Mangrove Classification and Statistics

Statistics have been calculated based on individual typological units (See 1., below) and to the jurisdictional, regional, and global level. Jurisdiction and region-level statistics are based on the sum of the values from the typological units assigned to that jurisdiction or region. Typological units have been assigned to the country in which they predominantly located.

1. **Mangrove type** – Coastal embayments of >1km^2 were identified using a modified version of the GADM administrative area dataset https://gadm.org/index.html. The coastal embayment polygons were classified into one of four groups (delta, estuaries, lagoons or bays) based on their geomorphological characteristics. Deltas in mangrove areas (n = 81) were identified from those listed in the World Atlas of Mangroves (Spalding *et al.* 2010), The Major River Deltas Of The World (Huh *et al.* 2004) and Major World Deltas: A Perspective From Space (Coleman & Huh 2003). A further 21 deltas were identified by examining coastal embayment polygons that had >2 outlets to the ocean. Using online sources multiple coastal embayment polygons were merged to create a single delta's extent. Those polygons that we designated as part of deltas were removed from the coastal embayment polygon dataset. The remaining coastal embayment polygons were then classified as either bays, estuaries or lagoons. The classification was based ten variables describing the shape of the polygons, the area of their associated hydrological catchment and the amount of precipitation entering the catchment and used a random forest classifier (randomForest package; Liaw & Wiener 2002). Once the coastal embayment polygons had been defined the mangrove polygons within the GMW dataset were classified into one of four types, deltaic, lagoonal, estuarine or fringing. Further these mangroves polygons were split into individual units, for deltaic, lagoonal, estuarine mangroves based on proximity to coastal embayment polygons of the same type. The overall extent was created by merging the mangrove extents from the GMW 1997, 2007, 2010 and 2016 timesteps. Assigning the mangrove polygons to a typological class and an individual coastal embayment polygon followed a stepwise procedure based on the proximity of mangrove patches to the coastal embayment polygons. Following the stepwise procedure several rounds of visual quality assessment and corrections were carried out. The manual interventions following the stepwise procedure (N.B. there had be minor manual intervention during the stepwise procedure) resulting in variation in the number of polygons assigned to each class particularly increasing the amount of lagoonal mangrove.
2. **Maximum Mangrove Area 1996 - 2016** – To determine the maximum mangrove area over the past 20 years, timesteps from the Global Mangrove Watch dataset depicting mangrove extents from 1996, 2007, 2010 and 2016 were joined via a union. More information on Global Mangrove Watch can be found at https://www.globalmangrovewatch.org/.

3. **Area of Loss** was calculated using the Maximum Mangrove Area in the Last 20 Years dataset (union of Global Mangrove Watch mangrove extents from 2007, 2010, and 2016). Areas of loss were defined as extents within that union where no mangroves existed in 2016. These areas were summed to create a total area of loss per typological unit.
4. **Restorable Mangrove Area** was calculated by taking the total area of loss and subtracting the area of loss assumed to be converted to either an urbanized area, or an eroded area within each typological unit. Mangroves lost to these causes are unlikely to offer great scope for restoration due to the likely level of geomorphological and hydrological change and the high opportunity costs of converting these areas. Urban areas were identified from the Global Urban Footprint dataset which provides the extent of built-up areas, defined as man-made building structures with a vertical component (Esch *et al.* 2011, 2017). The data were derived from satellite images mostly collected between 2011 and 2012 and available at a resolution of 0.4 arc seconds (~12 m, near the equator). The urban footprint was intersected with areas of mangrove from the loss identified from the union of 1996, 2007, 2010 and 2016 GMW timesteps. Any patch of mangrove loss that overlapped the urban footprint, the loss was classified as being due to urbanization. Areas of erosion were identified using a combination of three data layers, extent of mudflats, extent of bare ground and water occurrence change intensity. The extent of global mudflats for the year 2016 was derived from multiple Landsat images (N. Murray, unpublished data) and showed areas of mudflat presence at a resolution of 1 arc-second per pixel (approximately 30 meters per pixel at the equator). The bare ground for the circa 2010 peak growing season was downloaded from https://landcover.usgs.gov/glc/. The data were derived from Landsat 7 ETM+ cloud-free composites and estimates the minimum percentage of bare ground per pixel (Hansen *et al.* 2013). For this analysis a pixel was classified as bare if it had >= 50% bare ground. Data on water occurrence change intensity was downloaded from https://global-surface-water.appspot.com/download. Water occurrence change intensity shows areas where water occurrence increased, decreased or remained the same between 1984-1999 and 2000-2015 (Pekel *et al.* 2016). Change was computed by matching monthly observation in both time periods and is percentage change in occurrence between the two time periods. For the analysis, we identified areas that had had a 20% or greater increase in water intensity between the two time periods. Areas of erosion were identified by overlaying extent of mudflats, extent of bare grounds and water occurrence change intensity on top of the areas of loss. Erosion was assumed in those loss areas where was water occurrence change intensity was present within a 100m buffer of the coastline (coastline from a modified version of GADM) or loss areas where mudflats were present in 2016. In addition, if loss areas were overlaid by combinations of bare ground and water occurrence change intensity, mudflats and bare ground, mudflats and water occurrence change intensity, and all three of mudflats, bare ground and water occurrence change intensity then this was assigned to erosion. Areas

of erosion were removed if they intersected with urban area (see above) or layers representing Global Tree Canopy Cover for circa 2010 (Hansen *et al.* 2013) or Global 30m Cropland Extent (Gumma *et al.* 2017; Massey *et al.* 2017; Oliphant *et al.* 2017; Phalke *et al.* 2017; Teluguntla *et al.* 2017; Xiong *et al.* 2017; Zhong *et al.* 2017) Thus, the formula for calculating restorable area from loss within a typological unit is: (Total area of loss) – (% conversion to urbanization * Total area of loss)– (% eroded * Total area of loss).

5. **Degraded Area** in mangrove forests was examined via temporal changes in several vegetation indices across the period ~1984 - to the present day. Degradation was examined for mangroves present in the 2016 timestep of the Global Mangrove Watch (GMW) data layer. Given the temporal and spatial scale of the analysis, Google Earth Engine was used. Google Earth Engine is a cloud-based geospatial analysis platform, housing an extensive data catalogue which can be explored and analysed using a large parallel processing system (Gorelick *et al.* 2017). Google Earth Engine contains analysis ready images for the entire Landsat archive (Gorelick *et al.* 2017). Pre-processed atmospherically corrected surface reflectance images from the Landsat 4 and 5 ETM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS sensors were used. For each image areas of cloud or cloud shadow that might affect the vegetation indices calculation were removed using the CFMask algorithm (Foga *et al.* 2017). The images from each of the four Landsat missions were combined into a single collection and for each image four vegetation indices were calculated. The Normalized Difference Vegetation Index (NDVI) is the normalized ratio of the near infrared (NIR) band which is reflected by vegetation and red band which is absorbed by vegetation.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Values range between -1 and +1, with values closer to +1 representing areas of dense green leaves. One of the limitations of NDVI is that it is influenced by background soil brightness, with higher NDVI values in areas of darker soils (Huete 1988). The Soil-Adjusted Vegetation Index (SAVI) is a modified version of the NDVI index, designed to minimise the soil brightness influence (Huete 1988).

$$SAVI = \frac{(1 + L)(NIR - Red)}{(NIR + Red + L)}$$

An adjustment factor (L) of 0.5 was shown to successfully minimise soil brightness effects (Huete 1988). The enhanced vegetation index (EVI) was developed to reduce influence of atmospheric conditions and decouple the canopy background signal (Huete *et al.* 2002). In addition to the NIR and red bands used in NDVI and SAVI, EVI uses the blue band to reduce the impact of atmospheric effects (Schultz *et al.* 2016).

$$EVI = \frac{(NIR - Red)}{(NIR + C1 \times Red - C2 \times Blue + \mathrm{L})}$$

The coefficient L is the canopy background adjustment and C_1 and C_2 are used with the blue band to reduces aerosol influences in red band (Huete *et al.* 2002). Values of L = 1,

C_2 = 6, C_2 = 7.5, and G = 2.5 were used based on Huete *et al.* (2002). The Normalized Difference Moisture Index (NDMI) is the normalized ratio of the NIR and Short Wave Infrared (SWIR) bands.

$$NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

SWIR represents changes in vegetation water content and structure of spongy mesophyll. The index has been used to assess vegetation moisture condition (Ji *et al.* 2011). The overall image collection was split into five timesteps, reference (earliest image in the collection – 2000), T_1 (2000 – 2005), T_2 (2005 – 2010), T_3 (2010 – 2015), and T_4 (2015 – latest image in the collection). Degradation was evaluated at the pixel (30m resolution) scale and only Landsat pixels that intersected the 2016 GMW mangrove extent were considered. The number of images per pixel in each timestep were calculated. Pixels that had fewer than ten images in the reference period were removed as were ones where there were fewer than ten images in two of the other timesteps. If there were fewer than ten images in just one timestep the vegetation indices from the preceding timestep were used. To assess change in mangrove condition, per pixel within each timestep three values were calculated, the median, 10 – 90% interval mean and 25 – 75% interval mean of each of the four vegetation indices. This resulted in 12 degradation metrics. For each degradation metric the percentage difference of each timestep relative to the reference period was calculated. Areas where degradation had taken place were identified as those where the vegetation index was >= -40% of the reference value in any of the timesteps. To remove areas of regeneration, the T_4 value relative to the reference was assessed with a >= -20% value suggesting ongoing degradation. For a pixel to be classified as degraded, ten out of 12 degradation metrics had to have a timestep where the percentage change was >= -40% and zero out 12 degradation metrics had to have T_4 value >= -20% of the reference.

Restoration Potential Score and Inputs

1. **Restoration Potential Score** ranges from 0 – 100 were a low score represents a typology unit that is not a good candidate for restoration and a high score represents a typology unit that is a good candidate for restoration activities. The score is calculated based on seven variables described below. The variable weightings and the individual category scores were derived by an expert panel using a Delphi type approach. The expert panel were asked to provide a value between zero and ten for each category in each variable in terms of increasing restoration potential. The most important category was given a score of ten with the other categories scored relative to this. More than one category could be given a score of ten. For the variable weightings the score was again relative to each other and could take a value of 0, 10, 20, 30 ,40, 50. A score of 0 meant that at the typological unit scale a variable has no importance to mangrove restoration potential. A

variable scored 20 was twice as important to restoration potential as a variable scored 10. The first iteration had 10 respondents and the median category scores and variable weightings were computed. The respondents were then asked to rescore both the categories and variables while considering the current group consensus. The respondents were asked to give special consideration to those scores where they were an outlier from the group consensus, that is ± one rank from the median score. The intent of this follows standard Delphi approaches, where error is reduced by the sharing of expertise and the sharpening of definitions. Where respondents felt that the current group consensus was incorrect, and they wished to retain the outlier score, they were asked to provide anonymous feedback. After the second round of responses (n = 9), the median category scores and variable weightings were again computed. The respondents were given a final opportunity to re-score the categories and variable weighting based on the second-round consensus and the anonymous feedback. The variable weightings and the individual category scores were then converted into each typological unit's restoration score using the Simple Multi-Attribute Rating Technique (SMART). In SMART individual variable weightings are normalized based on the sum of all variable weighting and then multiplied by the category score (divided by 10).

a. **Tidal Range -** The extent of tidal flooding and its duration and frequency are critical to the survival of mangrove forests (Lewis 2005). These factors are controlled by the topography of the site and local tidal characteristic (Friess *et al.* 2012). Tidal amplitude data were accessed from AVISO+ products (https://www.aviso.altimetry.fr). From this dataset, the tidal amplitude value nearest to the mangrove typology centroid was calculated. The mangrove typology was classified based on the tidal range (amplitude x 2) as microtidal (0–2 m, n = 5274), mesotidal (>2–4m, n = 883) and macrotidal (>4m, n = 128).
b. **Antecedent SLR -** Antecedent Sea Level Rise (ASLR) data were accessed from http://www.esa-sealevel-cci.org/ in the form of regional mean sea level trends (Quartly *et al.* 2017; Sea Level Climate Change Initiative (SL_cci) 2017; Legeais *et al.* 2018). The data are based on altimeter measurements from multiple satellite missions and represents regional sea level trends between January 1993 and December 2015 (Legeais *et al.* 2018). Spatial variation in regional sea level trends generally ranges between -5 and +5 mm yr^{-1} around the global mean of 3mm yr^{-1} (Legeais *et al.* 2018). Extreme values (> |5|mm yr^{-1}) observed in the dataset are subject to high levels of uncertainty (Sea Level CCI team, pers. comm.), therefore values > 5mm yr^{-1} were truncated to 5mm yr^{-1}. The ASLR value nearest to the mangrove typology centroid was calculated. Risk from ASLR was calculated as a function of tidal amplitude, where higher values represent a greater risk. Where tidal amplitude was zero (n = 24) the ASLR/M2 Tidal Amplitude value was set to the ASLR value. Those patches where sea level had declined (n = 52) the ASLR risk was categorized as 'none'. For the remaining patches ASLR risk was grouped

using a k-means cluster (Hartigan & Wong 1979), which categorized the sites as being either high (n = 2123) or low risk (n = 4110).

c. **Future SLR -** The long-term survival of many mangrove ecosystems is threatened by sea level rise (Friess *et al.* 2012). Changes in sea level have the potential to disrupt the balance between the tidal frame and the surface elevation of mangrove forests. Mangrove loss may result if future sea level rise (SLR) increases the frequency and duration of tidal inundation beyond species physiological thresholds (Ball 1988). SLR predictions were accessed from http://icdc.cen.uni-hamburg.de/1/daten/ocean/ar5-slr.html. The predictions are derived from 21 Coupled Model Intercomparison Project phase 5 Atmosphere–Ocean General Circulation Models (Church *et al.* 2013). For the analysis we selected the medium-high representative concentration pathway (RCP) scenario 6.0. The SLR value nearest to the mangrove typology centroid was calculated. Risk from SLR was calculated as a function of tidal amplitude, where tidal amplitude was zero the SLR/M2 Tidal Amplitude value was set to the SLR value. SLR risk was grouped using a k-means cluster (Hartigan & Wong 1979), which categorized the sites as being either high (n = 1802) or low risk (n = 4483).

d. **Sediment Change -** Areas of high erosion may undermine restoration effort. Sediment change may be used as a proxy for upstream hydrological modification that may impact restoration efforts. Data on inorganic suspended particulate matter concentration (g/m^3) were downloaded from the Globcolor website http://www.globcolour.info/. The Globcolor project merges outputs from different satellite sensors to improve spatial and temporal coverage (ACRI-ST GlobColour Team 2017). Two hundred and forty individual processed Level-3 files representing monthly inorganic suspended particulate matter concentration were selected for the period of January 1998 to December 2017 (20 years). These data combine measurements from the SeaWIFS, MERIS, MODIS and VIIRS satellite missions. Inorganic suspended particulate matter was calculated as the difference between total suspended matter and phytoplankton biomass and is mostly dominated by mineral matter (Gohin 2011). The inorganic suspended particulate matter data were imported into Google Earth Engine and the monthly layers were merged into a 240-image stack. The SPM-OC5 algorithm used to derive inorganic suspended particulate matter concentration computes values ranging between 0 and 100 g/m^3 but is only validated for values less than 50 g/m^3 (The GlobColour Team, pers. comm), therefore values above 50 g/m^3 were truncated. Within the image stack, pixels were removed that had fewer than 120 records. To determine the sedimentary class of each mangrove typology patch, the mean inorganic suspended particulate matter concentration value of each pixel within the stack was calculated. To examine trends in inorganic suspended particulate matter concentration a linear regression model was fitted through the pixels at each location in the stack. The regression model took the form:

$$y = \alpha + \beta_1 month + \beta_2 year$$

The aim was to determine the direction (positive or negative) of the β_2 coefficient to evaluated increases or decreases in sediment availability across the 20 years of data. The month variable was included to correct for missing values. The output of the regression model was masked to only return values where the overall model and the regression coefficient for β_2 were significant at $p <= 0.05$. The F value for the overall model was assessed against a critical value of 3.07376290 which equates to $p = 0.05$ for $F_{2,117}$ and the t value for β_2 assessed against a critical value of ±1.98044759 which equates $p = 0.05$ for t_{117}. The degrees of freedom for F and t were selected for the worst-case scenario of only 120 images in the image stack. The sedimentary class of the mangrove patches was calculated from the mean inorganic suspended particulate matter concentration layer. One hundred and sixty-seven training locations of known typological (riverine or non-riverine) and sedimentary (terrigenous or carbonate) status were identified from the literature or by an expert working group. The approximate geographic position of these training locations was determined. The training locations were imported into ArcGIS, location outside a 10km buffer around the GMW maximum extent layer were removed (n = 15). Following Balke and Friess (2016) we determined the sediment regime (in our case inorganic suspended particulate matter concentration rather than total suspended matter) and M_2 tidal amplitude of the site. M_2 tidal amplitude data used was as above with the value nearest to the training location was calculated. The data were imported into R and riverine (n = 70) sites were removed from the data set. The remaining 82 sites were used to predict whether a site was terrigenous or not based on its M_2 tidal amplitude and mean inorganic suspended particulate matter concentration. The data was modelled using a binomial generalized linear model with a logit link. For the 6285 typological units, riverine and deltaic mangroves were classed as terrigenous, with the model used to classify the lagoonal and fringing mangroves. The mean inorganic suspended particulate matter concentration value nearest to the mangrove typology centroid was calculated and this in combination with the M_2 tidal amplitude value and the model coefficients was used to define whether a site was terrigenous of carbonate. To determine the trends in inorganic suspended particulate matter concentration the β_2 value layer was imported into ArcGIS. Slope $\beta 2$ values <= 0 were reclassified to -1 and values > 1 to 1. A point was placed in the centre of each remaining raster cell, with the point value representing the positive (+1) or negative (-1) slope. The number of positive and negative points in a 50km buffer around each typological unit's mangrove extent was then calculated. Terrigenous typological units were deemed to have a positive or negative trend in inorganic suspended particulate matter concentration if there were at least 20 cells with significant trends and 75% of the significant trends were in the same direction.

e. **Time Since Loss -** Areas that have been cleared of mangroves more recently may have a higher restoration potential. Time since loss was calculated using the Maximum Mangrove Area in the Last 20 Years dataset (union of Global Mangrove Watch mangrove extents from 2007, 2010, and 2016). The loss was based on the most recent change from presence to absence and could be either 2007, 2010 or 2016. The timing of the loss was the timestep (either 2007, 2010, 2016) in which the most loss had taken place in each typological unit.
f. **Median Patch Size –** Area of Loss was calculated using the Maximum Mangrove Area in the Last 20 Years dataset (union of Global Mangrove Watch mangrove extents from 2007, 2010, and 2016). Areas of loss were defined as extents within that union where no mangroves existed in 2016. The areas of loss were merged into single extent and then disaggregated into individual patches independent of the timing of that loss. The area of these patches was calculated in km^2, and the number of patches per typological unit determined. The area and the number of patches was used to calculate the mean loss patch size in each typological unit. Mean loss patch size was categorised using a k-means cluster (Hartigan & Wong 1979) in R. Given the extreme positive skew of the data, prior to analysis the mean loss patch size values were logged. The number of clusters was *a priori* set to three to represent small, medium and large mean patch sizes. The k-means cluster categorised 1610 typological units as having a small (0.0005 – 0.0022 km^2), 2734 typological units as having a medium (0.0023 – 0.0074 km^2) and 1288 as having a large (0.0075 – 0.8903 km^2) mean loss patch size.
g. **Proportion of lost mangrove contiguous with extant –** Patches of loss contiguous with remaining mangrove areas may benefit from greater natural regeneration. Area of Loss was calculated using the Maximum Mangrove Area in the Last 20 Years dataset (union of Global Mangrove Watch mangrove extents from 2007, 2010, and 2016). Areas of loss were defined as extents within that union where no mangroves existed in 2016. The areas of loss were merged into single extent and then disaggregated into individual patches independent of the timing of that loss. The loss patches were intersected with the GMW 2016 extent to find the percentage of loss mangrove that was contiguous with extant mangrove patches. The percentages were grouped into deciles.