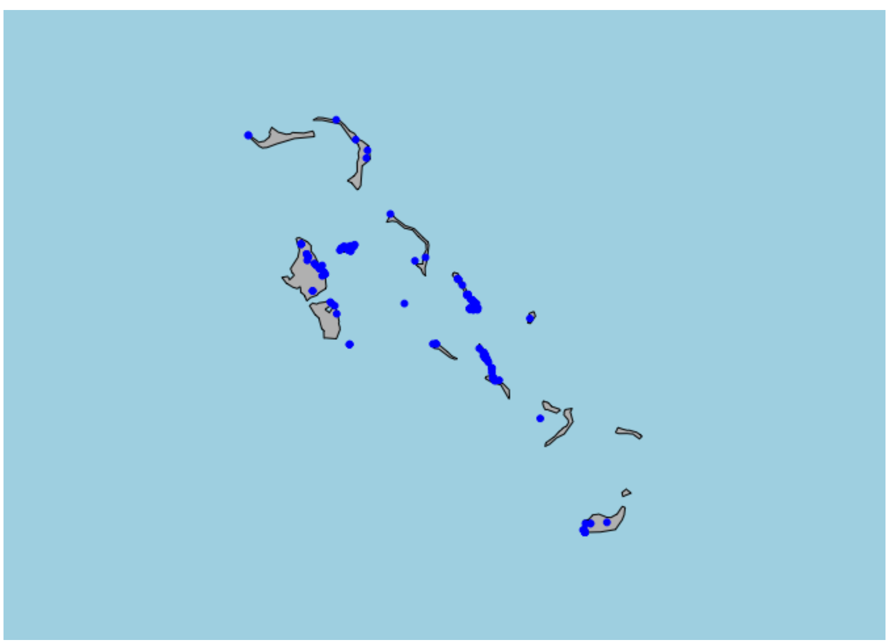
4.2 Example 2: Occurrence records for a country

Since we may be interested in a particular geographic area, rather than a particular set of species, there are also options to easily extract data by political region as well.

```
Bahamas <- BIEN_occurrence_country(country =  "Bahamas")


#Let's see how many species we have

length(unique(Bahamas$scrubbed_species_binomial))
```

```
## [1] 999
```

```
#Nearly 1000 species, not bad.


#Now, let's take a look at where those occurrences are:

map(regions = "Bahamas" ,fill=T , col= "grey", bg="light blue")


points(cbind(Bahamas$longitude,Bahamas$latitude),col="blue",pch=20,cex=1)
```



```
#Looks like some islands are considerably better sampled than others.
```

5 Range maps

These functions begin with the prefix “BIEN_ranges_” and return (unsurprisingly) species ranges. Most of these functions work by saving the downloaded ranges to a specified directory in shapefile format, rather than by loading them into the R environment.

Functions include:

1. BIEN_ranges_species Downloads range maps for given species and save them to a specified directory.
2. BIEN_ranges_genus Saves range maps for all species within a genus to a specified directory.
3. BIEN_ranges_load_species This function returns the ranges for a set of species as a SpatialPolygonsDataFrame object.

The range functions have different arguments than we have seen so far, including:

1. directory This is where the function will be saving the shapefiles you download
2. matched If TRUE, the function will return a dataframe listing which species ranges were downloaded and which weren’t.
3. match_names_only If TRUE, the function will check whether a map is available for each species without actually downloading it
4. include.gid If TRUE, the function will append a unique gid number to each range map’s filename. This argument is designed to allow forward compatibility when BIEN contains multiple range maps for each species.

5.1 Example 3: Range maps and occurrence points

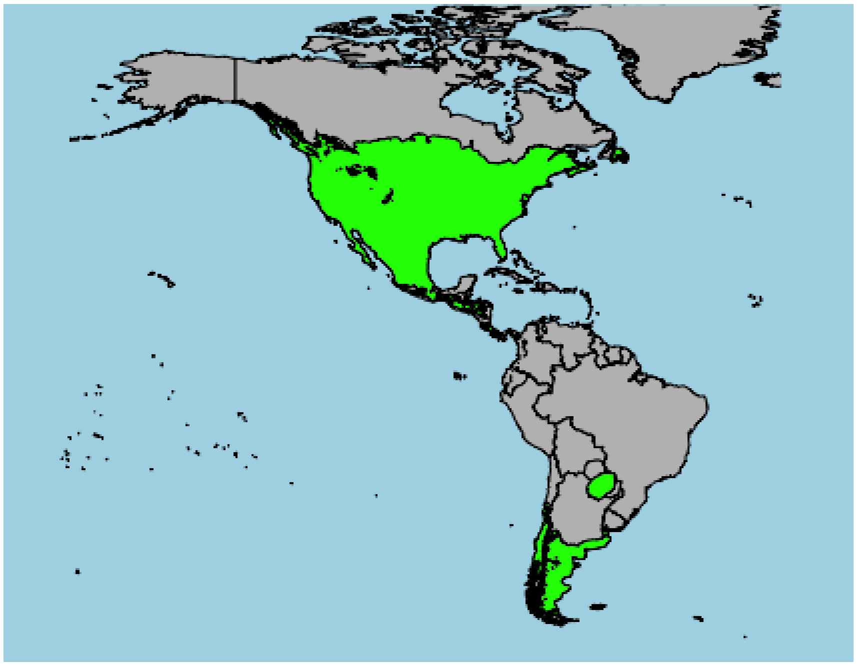
To load a range map we can use the function `BIEN_ranges_load_species`.

```
Xanthium_strumarium_range <- BIEN_ranges_load_species(species = "Xanthium strumarium"
)

# note that you might get an error here if you have an old version of the PROJ librar
y
```

The range map is now in our global environment as a Spatial polygons dataframe.

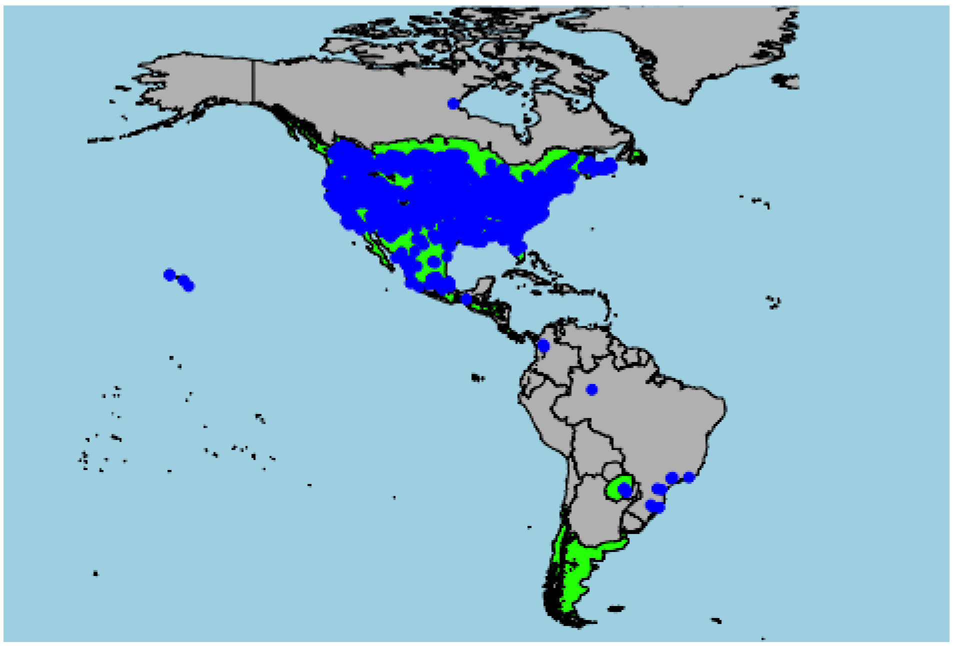
```
#First, let's add a base map so that our range has some context:


map('world',fill=T , col= "grey", bg="light blue",xlim = c(-180,-20),ylim = c(-60,80)
)

#Now, we can add the range map:
```

```
plot(Xanthium_strumarium_range,col="green",add=T)
```



Now, let's add those occurrence points from earlier to this map:

```
map('world',fill=T , col= "grey", bg="light blue",xlim = c(-180,-20),ylim = c(-60,80)
)

plot(Xanthium_strumarium_range,col="green",add=T)

points(cbind(Xanthium_strumarium$longitude,Xanthium_strumarium$latitude),col="blue",p
ch=20,cex=1)
```



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