Global Change Biology

Global Change Biology (2013), doi: 10.1111/gcb.12176

Making predictions of mangrove deforestation: a comparison of two methods in Kenya

ALASDAIR J R RIDEOUT*, NEHA P JOSHI†, KARIN M VIERGEVER†, MARK HUXHAM* and ROBERT A BRIERS*

*School of Life, Sport and Social Sciences, Edinburgh Napier University, Sighthill Campus, Edinburgh, EH11 4BN, UK, †Ecometrica Ltd., Top Floor, Unit 3B, Kittle Yards, Edinburgh, EH9 1PJ, UK

Abstract

Deforestation of mangroves is of global concern given their importance for carbon storage, biogeochemical cycling and the provision of other ecosystem services, but the links between rates of loss and potential drivers or risk factors are rarely evaluated. Here, we identified key drivers of mangrove loss in Kenya and compared two different approaches to predicting risk. Risk factors tested included various possible predictors of anthropogenic deforestation, related to population, suitability for land use change and accessibility. Two approaches were taken to modelling risk; a quantitative statistical approach and a qualitative categorical ranking approach. A quantitative model linking rates of loss to risk factors was constructed based on generalized least squares regression and using mangrove loss data from 1992 to 2000. Population density, soil type and proximity to roads were the most important predictors. In order to validate this model it was used to generate a map of losses of Kenyan mangroves predicted to have occurred between 2000 and 2010. The qualitative categorical model was constructed using data from the same selection of variables, with the coincidence of different risk factors in particular mangrove areas used in an additive manner to create a relative risk index which was then mapped. Quantitative predictions of loss were significantly correlated with the actual loss of mangroves between 2000 and 2010 and the categorical risk index values were also highly correlated with the quantitative predictions. Hence, in this case the relatively simple categorical modelling approach was of similar predictive value to the more complex quantitative model of mangrove deforestation. The advantages and disadvantages of each approach are discussed, and the implications for mangroves are outlined.

Keywords: Categorical model, mangrove deforestation, prediction, quantitative model, risk factors

Received 13 December 2012 and accepted 3 February 2013

Introduction

The importance of tropical forests for biodiversity, biogeochemical cycles and the provision of goods and services to local people has been acknowledged for decades. More recently, recognition of their role in carbon sequestration and climate regulation has added new emphasis to calls for conservation. Emissions from land use changes (predominantly tropical forest loss) are the second largest source of anthropogenic carbon, with around 1.2 Pg entering the atmosphere in 2008 (le Quéré *et al.*, 2009). Loss of mangrove forests is of particular concern; despite accounting for only approximately 0.7% of all tropical forest, or 0.1% of the global land surface (Giri *et al.*, 2011), they contain 4.03 Pg of sequestered carbon (Twilley *et al.*, 1992), and are of global importance to carbon dynamics in the coastal zone (Bouillon *et al.*, 2008). The large quantities of carbon stored belowground in mangroves make them amongst the most carbon-dense of all habitats (Donato *et al.*, 2011). Furthermore, mangroves offer a wide range of other ecosystem services including the mitigation of tsunamis and storm surges (Kathiresan & Rajendran, 2005) and reduction in coastal erosion (Thampanya *et al.*, 2006), the provision of nurseries for pelagic and reef fish, including commercially important species (Rönnbäck, 1999) and the production of forest goods including timber (López-Hoffman *et al.*, 2006). Despite their ecological and economic importance, around 35% of mangroves were lost globally between 1980 and 2000 (Millennium Ecosystem Assessment, 2005) with annual global loss rates of approximately 1–2% per year (Farnsworth & Ellison, 1997). At the current rate, mangrove forests could be lost entirely by the end of the century (Duke *et al.*, 2007).

Modelling deforestation and attempting to identify factors associated with risk of forest loss has been performed in a variety of contexts and utilizing a range of techniques of varying degrees of complexity (e.g. Ludeke *et al.*, 1990; Kaimowitz & Angelsen, 1998; Cropper *et al.*, 1999; Serneels & Lambin, 2001; Agarwal *et al.*, 2005; Nakakaawa *et al.*, 2011; Nahuelhual *et al.*, 2012).

Correspondence: Robert A. Briers, tel. + 44 (0) 131 455 2503, fax + 44 (0) 131 455 2291, e-mail: r.briers@napier.ac.uk

The availability of large amounts of spatial data combined with rapid computer processing makes the construction of complex statistical models and simulations possible. However, the complexity of many of the processes involved in deforestation, the importance of idiosyncratic local influences and multiple correlations amongst possible causal factors, all mean that producing quantitative predictive models of deforestation risk is challenging and risks spuriously implying precision and confidence. An alternative to such statistical approaches is to model risk using broad categorical classifications. Boonyanuphap *et al.* (2001), and Boonyanuphap (2005) demonstrated the utility of such models using the Composite Mapping Analysis (CMA) technique to estimate the risks of wildfire and deforestation in different systems. Vulnerability of forest units was estimated using a series of equations based upon relative weights of certain predictive factors; overall risk was calculated as a function of these composite vulnerabilities. Similarly Castillo-Santiago *et al.* (2007) predicted risk categories for deforestation in Mexico based on a series of categorical assessments of risk factors, which were then correlated with observed change. One significant advantage of such approaches is their relative simplicity in development, comprehension and application; reviews of deforestation modelling (e.g. Kaimowitz & Angelsen, 1998) have highlighted the weaknesses and limitations of more sophisticated statistical models, but there has been a lack of comparison between the different approaches, which would facilitate better evaluation of their relative efficacy.

Despite the extensive literature on deforestation, work on risk factors to mangroves is rare and there are very few attempts at quantitative predictive modelling. Some studies have used a land-use and cover-change (LUCC) approach to identify the land-uses that replace mangroves when they are lost (e.g. Giri & Muhlhausen, 2008). Hirales-Cota *et al.* (2010) used semi structured interviews with local residents to identify perceived drivers of change in mangrove cover in Mexico. Recently Omo-Irabor *et al.* (2011) utilized Spatial Multi-Criteria Analysis based on expert opinion to develop a mangrove vulnerability model for the Niger delta, incorporating a range of socio-economic and environmental criteria, but this was not tested against observed change in mangroves to determine the extent to which the model provided an accurate prediction.

The current study aimed to extend previous work through the assessment of putative drivers of mangrove loss along the coastline of Kenya using a combination of quantitative statistical and qualitative categorical modelling approaches. Quantitative and categorical models of mangrove deforestation risk were derived and compared against observed losses to examine the differing benefits of the two approaches, when applied to the same dataset. Hence, this work had three objectives: first, to identify mangrove deforestation risk factors in Kenya using historical data. Second, to model these risks using two different approaches and to produce assessments of high risk areas for use in future planning. Third, to directly compare the statistical and categorical modelling approaches by deriving predictions from both that were tested against observed changes in forest cover.

Materials and methods

Study site

The location used for this study is the 575 kilometres long coastline of Kenya, from 1° 40′S to 4° 41′S (Abuodha & Kairo, 2001). The mangroves here often occur in the proximity of significant human settlement; Mombasa, Lamu, and Malindi are all situated on the coast, with Mombasa being the second largest city in the country and the centre of its tourism industry (WRI, 2007). In common with mangroves in most countries, those in Kenya have suffered significant anthropogenic cover loss; using Landsat data, it has been estimated that 18% of total cover was lost between 1985 and 2010 (Kirui *et al.*, in press).

Data sources

Changes in the extent of mangrove cover in the different time periods were based on Landsat-derived estimates taken from Kirui *et al.* (in press). Data on potential drivers of mangrove deforestation were collated from a variety of sources (Table 1). Variables were selected on the basis of biological plausibility and on the available data sources. The variables selected were primarily related to human activity; they either modelled proximate effects of human activity or served as proxies. Although similar data sources were used in both models, the manner in which they were incorporated differed (see below and Table 2).

Quantitative Model development

Initially all data were analysed at 100 m^2 resolution, but there were computations difficulties encountered when deriving models at this resolution. Therefore, all data sources were resampled to 1 km^2 resolution. For variables such as distance to road, a mean value was calculated for each 1 km^2 area analysed. All continuous predictor variables were log + 1 transformed prior to analysis to conform to analytical assumptions, with the exception of proportional mangrove loss which was arcsine transformed. Soil type was included as a categorical variable, along with water deficit, which had a limited range of values and was converted into categories for analysis (see Table 1). A total of 1531 1 km^2 areas were used in model development.

Generalized Least Squares (GLS) served as the basis for the quantitative model, based on changes in mangrove cover

Table 1 Variables used for construction of models of mangrove loss in Kenya

Variable	Source	Definition	Year
Mangrove Forest Loss	Kirui *et al.* (in press)	Proportional loss of mangrove cover	1992/2000 2000/2010
Population Density	GPW*/Afripop	Mean density within 2 km of loss cell	1995, 2005, 2010
Hotels	WRI†	Number of hotel beds within a 2 km radius of each cell.	2003
Proximity to Roads	WRI/IGAD/Geocommons‡	Distance in metres to nearest road	Information derived from combination of data from different years
Road Network Extent	WRI/IGAD/Geocommons	Total road length within 2 km	As above
Travel Time¶	IGAD§	The travel time to the nearest urban centre	2009
Soil Type	IGAD	Nonsoil (marine) = 0, nonclay soil = 1, clay-based soil = 2	1997
Water Table Deficit	WRI	The deficit of water in m^3/day	1990, projections for 2000 and 2010
Water Table Yield	WRI	The yield of water in m^3/day	2000
Protected Status	WRI	Areas given protected area status	2007

*Gridded Population of the World, version 3.
†World Resources Institute (WRI); Department of Resource Surveys and Remote Sensing Ministry of Environment and Natural Resources Kenya; Central Bureau of Statistics Ministry of Planning and National Development Kenya; and International Livestock Research Institute (2007) Nature's Benefits in Kenya, An Atlas of Ecosystems and Human Well-Being. Washington, DC and Nairobi: World Resources Institute).
‡Data derived from a combination of different sources to give best overall representation of the road network.
§Intergovernmental Authority on Development (www.igad-data.org).
¶Estimates of travel time to an urban area ($\geq$2500 people km^{-2}) were derived from a friction model, based on a combination of surface type and topography. Some parts of the northern mangrove fell outside areas where estimates had been calculated; values for these areas were estimated as means of a two cell neighbourhood.

between 1992 and 2000. Initial analyses identified strong spatial autocorrelation, therefore a spatial error term was included in the model. A number of spatial correlation structures (exponential, linear, Gaussian, spherical, and rational quadratic) were tested; a spherical correlation structure incorporating a nugget effect was found to give the best fit to the null model, and residual variograms showed no evidence of significant remaining spatial correlation structure.

A model selection approach (Burnham & Anderson, 2002) was used to construct the quantitative model. A total of 64 candidate models were constructed using ecologically plausible combinations of the predictor variables. The fit of the different models was assessed using AIC_c, although ranking using uncorrected AIC values gave similar results. Models were compared based on ΔAIC_c values and Akaike weights (Burnham & Anderson, 2002). As no single model dominated in terms of fit to the data, model averaging was used (Burnham & Anderson, 2002); models with a ΔAIC_c value of <3 were used to synthesize the coefficients. All analysis was undertaken using R version 2.15.0 (R Development Core Team, 2012), using the nlme (Pinheiro *et al.*, 2012) and MuMIn (Bartoń, 2012) packages.

Validation of Quantitative Model

In order to validate the quantitative model, predictions of mangrove loss between 2000 and 2010 were generated using the coefficients from the final averaged model. Owing to a lack of temporal data (road network, hotel capacity) or presumed lack of change (soil type, travel time) the majority of predictor variables were assumed to be constant. However, population data were updated to use 2005 densities, and water deficit values to projections for 2000. The loss of mangrove predicted for 2010 by the model was compared with the observed loss based on Landsat derived estimates for this period (Kirui *et al.*, in press) using Pearson correlation.

Categorical Model development

The categorical model is a simple spatial model developed based on the ACEU parameters; this assumes that land that is Accessible (A), Cultivable (C), has Extractive value (E) and is Unprotected (U) is at highest risk from deforestation unless conserved (Garrett *et al.*, 2009; Grace *et al.*, 2010). Definitions of A, C, E and U, and the causes that contribute to risk within each (Table 2) were derived based on the literature and local knowledge (Langan, 2011). Data layers were resampled to 30 m resolution prior to analysis for consistency with the original Landsat mangrove cover estimates. Each contributing cause of deforestation was examined individually, and areas affected by it were mapped to identify the location and extent of influence of the cause. These maps were then classified into discrete categories and given risk indices. The number of categories to divide areas into was

Table 2 Risk factors used in the categorical model and basis for inclusion

Cause of risk	Basis for risk
Protection Type (R_U)	
Protected Areas	Risk to both protected and unprotected areas was calculated similarly, assessing factors of accessibility, cultivability and extractability. As a last step, protected areas (such as marine natural reserves and biosphere reserves) have their risk index downgraded by one level.
Cultivable Value (R_C)	
Total water yield	Areas with higher water yield are assumed to be at higher risk from cultivation or industry, whereas those with lower yield at lower risk. Four risk indices were assigned to identify areas of relatively high water yield and low water yield.
Population Density	Demand, and thus risk, for cultivation in mangrove areas is assumed to be higher around high population density centres. Areas of high population density were first determined by identifying hotspots (cities, towns, ports) which contained >50% of Kenya's population. Four risk indices were then assigned to areas within 20 km, 15 km, 10 km and 5 km of these hotspots.
Soil Type	Unmanaged and unsustainable felling for aquaculture is a threat to mangroves (Barbier *et al.*, 2008; Walters *et al.*, 2008). Clay soils, which are better suited for aquaculture (Loganathan, 1987) were assumed to pose a higher risk to mangroves than nonclay soils. Thus, two risk indices were assigned based on clay or nonclay soil type.
Extractable Value (Economic Pressures) (R_E)	
Woodcutting	Ease of accessibility into mangroves, assessed by distance from the mangrove edge, was used as an indicator of risk from woodcutting. Three risk indices were assigned for areas within 600 m, 400 m and 200 m buffers around the mangrove edge.
Access to markets	Areas at which higher travel time to an urban area is estimated are assumed to have a lower risk. A travel time map was analyzed and categorized into four risk indices of travel time of <200 h, <400 h, <600 h and $\geq$600 h.
Tourism	Tourism was assumed to increase risk to mangroves (Food & Agriculture Organization of the United Nations, 2007), through associated developments. Four risk indices were assigned to areas based on number and beds provided at hotels.
Accessibility (R_A)	
Distance to Water Edge	Shorter access distance to mangroves from the water edge was assumed to further increase their potential risk of deforestation. Three risk indices were assigned at 600 m, 400 m and 200 m buffers from the water edge.
Distance to Road	Mangroves in close proximity to roads, which allow access to markets for mangrove products, were assumed to be at high deforestation risk. Five risk indices were assigned for areas within 10 km, 8 km, 6 km, 4 km and 2 km of all roads.

based on expert and local knowledge of each cause of deforestation in the mangroves of Kenya (see Langan, 2011). The minimum number of categories for a cause was two (e.g., protection status was given a Y/N binary attribute indicative of unprotected/protected) and the maximum number of categories was five (risk indices from 1 to 5), indicating the relative level of risk (low to high, respectively) the cause poses to mangroves at a given location. The total risk level at a location was then calculated as the sum of the risk indices associated with three of the four ACEU parameters (risk of extractability, accessibility and cultivability). These values were then rescaled into 5 equal-interval risk bands (values 1–5), reflecting very low, low, medium, high and very high risk. Protected status was then taken into consideration by subtracting 1 from the risk index value if the area had protected status (Eqn [1]). Thus, the final output is a map that spatially classifies mangroves into risk bands based on their relative risk of deforestation.

$$\mathrm{Risk} = (R_C + R_E + R_A) - R_U \tag{1}$$

Comparison of approaches

Due to cloud cover in the original Landsat images, outlines of mangrove extent in different years were incomplete (Kirui *et al.*, in press). Only areas that showed complete cloud-free coverage within individual 1 km^2 quadrats in both years (1992 and 2000) were used in deriving the quantitative model; this meant that certain areas were excluded from consideration. As the categorical model included explicit consideration of edge effects on the risk of loss, which was not possible in the quantitative model due to the resolution of the data used, direct comparison of losses predicted by both models based on 2000 data with actual losses by 2010 was not possible.

As an alternative, mangrove extent for 2010, derived from classification of cloud-free SPOT satellite imagery (which was not available for earlier time periods), was used as the basis for comparison of the two approaches. Loss predictions from the quantitative model and risk index values from the qualitative model were derived using the relevant population and water deficit data for 2010. Qualitative risk index values were averaged for mangroves in each 1 km^2 area, and the models compared by correlating the current mean risk status of mangrove areas with the amount of forest loss predicted to have occurred over the past decade by the previously validated quantitative model. This does indicate that the validation of the categorical model is predicated upon that of the quantitative. As parametric assumptions were not met, particularly in the non-normally distributed risk values, Spearman's rank correlation was used for comparison.

Results

Quantitative Model

Table 3 gives details of the top sixteen of the alternative models, ranked by AIC_c values. The top four models in the table, which incorporated with varying frequencies all the predictors chosen, were used as the basis for the averaged coefficients (Table 4). The direction of the coefficients for the variables in the model generally conformed to expectations; higher population density, number of hotel beds and total road length, all within 2 km, along with greater water yield (which would indicate a higher possibility of development) and higher levels of water deficit (which may indicate greater stress to the mangroves) were associated with higher forest loss. Conversely, a greater distance to the nearest road and greater travel time to urban areas were associated with lower loss. Mangrove loss appeared slightly higher in intertidal areas than on fully terrestrial soils, but the difference is marginal and there was also no strong difference between clay and nonclay soil types. Although in reality mangroves all have essentially the same peaty soil type, the mapping of the soil type data in the original GIS files effectively allows it to serve as a proxy for susceptibility to development in the immediate vicinity. Population density, distance to road and soil type were represented in all the models used to derive the final quantitative model, indicating the importance of these variables in describing the loss data, followed in frequency by number of hotel beds and water yield. Other variables were included with lower occurrences in the models incorporated.

Quantitative Model validation

Predictions of loss derived from the averaged model coefficients were strongly correlated with observed loss over the same period ($r = 0.657$, $P < 0.0001$, Fig 1) indicating that the model effectively allowed prediction of the probable loss in mangrove over time.

Qualitative Model

The qualitative model allowed the production of a map showing areas at risk of deforestation, with values ranging from 1 in the areas at lowest risk, to 5 in those areas situated amongst significant urban development, such as near Mombasa (Fig 2b).

Table 3 The combinations of variables included in the top sixteen ranked models from the candidate set

Model rank	Population density	Hotel beds	Distance to road	Density of roads	Travel time	Soil type	Water yield	Water deficit	AIC_c	ΔAIC_c	Akaike weight
1	+	+	+	–	–	+	+	–	–1806.9	0	0.379
2	+	+	+	–	+	+	+	–	–1805.9	1.07	0.222
3	+	+	+	+	–	+	+	–	–1805.0	1.97	0.142
4	+	–	+	–	+	+	–	+	–1804.7	2.26	0.122
5	+	+	+	–	+	–	–	–	–1803.1	3.83	0.056
6	+	–	+	–	+	–	–	+	–1803.3	5.62	0.023
7	+	+	+	+	+	–	–	–	–1801.1	5.85	0.020
8	+	+	+	–	+	+	–	–	–1800.0	6.93	0.012
9	+	+	+	–	+	–	–	+	–1799.5	7.46	0.009
10	+	+	+	–	+	+	+	+	–1798.1	8.85	0.005
11	+	+	+	+	+	+	–	–	–1798.0	8.95	0.004
12	+	+	+	–	–	+	–	+	–1797.0	9.95	0.003
13	+	+	+	–	+	+	–	+	–1795.7	11.24	0.001
14	+	+	–	+	+	+	–	+	–1795.4	11.56	0.001
15	+	+	+	+	–	+	–	+	–1795.0	11.93	0.001
16	+	+	+	+	+	+	–	+	–1793.7	13.23	0.001

Table 4 Averaged model coefficients and the relative importance of variables for the final quantitative model. Values for soil type and water deficit are given as contrasts due to their categorical values

	Intercept	Population density	Soil type	Distance to road	Hotel beds	Water yield	Travel time	Density of roads	Water deficit
Coefficients	0.0255	0.0202	Intertidal: 0 nonclay: −0.00993 Clay: −0.0082	−0.0021	0.00204	0.0034	−0.0015	0.0021	0: 0 1: 0.0038 2: 0.1077 3: 0.1771 4: 0.0341
Relative importance of variable*	1.00	1.00	1.00	1.00	0.86	0.86	0.40	0.16	0.14

*sum of the Akaike weights over all of the models in which the variable appears.

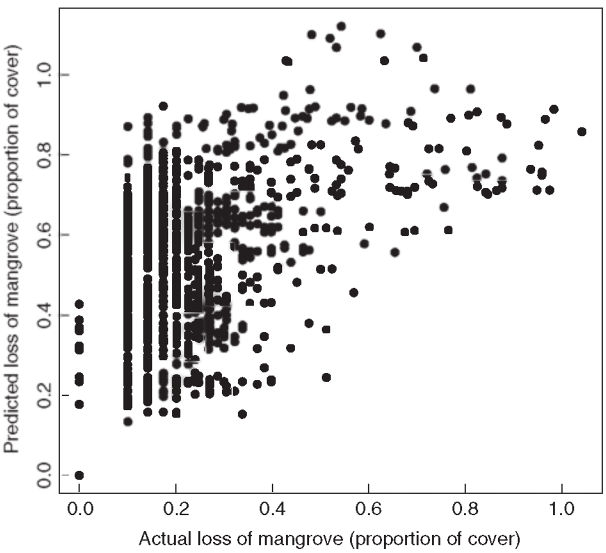

Fig. 1 Comparison of predicted loss of mangrove cover (proportion lost per 1 km^2 area) with observed change in extent (both arcsine square-root transformed), based on Landsat-derived estimates from Kirui *et al.* (in press).

Comparison of modelling approaches

Mean risk values derived from the categorical model for 1 km^2 areas were positively correlated with the loss predicted by the quantitative model (Spearman rank correlation, $r_s = 0.541$, $P < 0.0001$). Fig 2 depicts the output of both models for the extent of the Kenyan coast, showing the overall congruence of the two approaches.

Discussion

Three main predictors appeared in all the constituent versions of the quantitative model, namely population density, distance to roads and soil type, which can be considered as proxies of three main genera of drivers: population effects, accessibility and suitability for development. Population density is one of the most widely identified, but also controversial, risk factors in deforestation studies (see review in Kaimowitz & Angelsen, 1998; as well as more specifically for mangroves Omo-Irabor *et al.*, 2011). Rising population density can have a number of obvious direct effects on deforestation, such as increased demand for timber for housing use (particularly relevant in the case of mangroves; Nfotabong-Atheull *et al.*, 2011) or for fuel, but may also reflect other drivers such as the quality of land for agriculture and the distance to markets for timber products (Kaimowitz & Angelsen, 1998).

In this study, there is evidence for additional independent effects of both accessibility from roads and soil type on mangrove loss rates in Kenya. There is extensive literature evaluating the influence of roads on deforestation rates. Although the effects of roads are generally negative (Chomitz & Gray, 1996; Nelson & Hellerstein, 1997; Cropper *et al.*, 2001; Patarasuk & Binford, 2012), this is not always the case; de las Heras *et al.* (2011) found that as the road network reaches a certain level of saturation, the primary influences on deforestation become topographical features, and Deng *et al.* (2011) found no effects on forests from road developments in China. The observed effects in the case of mangroves are likely to relate to both the ease of extraction and also the ability to transport timber to markets in urban centres (Salonen *et al.*, 2012), hence the inclusion of travel time to urban centres as a modifying influence on the extent of roads in the vicinity of the mangrove area. Distance to, and accessibility of, markets does not just affect direct use of mangrove products, but also the profitability of other uses of the land, such as aquaculture (Barbier & Cox, 2004).

Evidence for the effects of soil type on deforestation is mixed, with some studies finding clear effects of soil quality for agriculture on rates of deforestation (Deininger & Minten, 2002; Witcover *et al.*, 2006), but others finding

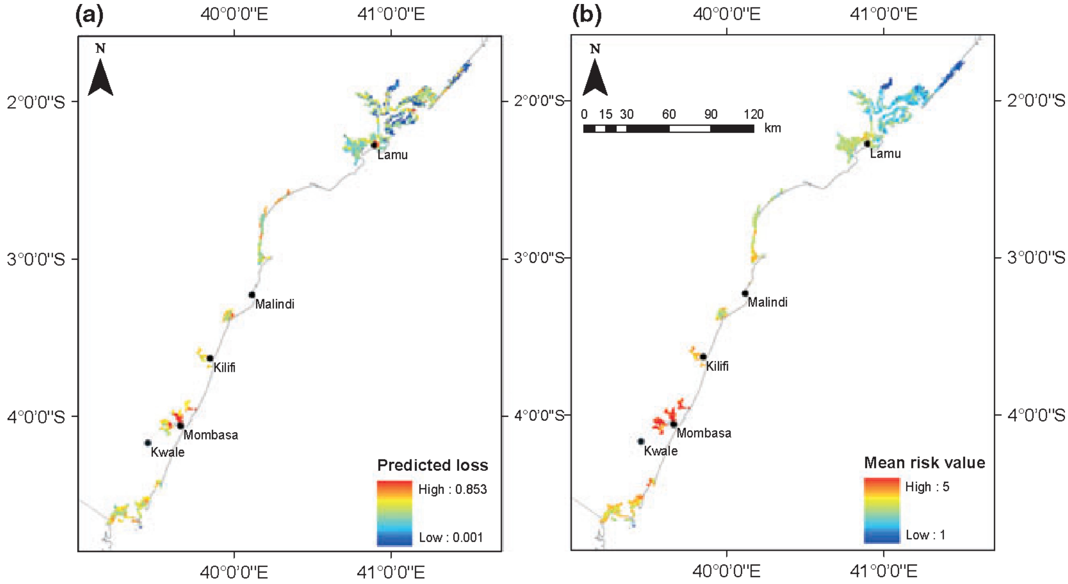

Fig. 2 Maps showing (a), predicted proportional loss of mangrove over a 10 year period derived from the quantitative model parameterised using 2010 data and (b), mean risk values derived from the qualitative model using the same data sources and for the same areas.

no effect (Kaimowitz & Angelsen, 1998). For mangroves, the effect of soil type is likely to be linked to the potential for both agricultural use, which LUCC studies in other mangroves have identified as a major constituent of mangrove replacement (Giri & Muhlhausen, 2008) and also aquaculture, particularly the establishment of shrimp farms (Beland *et al.*, 2006). For the Kenyan mangroves, the largest effect of soil type was between areas identified as marine and those identified with a terrestrial soil type. As the soil data included many different types, this conforms to expectations; terrestrial soil types are inevitably more susceptible to development. However, the relative lack of distinction between the terrestrial types perhaps indicates that there is no particular land-usage deforesting the mangrove, but that rather a cumulative effect of many industries is taking place.

Development of coastal tourism was also identified as a driver of mangrove loss, potentially through the increased need for building materials and related infrastructure. Such developments are currently limited in their distribution, with a notable concentration around Mombasa, where mangrove cover is already low. Water yield and water deficit, serving as proxies for the potential for agricultural development and the effect of existing developments on water balance, were also relevant to predicting loss. Other studies have demonstrated the sensitivity of mangroves to hydrological disturbance, through changing water inputs in coastal regions (Restrepo & Kettner, 2012).

The quantitative model performed well in hindcasting mangrove deforestation over the 2000–2010 time period, with a highly significant correlation with the observed change. However, around 35% of the variation remains unexplained (Fig 1). At least part of this variation is likely to be due to unaccounted-for temporal changes in the factors considered, particularly the extent of the road network. Due to incomplete information at the different time periods it was necessary to use a composite data layer for the derivation of the quantitative model and the prediction of loss between 2000 and 2010. In addition, the broad geographical scale (whole coastline) and spatial resolution (1 km^2) of the analysis meant an inevitable failure to capture all smaller scale, more local effects. However, on a broad scale, the model developed would seem to be an adequate predictor of loss rates in Kenya, and can help highlight areas under high risk of future degradation and loss.

The secondary objective of the current work was to compare the benefits of the two contrasting approaches: statistical and categorical modelling. Despite the long history of deforestation modelling (Kaimowitz & Angelsen, 1998) and the potential importance of being able to compare different approaches, as far as we know this is the first time that the results from two contrasting approaches have been assessed when applied to the same dataset. The categorical model produced results consistent with the quantitative when parameterized for the same time period. Deviation between the two methods appeared to be most marked in the northern parts of the mangrove area (Fig 2). These areas comprise the most extensive mangroves within Kenya and the differences shown by the two methods may have been linked to the incorporation of accessibility factors relating to the size of mangrove areas in the categorical model which were not included in the quantitative model. The close correlation between the predictions of the two approaches suggests that the categorical approach is of similar utility in predicting mangrove loss to the quantitative model with the proviso that there is residual variation unaccounted for by either approach. Despite this, the ability of the categorical model to reflect broad-scale patterns in mangrove forest loss is encouraging. The ACEU approach employed here (or similar categorical risk ranking methods, such as that used by Omo-Irabor *et al*., 2011) is simpler to apply and faster to develop. It did not suffer from the computational limitations encountered with the quantitative model and hence could be applied at a higher resolution and is also more easily understood by non-specialists than quantitative statistical models. Hence, the strong concurrence between the quantitative and qualitative models reported here suggests that the latter approach is sufficient to highlight areas at high risk and to act as a management tool.

Acknowledgements

This work, which is part of the Swahili Seas Project (NE/I003401/1), was funded with support from the Ecosystem Services for Poverty Alleviation Programme (ESPA). The ESPA programme is funded by the Department for International Development (DFID), the Economic and Social Research Council (ESRC) and the Natural Environment Research Council (NERC). Planet Action provided the SPOT data used for the 2010 mangrove cover assessment. We thank our friends and colleagues in Kenya, particularly Dr James Kairo, Kenya Marine and Fisheries Research Institute staff and the Gazi Research Station, for provision of expert advice and other support and the anonymous reviewers for the comments on the paper.

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