ASSESSMENT OF THE VULNERABILITY OF COASTAL MANGROVE ECOSYSTEMS IN MOZAMBIQUE

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Introduction

Mangrove forests are among the most productive ecosystems on Earth. However, there is still insufficient information available for strategic prediction of conservation and management intervention, particularly in the case of Mozambique. This country has the longest coastline and mangrove forests of Eastern Africa, but is prone to global climate hazards. Although with several limitations due to inaccuracy of sources and biases, species distribution models (SDMs) are widely used to estimate the geographical distribution of species, being key modeling tools in ecology (Guisan and Thuiller, 2005) and conservation (Kaky and Gilbert, 2016). Several studies using distribution models were published about Mozambique fauna (e.g. Monadjem et al., 2010) but very few studies used models to predict flora distributions in this country, which lacks well sampled local inventories for some areas and taxa. Moreover, the availability and quality of existing data, such as those found in public repositories (e.g. https://www.gbif.org/) are still insufficient to adequately feed such models.

Aims

Our study has the following goals: (i) to identify the most important environmental variables affecting the mangroves distribution patterns; (ii) to predict the spatial distribution pattern and suitable areas for their development; (iii) to quantify *A. marina* and *R. mucronata* exposure to climate hazards and erosion (EI); and (iv) to provide new insights for the future management and conservation of coastal habitats, which are seriously threatened by a number of hazards, of both natural and anthropogenic origin.

Methods

Species data: Our field data was collected in mangrove areas of the Sofala Province (Mozambique), from November 2018 to February 2019. We collected 58 occurrence records, including 24 of *A. marina* and 34 of *R. mucronata*. The field data was complemented with available information: (i) in GBIF (2018) (https://www.gbif.org/) (65 occurrence records); (ii) herbarium specimens housed by the Herbarium of the Instituto de Investigação Científica Tropical, University of Lisbon (LISC) (11 records); and (iii) literature search (e.g. Barbosa et al., 2001; Sitoe et al., 2014).

Environmental predictors: Initially we had 29 bioclimatic, hydrological, and geomorphological variables, including 19 bioclimatic data (bio1 to bio 19), salinity, land cover map of year 2016 (20m resolution), land surface elevation, digital elevation model (DEM), slop, maps of mangrove aboveground biomass, maximum canopy height, basal-area weighted height, and Flow accumulation. To avoid model over-fitting (Graham, 2003), the collinearity test was conducted by applying the Variance Inflation Factor (VIF) in R v3.6.0 (´car` package) (Hijmans and Van Etten, 2012) and 18 variables were removed; only 11 variables remained for use as model predictors (Table 1).

Species distribution modelling: The SDMs was produced using Maxent 3.4.1, which allows us to use presence-only data. The evaluation of the model accuracy was based on the area under the ROC curve (AUC) and the regularized training gain. The importance of the environmental predictors was analyzed using three different approaches in MaxEnt: the percent contribution, the permutation importance and the Jacknife test (Phillips et al., 2006). For Mozambique, the EI ranged from 1.39 to 4.26 and was categorized into five quantiles: “Very low” (< 2.54); “Low” (2.54–2.90); “Moderate” (2.90–3.22); “High” (3.22–3.53); and “Very high” (> 3.53). Further information about the EI calculations can be found in Cabral et al. (2017).

Final Remarks

.Our study revealed that average wind speed of the summer season, Mean Diurnal Range, elevation, and salinity (saltwater exposure) played a determinant role on the *A. marina* and *R. mucronata* distribution model. The most suitable areas for these two emblematic mangrove species are Maputo Bay, already with most of its perimeter covered with mangrove forests, and the stretch from the northern bank of the Save River up to Angoche, in Nampula province.

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Results

Table 1. Environmental variables used in this study, percent contribution and permutation importance. Variables in bold were selected through the multi-collinearity test and then used for the model.

Code	Environmental variables	Unit	% Contribution	Permutation importance
BIO1	Annual Mean Temperature	◦C		
BIO2	**Mean Diurnal Range (Mean of monthly (max temp - min temp))**	**◦C**	**13.1**	**44.1**
BIO3	Isothermality (BIO2/BIO7) (* 100)			
BIO4	**Temperature Seasonality (standard deviation *100)**	**(coeff. of variation ◦C)**	**0.6**	**7.7**
BIO5	**Max Temperature of Warmest Month**	**◦C**	**1.9**	**0.2**
BIO6	Min Temperature of Coldest Month	◦C		
BIO7	Temperature Annual Range (BIO5-BIO6)	◦C		
BIO8	Mean Temperature of Wettest Quarter	◦C		
BIO9	Mean Temperature of Driest Quarter	◦C		
BIO10	Mean Temperature of Warmest Quarter	◦C		
BIO11	Mean Temperature of Coldest Quarter	◦C		
BIO12	Annual Precipitation	mm		
BIO13	Precipitation of Wettest Month	mm		
BIO14	**Precipitation of Driest Month**	**mm**	**0.7**	**5.3**
BIO15	Precipitation Seasonality (Coefficient of Variation)	(coeff. of variation; %)		
BIO16	Precipitation of Wettest Quarter	mm		
BIO17	Precipitation of Driest Quarter	mm		
BIO18	**Precipitation of Warmest Quarter**	**mm**	**1.3**	**2.5**
BIO19	**Precipitation of Coldest Quarter**	**mm**	**0.5**	**0.6**
hmax	Mangrove canopy maximum height (height of the tallest tree)	m		
agb	Aboveground mangrove biomass	Mg ha^{-1}		
hba	Mangrove basal area-weighted height (individual tree heights weighted in proportion to their basal area)	m		
LULC	**land use/land cover**	**10 types**	**0.6**	**0.9**
SLO	**Slope**	**Degree**	**1.4**	**3.2**
Elev	**Land surface elevation**	**m**	**25.1**	**13.9**
SW	**Average wind speed in summer**	**m s^{-1}**	**49.4**	**8.1**
WW	Average wind speed in winter	m s^{-2}		
Na	**Saltwater exposure/salinity (Soil sodium concentration)**	**cmolc kg^{-1}**	**5.4**	**13.6**
FlowAcc	Flow accumulation	m^2		

Mangrove species distribution in Mozambique

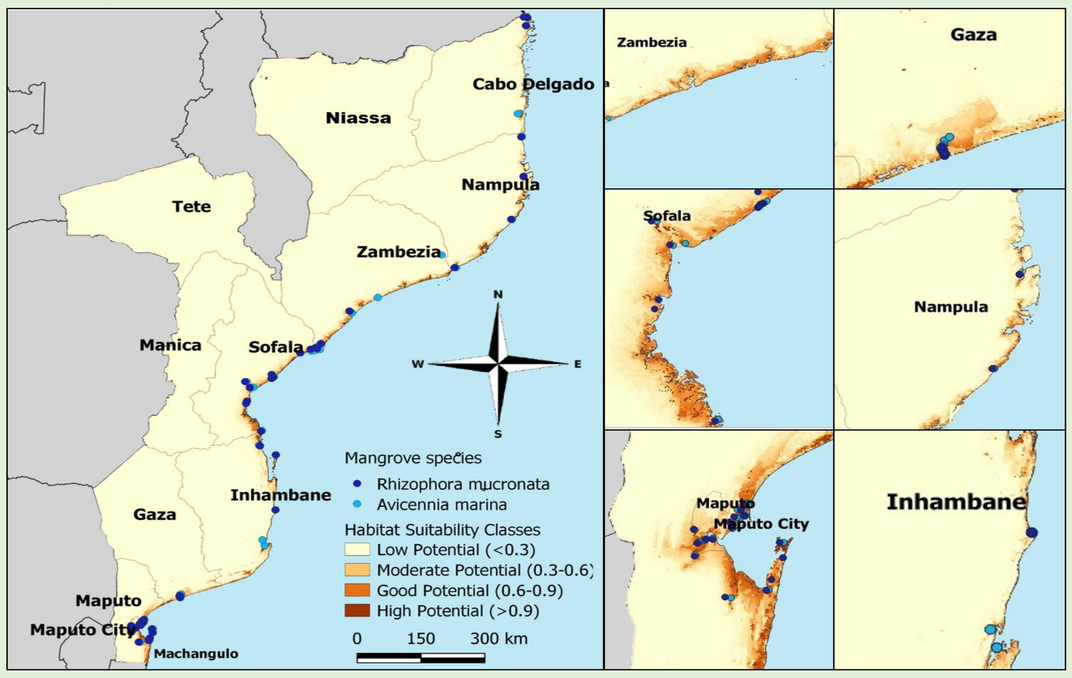

Figure 1. Predicted potential distribution of mangrove species (*A. marina* and *R. mucronata*) in the coastal area of Mozambique.

Exposure Index for A. marina and R. mucronata

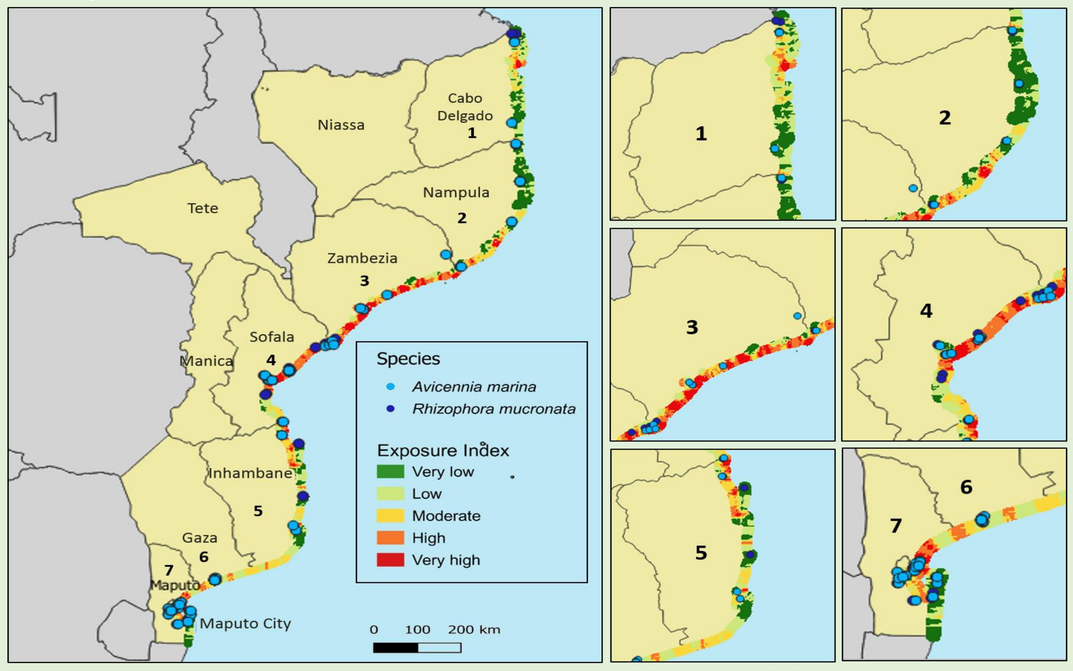

Figure 2. The sample points of *A. marina* and *R. mucronata* and the exposure index (EI) to coastal climate hazards and erosion of Mozambique (left). Details for each of the seven coastal Mozambique provinces are provided (right). Adapted from Cabral et al. (2017).

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