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LETTER

A New Framework to Assess Relative Ecosystem Vulnerability to Climate Change

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Abstract

Climate change poses a growing risk to global biodiversity. To prioritize conservation efforts, identification of the species and ecosystems most at risk from further changes in climatic conditions is critically needed. Although frameworks are available to assess species vulnerability to climate change, we still lack an easily implementable, ecosystem-level perspective to inform landscape management. Here, we introduce a novel, spatially explicit vulnerability framework able to generate assessments at the ecosystem scale and apply it to Mozambican forest mangroves, which are under growing pressures from climate change. Results show that most of these ecosystems are currently highly vulnerable to sea level rise, while mangroves in the Zambezia and Nampula districts are highly vulnerable to both sea level rise and tropical storms. Altogether, we believe the introduced assessment framework has clear potential to inform conservation planning and management at various spatial scales, and help achieve adaptive management in the face of climatic uncertainties.

Introduction

Climate change is unequivocal and along with ocean acidification and land use change, represents one of the greatest global threats to biodiversity and associated ecosystem services in the coming decades (Bellard *et al.* 2012). Accounting for a changing climate is becoming a necessity for environmental managers, requiring them not only to rely on geographically fixed entities such as protected areas for biodiversity conservation, but also to consider more adaptive approaches. Current thinking increasingly recognizes the need to integrate differences in vulnerability to climate change into conservation planning (Heller & Zavaleta 2009). Despite this, there are still limited examples where future threats are fully incorporated into the planning process (Watson *et al.* 2013).

Vulnerability assessments are an attempt to integrate threats such as climate change into the planning of conservation actions, by evaluating a system's exposure, susceptibility, and its ability to cope with a hazard (McCarthy *et al.* 2001). So far, however, available vulnerability assessments mostly focused on species (see, e.g., Pacifici *et al.* 2015), with few performed at the ecosystem scale. Vulnerability assessments that are carried out at an ecosystem level are rarely spatially explicit, despite its importance for prioritization (Wilson *et al.* 2005). Spatially explicit, global-scale vulnerability assessments do exist, but are unlikely to be accurate at a regional scale, or within specific ecosystems. Studies by Seddon *et al.* (2016) and Watson *et al.* (2013), for example, derived rough global biodiversity vulnerability assessments using single measures for exposure and adaptive capacity. Their results provided a useful initial assessment to identify potentially vulnerable areas at a global scale, but not specific ecosystems. They also did not consider underlying physical and biological processes that may drive differential vulnerability between species and ecosystems (such as exposure to threats due to geographic location). Conversely, Lindner *et al.* (2010) focused on forests in

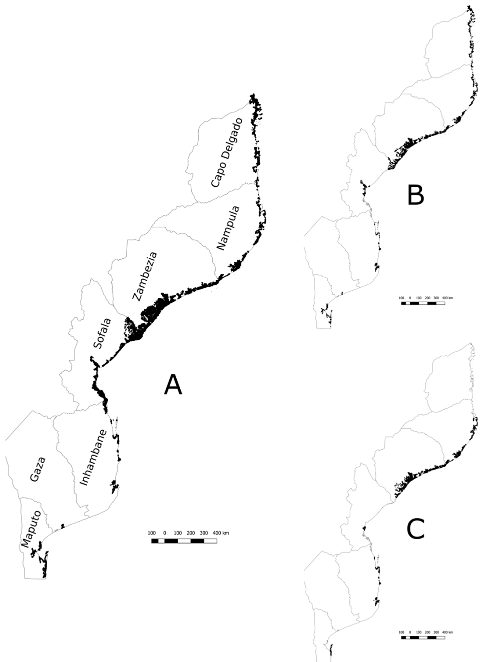

Figure 1 Mozambiacan coastline, detailing the different districts where mangrove forest ecosystems can be found. Distribution of mangrove forests in Mozambique (A). Mozambican mangrove forests that display high vulnerability to tropical storms (B) and SLR (C) are also mapped.

Europe and reviewed abilities of the various forest biomes to provide ecosystem services under climate change. While this study revealed an interesting association between biome entity and climate change impact on ecosystem services delivery, the results are unlikely to be useful to conservation regionally, due to the coarse resolution considered and the assumption that all areas within the same bioclimatic zone have homogenous vulnerability. Our point here is that, currently: (1) vulnerability assessments mostly focus on species, (2) the ones that do focus on ecosystems are rarely spatially explicit, and (3) the ones that do focus on ecosystems and are spatially explicit only consider extremely coarse spatial resolutions, delivering outputs unlikely to be useful to environmental management locally.

This work aims to further develop the toolbox of available vulnerability assessments methodologies by developing a spatially explicit vulnerability assessment framework at the ecosystem scale, which we believe has not been attempted before. To demonstrate this framework, we apply it to all mangrove forest ecosystems in Mozambique (Figure 1). Mangroves are particularly threatened ecosystems globally that yet provide an estimated \$194,000 $ha^{-1}yr^{-1}$ in ecosystem services worldwide (Costanza *et al.* 2014). They are among the world's most carbon-rich ecosystems and can provide coastal protection from storms by buffering the impacts of waves and storm surges (Giri *et al.* 2011, Alongi 2012). Their potential role in ecosystem-based mitigation and adaptation strategies in the face of climate change is clear; at the same time, recent studies have raised concerns regarding the increasing importance of climate change as a threat to mangroves (Lovelock *et al.* 2015). While focusing on mangroves in Mozambique, we hope to highlight the key underlying biophysical and socioeconomic processes shaping climate change vulnerability in these key ecosystems.

Material and methods

Definitions

The proposed vulnerabilty assessment framework only applies to coupled human-environment systems, which includes both the ecosystem and the neighboring biophysical and socioeconomic environment that can impact the ecosystem (Schröter *et al.* 2005). An essential component of any vulnerabilty assessment is the definition of the attribute of interest, chosen to represent the system as it is exposed to one or more specified hazards (Füssel 2007). Our vulnerabilty assessment targets the ecosystem level, and so potential candidates include metrics capturing changes in ecosystem area, structural attributes, functional attributes, and ecosystem composition. For the purpose of our framework, we define exposure as a metric capturing one or more characteristics of a given hazard that may lead to damage to the system considered (McCarthy *et al.* 2001). For example, exposure will relate to the rate of sea level rise (SLR) at a particular location, if the hazard considered is SLR (Lovelock *et al.* 2015). Sensitivity here describes the intrinsic ability of the system to tolerate and recover from the hazard it is exposed to (Adger 2006), with recovery defined as the system's ability to return to its initial state following perturbations. Adaptive capacity finally describes the system's intrinsic capacity to change to reduce the impacts of the hazard (McCarthy *et al.* 2001).

Study area, targeted hazards, and attribute of concern

Our vulnerabilty assessment framework is applied to mangrove forests in Mozambique, a country ranked as the most susceptible, and seventh most vulnerable, to natural hazards worldwide (Garschagen *et al.* 2014). Mozambique is estimated to have the 13th largest mangrove cover in the world (Giri *et al.* 2011) and second largest in Africa (Fatoyinbo & Simard 2013). For the pur-

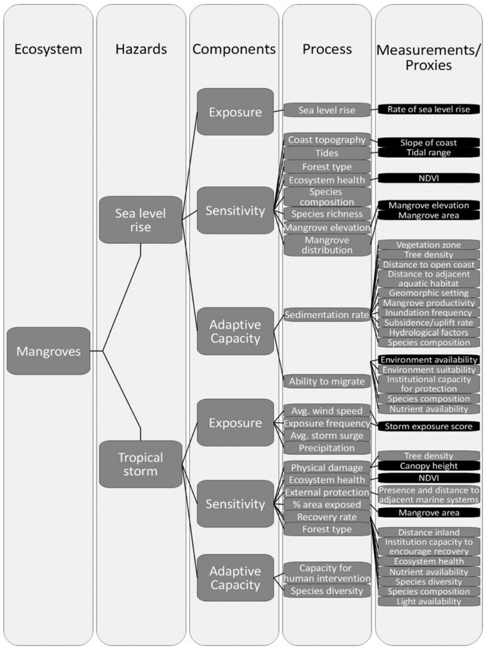

Figure 2 Hazard-driven processes that can negatively impact mangrove primary productivity, for each of the vulneability component considered (namely, exposure, sensitivity, and adaptive capacity). Possible measurements or proxies that can be used to index these processes are shown; those used for our analyses (namely rate of SLR, slope of coast, tidal range, NDVI, mangrove elevation, mangrove area, environmental availability for migration, storm exposure score, and canopy height) are highlighted in darker boxes.

pose of this case study, we focus on two hazards directly connected to climate change; SLR and tropical storms.

SLR has been highlighted as the greatest climate change-related threat to mangroves, as most mangrove sediment surface levels are being outpaced by SLR (Gilman *et al.* 2008). Mangrove forests in Mozambique were recently shown to be among the most affected by SLR due to the low-lying coastline (Alongi 2012). Tropical storms also pose an important threat to mangroves in Mozambique (Massuanganhe *et al.* 2015), with increased storm intensity and increased number of severe storms both expected in the region in the coming decades (Fitchett & Grab 2014).

Given the two hazards considered, the chosen attribute of concern is loss of productivity, which is indeed a key ecosystem function that is related to the vigor of an ecosystem, itself a component of a healthy ecosystem (Costanza & Mageau 1999). We performed a literature search for processes linking the two hazards considered with change in mangrove primary productivity. The identified processes and proxies are detailed in Table S1 (see also Figure 2).

Data

Mangove distribution and primary productivity assessment

Sixteen Landsat 8 scenes were downloaded from the United States Geological Survey (http://earthexplorer.usgs.gov/). To further inform the mapping of mangroves in Mozambique and derive information about the height of the top of the canopy in these ecosystems, data from the Shuttle Radar Topography Mission, which provides a global digital elevation model, were also downloaded (Fatoyinbo *et al.* 2008). The downloaded images were processed and mosaicked, creating a single image for each band for the entire coastline (Wegmann *et al.* 2016). Because active sensors can help map mangroves in cloudy environments, 14 Sentinel-1 Synthetic Aperture Radar images were downloaded from the Sentinels Scientific Data Hub (https://scihub.copernicus.eu/dhus), to inform the land cover classification process. The 14 images were processed and mosaicked, producing two bands (VV and VH) of data.

Hazard data

To assess exposure of mangroves to the hazards considered, all storm track data between 2002 and 2014 within the southern hemisphere were downloaded from The Joint Typhoon Warning Center Tropical Cyclone Best-Tracks Data Site (http://www.usno.navy.mil/NOOC/nmfc-ph/RSS/jtwc/best_tracks/shindex.php). It provided the coordinates for the centers of the storms, maximum sustained winds (Vm), and radius of maximum winds (Rmax) every 6 hours along each storm track. Reconstructed sea level data along the Mozambican coast from 2000 and 2009 were downloaded from the Physical Oceanography Distributed Active Archive Center (http://podaac.jpl.nasa.gov/dataset/RECON_SEA_LEVEL_OST_L4_V1). Maximum tidal range data were collected from tide forecast (http://www.tide-forecast.com/).

Analyses

Land cover classification

Mangrove distribution was assessed based on the information captured by the Landsat 8 OLI bands 1-7 and the two (VV and VH) SAR bands. The Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index were also calculated and used together with the other bands as a predictor during the land cover classification process (Wegmann *et al.* 2016). A supervised maximum likelihood classification was performed on the selected bands and indices using the package "RStoolbox" in R (R Core Team 2013). To reduce the number of potentially misclassified pixels, all areas above 35 m were masked, as mangroves do not grow over this threshold (Fatoyinbo *et al.* 2008). Training and validation polygons were created using the images provided from Google Maps using a semiautomatic classification plugin (Congedo *et al.* 2013). Land cover classes considered include mangrove forests, sand, other forested areas, urban areas, and water body. The validity of our classification was assessed using a confusion matrix and associated statistics (Wegmann *et al.* 2016).

Storm exposure, sensitivity, and adaptive capacity

Wind speeds at radius r (Vr) were calculated using the following equations (Anthes 1982):

$$\mathrm{Vr} = \mathrm{Vm}^{*}(\mathrm{r}/\mathrm{Rmax})^{\mathrm{x}} \quad (1)$$

$$\mathrm{Vr} = \mathrm{Vm}^{*}(\mathrm{Rmax}/\mathrm{r})^{\mathrm{x}}. \quad (2)$$

Equation (1) was used when r > Rmax, and Equation (2) when r < Rmax. The x is a constant that is estimated to be 0.7 by Batke *et al.* (2014). Fifty kilometer wide buffers around each storm track were created using the R package "rgeos." Wind speeds were calculated for each point within the storm track. All buffers with wind speeds less than 14 ms^{-1} were removed, as only winds stronger than this threshold are classified as tropical depressions within the South West Indian Ocean by Meteo France's La Reunion tropical cyclone center, which monitors the region. Following this guideline, there were no storms with an area of disturbance greater than 500 km from the center of the storm. Storm exposure scores, which combine information on storm frequency and intensity, were then calculated by summing the wind speeds for every mangrove pixel.

Tree height (Alongi 2008), mangrove forest area (Aung *et al.* 2013), and vegetation vigor (MacDougall *et al.* 2013) were all expected to shape mangrove sensitivity to storm. Tree height was calculated using Simard *et al.*'s (2006) approach (see also Fatoyinbo *et al.* 2008), while forest area was assessed manually by identifying forested units from the classified information. Vegetation vigor was indexed using the NDVI (Pettorelli 2013).

Human interventions, such as creating physical barriers to storm surges or enrichment planting of propagules in areas which have been completely destroyed, can strongly influence mangrove adaptive capacity to storms (Massuanganhe *et al.* 2015). We were unable to identify spatially explicit proxies capable of providing meaningful information on adaptive capacity for the Mozambican coastline.

SLR exposure, sensitivity, and adaptive capacity

Reconstructed sea level data were used to assess trends in SLR. The SLR value of the nearest ocean pixel was attributed to each mangrove pixel; this value determined the SLR exposure score of the pixel. Tidal range (Ellison 2012), mangrove forest area (Krauss *et al.* 2014), and vegetation vigor (Li *et al.* 2014) were all expected to shape mangrove sensitivity to SLR. Maximum tidal range data were spatially extrapolated for the whole of the Mozambican coastline, while forest area was assessed manually by identifying forested units from the classified information. As previously, vegetation vigor was indexed using the NDVI. Adaptive capacity was indexed as the ability for mangroves to migrate (Gilman *et al.* 2007). Specifically, mangroves pixels neighboring urbanized areas were classified as unable to migrate.

Ranking vulnerability

Measurements for the proxies considered were normalized and their distributions split into quartiles; the exception to this was the potential ability for mangroves to migrate, which was indexed as a binary variable. The quartiles were then given score representing relative vulnerability: the upper and lower quartiles were given scores representing low (1) or high (3) vulnerability, depending on the proxy. The pixels within the middle quartiles were given scores representing medium (2) vulnerability. Each pixel was then allocated a score for each proxy. Scores of 3 and 1 were given to pixels with mangroves that showed or did not show an ability to migrate, respectively. Normalization allowed direct comparison between measurements of different units (Ellison 2012), which can then be aggregated into a single vulnerability value. Several methods can be used to aggregate vulnerability components (Tonmoy *et al.* 2014): we decided to calculate the arithmetic mean for each pixel for all proxies within the same component (exposure, sensitivity, or adaptive capacity). The quartiles for these means were then defined, and reclassified from low to high to create a component score for each hazard. The arithmetic mean for the three (or two, in the case of storms) components were then calculated for each pixel, producing a final vulnerability score for each hazard, which was reclassified into quartiles for display (Figure 1B & C). Since there was insufficient information to differentially weigh the factors and proxies affecting mangrove vulnerability, they were all given equal weighting.

Results

Based on our classification, mangrove cover on the Mozambican coastline is 3,204 km^2, with our classifica-

Table 1 Sensitivity, specificity, and balanced accuracy of the image classifications for the Mozambican coast

	Mangrove	Sand	Other forested areas	Urban areas	Water bodies
Sensitivity	0.88	0.48	0.79	0.60	0.98
Specificity	0.97	0.98	0.90	0.85	0.98
Balanced accuracy	0.93	0.73	0.84	0.73	0.98

Five categories of land cover were distinguished during the classificaiton process: mangroves, sand, other forests, urban areas, and water bodies. The overall accuracy of the classification was 75.2%; the associated Kappa coefficient was 0.69.

tion being able to identify mangrove areas with a balanced accuracy of 93% (Table 1, Figure 1). Our analysis of the available storm data showed that storm exposure was highly variable in Mozambique, with no storm reported to affect the northern province of Capo Delgado during the period considered, and more frequent and/or intense storms found in the Zambezia region. SLR exposure was perhaps found to be more spatially consistent, being high across most of Zambezia and the northern parts of Nampula.

Mangrove sensitivity to storms and SLR was clearly highly variable: tree height was indeed found to be medium to low South of Beira (a city halfway through Sofala's coastline), while the only mangrove forest classified as continuous and large was at the Save River Delta (close to where Sofala joins Inhambane). Other mangroves in the Zambezi River Delta were quite fragmented. Generally, higher NDVI scores were found in the northern Mozambican mangroves and most mangroves in the Save River Delta had low NDVI scores. Tidal range scores across the coastline were split into three regions: the southern provinces of Maputo, Gaza, and most of Inhambane had high tidal range scores, while Capo Delgado, Nampula, and half of Zambezia had medium tidal range scores. Sofala, and the remaining areas of Zambezia and Inhambane, had the lowest tidal range scores.

Overall, Zambezia and Nampula mangrove forests were shown to have the highest average storm vulnerability scores, while Capo Delgado had the lowest score. Most mangrove forests in Mozambique were shown to be highly vulnerable to SLR, with mangroves in the Zambezia and Nampula districts being highly vulnerable to both SLR and tropical storms (Figure 1).

Discussion

This work provides for the first time a spatially explicit, ecosystem-scale framework able to capture fine-scale spatial nuances in vulnerability to climate change. The case study demonstrates that climate change vulnerability assessments require an integrative approach that acknowledges the different hazards associated with changing global climatic conditions and that considers spatial variation in exposure, sensitivity, and adaptive capacity. Doing so not only allows us to confidently and transparently highlight areas of high relative vulnerability, but also conservation strategies which may be most effective for a particular area. For example, the Maputo mangrove forests were mostly found to be mildly vulnerable to storms, due to a combination of low-to-medium storm exposure and high tree height scores, despite having small forests with low NDVI. Conversely, these forests were found to have relatively high SLR vulnerability score, due to high tidal range and migration ability scores, despite having low SLR exposure. Our results thus highlight how Maputo mangrove forests could greatly benefit from management actions that help reduce mangrove sensitivity to SLR (e.g., measures which increase sedimentation rate) as well as actions that improve adaptive capacity to SLR (e.g., policies banning coastal development in potential mangrove migration areas; Ellison 2012).

Our study moreover demonstrates how freely available satellite data and open-source software can be used to conduct vulnerability assessments at the ecosystem level, highlighting how such methodology can provide crucial information to support adaptive management in the decades to come. These products and tools indeed offer a relatively inexpensive and verifiable means of deriving complete spatial coverage of environmental information for large areas in a consistent manner that may be updated regularly (Pettorelli *et al.* 2014). New sensors are continuously being launched by space agencies, while these agencies are also making the data increasingly accessible to the scientific community, meaning that opportunities for satellite data to inform environmental planning, and in particular ecosystem-level vulnerability assessments, will likely increase in the coming years.

Interestingly, our study reports an overall increase in mangrove cover in Mozambique from previous estimates. The largest difference observed was in Zambezia, with a 75% increase in mangrove cover from previous studies (Fatoyinbo *et al.* 2008). A similar increase was observed by Shapiro *et al.* (2015), who attributed this increase to mangrove expansion happening mostly within mudflats and upstream areas. Our mangrove cover estimates were, however, smaller than previously reported in Sofala and Maputo, with our Maputo cover estimate down by 60% from previous ones (Fatoyinbo *et al.* 2008). Sofala and Maputo are the two provinces of Mozambique currently undergoing most coastal development (de Abreu 2010; Sitoe *et al.* 2014), and so our results suggest that these developments are posing a threat to mangrove forests locally. Further ground research is needed to confirm that this is indeed the case.

Admittedly, there are several shortcomings to the proposed approach. Historical data were used to assess exposure to hazards, as opposed to future climate predictions. This choice was partially driven by the lack of reliable, spatially explicit predictions for the two hazards and area considered. SLR was therefore assumed to be a linear process, which we know is a gross simplification, given that the rate at which SLR will occur will likely depend on a multitude of uncertain factors (Kopp *et al.* 2016). Similarly, it was assumed that areas already exposed to frequent and/or intense storms will continue to be most at risk from future storms. Because of this reliance on historical hazard data, the results generated here will only be valid in the short term, as the proxies used have limited prediction power. However, our results still provide key spatially explicit information on the current vulnerability to two major hazards known to already impact mangrove systems in the area. As better predictions for these hazards become available, the temporal reference used can be extended, and the results adapted.

Out of the 25 processes identified to affect mangrove vulnerability to storms and SLR (Figure 2), only 10 could then be proxied or measured remotely at an ecosystem scale. Many of the identified processes influencing sensitivity and adaptive capacity, such as species diversity and sedimentation rate, could not be indexed. Similarly, there was insufficient information to differentially weigh the factors and proxies affecting each vulnerability component, or to differentially weigh the components (sensitivity, exposure, and adaptive capacity) affecting mangrove vulnerability. By missing out on these identified processes and by assuming equal weighing, crucial information might be omitted from the vulnerability assessment, thus reducing its overall reliability in this particular study case. Various studies have now called for a better coordination of global monitoring efforts, to help improve the temporal and spatial coverage of key data sets (see, e.g., Pettorelli *et al.* 2014). As more data sets get shared and coordination improves, so will the reliability of our proposed methodology. Our framework can support these much needed developments, help identify crucial gaps in data availability, and potentially trigger new research in the rapidly developing field of remote sensing.

Despite these shortcomings, this study has been able to demonstrate how an ecosystem scale vulnerability assessment framework could be developed and implemented to inform conservation planning and management, making adaptive management a reality for highly threatened ecosystems. We believe the introduced assessment framework is a transparent, repeatable tool that has clear potential to inform management at various spatial scales.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table S1: Processes that can negatively impact primary productivity when mangroves experience SLR and tropical storms, for each of the vulnerability component considered (namely, exposure, sensitivity, and adaptive capacity)

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