

Original Articles

Global typologies of coastal wetland status to inform conservation and management

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ABSTRACT

Global-scale conservation initiatives and policy instruments rely on ecosystem indicators to track progress towards targets and objectives. A deeper understanding of indicator interrelationships would benefit these efforts and help characterize ecosystem status. We study interrelationships among 34 indicators for mangroves, salt-marsh, and seagrass ecosystems, and develop data-driven, spatially explicit typologies of coastal wetland status at a global scale. After accounting for environmental covariates and gap-filling missing data, we obtained two levels of clustering at 5 and 18 typologies, providing outputs at different scales for different end users. We generated 2,845 cells (1° (lat) × 1° (long)) globally, of which 29.7% were characterized by high land- and marine-based impacts and a high proportion of threatened species, 13.5% by high climate-based impacts, and 9.6% were refuges with lower impacts, high fish density and a low proportion of threatened species. We identify instances where specific actions could have positive outcomes for coastal wetlands across regions facing similar issues. For example, land- and marine-based threats to coastal wetlands were associated with ecological structure and function indicators, suggesting that reducing these threats may reduce habitat degradation and threats to species persistence. However, several interdimensional relationships might be affected by temporal or spatial mismatches in data. Weak relationships mean that global biodiversity maps that categorize areas by single indicators (such as threats or trends in habitat size) may not be representative of changes in other indicators (e.g., ecosystem function). By simplifying the complex global mosaic of coastal wetland status and identifying regions with similar issues that could benefit from knowledge exchange across national boundaries, we help set the scene for globally and regionally coordinated conservation.

1. Introduction

The natural world is under enormous pressure from human activities (Newbold et al., 2016; Mammides 2020), with coastal zones at the

interface of marine and terrestrial environments at considerable risk (He and Silliman 2019). There is an urgent need to limit and reverse habitat loss and degradation to enhance biodiversity, safeguard human livelihoods, slow climate change, and to define pathways to ocean sustainable

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development (Díaz et al., 2019). Large-scale initiatives and international policy instruments have been developed to help achieve these aspirations, such as the RAMSAR Convention on Wetlands, the UN Decade of Ecosystem Restoration, the UN Decade of Ocean Science for Sustainable Development, and the Convention on Biological Diversity's (CBD) Post-2020 Global Biodiversity Framework and Sustainable Development Goals (SDG) (Leal Filho et al., 2018; Davidson et al., 2019; CBD 2020; UN 2020). Nested within the SDGs are targets that provide tangible aspirations that will help achieve each goal, and indicators that track progress towards achieving targets (Waldron et al., 2013; Watson et al., 2020). The targets are interrelated, such that conservation actions that make progress on one are also likely to advance others. Expanding the protected area network, for instance, can also prevent the extinction of imperiled species, and enhance ecosystem services through reducing pollution (Kearney et al., 2018; Lindenmayer et al., 2018).

Opportunities to progress multiple interrelated targets should be reflected as the existence of underlying relationships among the indicators used to evaluate ecosystem status. But investigations into interrelationships at the global scale are lacking. Quantifying interrelationships – for example among indicators of pressures (e.g., fishing), ecological functions (e.g., fish productivity) and habitat loss – is thus an important step in identifying opportunities for conservation actions to have benefits for improving multiple targets. Existing indices of ecosystem status often assume these causal relationships exist (e.g., wilderness areas; Jones et al., 2018) or infer them from expert opinion (e.g., the Ocean Health Index (OHI); Halpern et al., 2007; Halpern et al., 2012). This is not a criticism of these well-designed and fit-for-purpose indices, but we acknowledge that intuitive causal relationships may not exist across large spatial scales, potentially affecting the conclusions drawn. For instance, the loss of mangrove forests is only weakly associated with cumulative impacts, and the effects of pressures vary by national governance (Turschwell et al., 2020). Relationships among different groups of cumulative impacts (i.e., a consequence of multiple pressures) can also be weak at the global scale (e.g., climate change and pollution from diffuse sources; Bowler et al., 2020). Studying interrelationships among a diverse suite of ecological indicators can confirm the validity of methods that assume indicator relationships, evaluate expert opinion used to quantify these relationships, be used to develop spatially explicit typologies of condition (sensu bio-regionalizations; Mackey et al., 2008; Woolley et al., 2020), and help set the scene for coordinated conservation actions that share information across regions facing similar issues.

Vegetated coastal wetlands – mangroves, saltmarsh, and seagrass – provide a valuable framework for exploring interrelationships among global indicators and identifying typologies to inform globally coordinated conservation actions. Coastal wetlands provide multiple ecosystem services, including protecting coastlines from storms (Menéndez et al., 2020), reducing the amount of pollutants entering the marine environment (Adame et al., 2019), sequestering large amounts of carbon, contributing to climate change mitigation (Duarte et al., 2013), and providing critical habitat for wildlife, including fisheries species and endangered megafauna (Carrasquilla-Henao and Juanes, 2017; Sievers et al., 2019; Unsworth et al., 2019b). Despite this, coastal wetlands have experienced global declines in extent and condition (Waycott et al., 2009; Davidson 2014; Gu et al., 2018), and are susceptible to cumulative land, marine and climate pressures, such as sea-level rise and eutrophication (Cloern et al., 2016; Schuerch et al., 2018; He and Silliman 2019; Tulloch et al., 2020). Coastal wetlands are also under-represented in global monitoring programs and indices of status and trends (Milošević et al., 2018; Brown et al., 2021), and receive less conservation funding than other coastal habitats, such as coral reefs (Duarte et al., 2008; Unsworth et al., 2019a). Increased awareness of these issues has spurred calls to enhance coastal wetland conservation action at the global scale (Cullen-Unsworth and Unsworth 2018; Friess et al., 2019; de los Santos et al., 2020). Several wetland indicators track change in individual ecosystem components (e.g., habitat extent change or animal

population size; Loh et al., 2005; Darrah et al., 2019) and a suite of globally-applicable datasets now exist for coastal wetland status indicators (Worthington et al., 2020).

Globally and regionally coordinated conservation would benefit from a deeper understanding of the interrelationships among key indicators of ecosystem status that are widely used to track progress towards various objectives and targets. Using coastal wetland ecosystems, we aimed to: (1) quantify interrelationships among 34 indicators relating to habitat extent change, ecological structure and function, and cumulative impacts for coastal wetlands globally, and (2) define combinations of indicator values that characterize relative status in different coastal wetland areas, or 'spatially explicit typologies'. Typologies thus reflect ecosystem status based on our indicators of interest (not delineations of global wetland types or distributions) and can inform coordinated conservation actions across regions facing similar issues.

2. Materials and methods

We explored interrelationships among ecosystem indicators of coastal wetlands and identified typologies of condition through nine key steps (Fig. 1). Our approach brings together ideas and concepts across disciplines, such as analyzing socio-ecological patterns of vulnerability (Kok et al., 2016), spatial correlations of global pressures (Bowler et al., 2020), and data-driven bioregionalizations (Woolley et al., 2020).

2.1. Indicator selection

We selected indicators based upon a review of relevant literature, existing indices, conceptual models of ecosystem processes, and data availability for mangrove, saltmarsh, and seagrass ecosystems. What we refer to as indicators, could also be considered *measures*, *metrics*, or *indexes*, however, we do not make this distinction and used *indicators* throughout. We compiled indicators that described ecosystem status under three thematic dimensions: habitat extent change (changes in the areal extent of the habitats), ecological structure and function (biotic indicators relating to the ecology of the ecosystem), and pressures ('cumulative impacts' based on Halpern et al., 2019) (see Table 1). We selected indicators which had globally, or near-globally, comprehensive datasets for a total of 34 ecosystem-specific indicators (Table 1; for full description, see Appendix A). Our modelling approach is not hindered

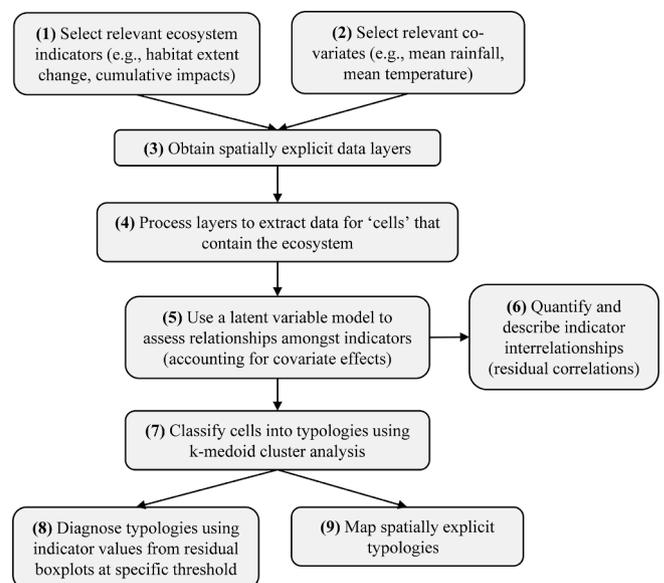


Fig. 1. Flow diagram of the nine key methodological steps used to map and diagnose spatially explicit typologies of coastal wetland ecosystem condition applicable at a global scale.

Table 1

Indicators used to define typologies, nested under the three thematic dimensions (extent change, ecological structure and function, and cumulative impacts). Asterisks (*) indicate the covariates that were applied to that indicator, (c) is current status, (r) is instantaneous rate of change, temporal periods for datasets are provided in parentheses, and † indicates the use of a composite dataset composed of data sources from several years. For full description of indicators and their processing, see Appendix A

Habitat	Thematic dimension	Ecological structure and function	Cumulative impacts	Co-variates
Mangroves	Mangrove loss rate (2000–2012)	Proportion of threatened mangrove affiliated species (animals & plants) (accessed 2020)	Climate (c; 2013) Land (c; 2013)	Mean annual sea surface temperature (2019; °C) Mean photosynthetically active radiation (2018)
		Threat score of mangrove affiliated species (animals & plants) (accessed 2020)	Marine (c; 2013) Climate (r; 2003–2013)	Mean annual rainfall (2019; cm) Mean annual air temperature (2019; °Kelvin)
Saltmarsh	Seagrass loss rate†	Fragmentation: mean patch area (c; 2012) Fragmentation: mean patch area (r; 2000–2012)*	Land (r; 2003–2013) Marine (r; 2003–2013)	Mean annual tidal amplitude (2019; m) Coastline length (km)
		Forest longevity (1996–2016) Mangrove height (2009)* Above-ground biomass (2009)* Total soil carbon (2000)* Fish density*† Invertebrate density*†	Climate (c; 2013) Land (c; 2013) Marine (c; 2013) Climate (r; 2003–2013) Land (r; 2003–2013) Marine (r; 2003–2013)	Mangrove extent (km ² ; 2010)
Seagrass	Seagrass loss rate†	Proportion of threatened seagrass affiliated species (animals & plants) (accessed 2020) Threat score of seagrass affiliated species (animals & plants) (accessed 2020)	Climate (c; 2013) Land (c; 2013) Marine (c; 2013) Climate (r; 2003–2013) Land (r; 2003–2013) Marine (r; 2003–2013)	

by the inclusion of correlated indicators; in fact, these enhance capacity to accurately gap-fill missing data and help identify spatially explicit typologies.

In addition to indicators that describe status, we also collated data on variables that describe site characteristics (hereafter “covariates”; Table 1). These covariates naturally influence some of the indicators, such as tidal range and sea-surface temperature. Their inclusion means we could remove variation in indicators that were hypothesized to be due to environmental variation or the size of habitats. Therefore, the diagnoses of coastal wetland condition more closely reflect human influences. For those indicators hypothesized to be influenced by the covariates, we included seven covariates in the statistical model (Table 1; also see ‘Statistical analysis’). We did not apply covariates to all indicators. If we include covariates in the responses of indicators that we do not expect them to explain, we risk removing variability due to spurious correlations.

2.2. Grid cells and variable measurement

We generated a grid of 1° (lat) × 1° (long) polygon cells (100 × 100 km at the equator), that included the distribution of mangrove, seagrass, and saltmarsh vegetation extent. To do this, the grid was spatially joined with vector shapefiles of the extent of mangrove (overall accuracy of 94.0%; Bunting et al., 2018), seagrass (UNEP-WCMC, 2017) and saltmarsh (Mcowen et al., 2017), and filtered to exclude polygons and points where these habitats were missing, resulting in 2,845 grid cells. We acknowledge the saltmarsh and seagrass layers are not always accurate at the local scale. However, the spatial resolution of our analysis accommodates the coarseness of the global data sets and are suitable for the global overview and proof of concept of our analyses.

We calculated the mean value for each indicator and covariate with globally comprehensive datasets, except for fragmentation indicators which were measured at the landscape level (i.e., each grid cell is the landscape boundary for which fragmentation is estimated; see Appendix A for a full description of indicator processing). For indicators that were not globally comprehensive (e.g., seagrass extent loss), we calculated mean values only for cells where data existed. Missing data due to the lack of congruence between habitat distribution and indicator data was rare (see Appendix A for full documentation of missing data for each indicator). We did not undertake any gap-filling of missing data prior to analysis because our statistical approach imputes missing data based on correlations amongst indicators to gap-fill during analysis. We used multivariate imputation with chained equations (MICE) to estimate plausible values when cells had missing data for covariates (Appendix B).

Cumulative impacts to mangrove, saltmarsh and seagrass habitats were calculated from 14 global pressure layers from (Halpern et al., 2019) (1 km² resolution; Appendix C). We rasterized spatial data layers (vector; polygon) mapping each habitat’s global distribution to 1 km² resolution (hereafter referred to as “habitat extent” rasters). To quantify the impact of individual pressures to each habitat, pressure rasters (re-scaled from 0 to 1, Appendix A) were multiplied by habitat extent rasters and a value representing the vulnerability of each habitat to each pressure (Halpern et al., 2019). The pressure impact rasters were then summed within driver origin (land- (n = 3), marine- (n = 8), or climate-based (n = 3); Tulloch et al., 2020) to obtain cumulative pressure impact rasters for each habitat-driver combination for each habitat (hereafter, cumulative impacts) and averaged to obtain a value for each grid cell in the years 2003 and 2013 (Appendix C). Values from 2013 were considered current cumulative impacts and change in cumulative

impacts was calculated as the instantaneous rate of change between 2003 and 2013.

Spatial data layers for mangrove and saltmarsh pressure indicators required additional processing (without doing so, 88% of mangroves and 85% of saltmarsh would not have corresponding data). In brief, we processed the global pressure data (Halpern et al., 2019) to extend landwards, so cumulative impacts could be quantified for all habitat extent. To assess and map cumulative impacts to these intertidal areas, we first calculated average pressure impacts at river mouths and then assigned river mouth pressure impacts to mangroves and saltmarshes in corresponding upstream basins (see Appendix C). Although direct impacts from some of these pressures might not be expected in intertidal areas (e.g., from fishing), indirect effects to the ecosystem from them are possible (e.g., water quality and trophic cascades).

Spatial processing and indicator measurement were conducted in ArcGIS Pro (v 2.5.0, ESRI Inc.) using the Geostatistical Analyst toolbox, or R (v 3.6.1, R Development Core Team, 2017) using the spatial packages ‘raster’ (Hijmans 2019), ‘sp’ (Pebesma and Bivand 2005; Bivand et al., 2013), and ‘sf’ (Pebesma 2016). Multivariate imputation was performed using the R package ‘mice’ (Van Buuren and Groothuis-Oudshoorn 2011).

2.3. Statistical analysis

2.3.1. Residual indicator values

We modelled relationships among indicators with a latent variable model (LVM). We use a Bayesian LVM framework due to several advantages. First, it enabled us to model the effects of covariates on indicators. The LVM models covariation in indicators due to natural environmental gradients and separates that from residual covariation among indicators that is not explained by the covariates. This residual covariation is of primary interest because it could be due to human influences. Second, Bayesian LVMs can model missing data by predicting missing indicator values based on the strength of their correlations with other indicators. Third, Bayesian LVMs can model different indicator types simultaneously, including continuous, proportional, and categorical data. The model was specified with the following equation (1) (Hui 2016):

$$\log(\mu_{ij}) = \theta_{0j} + x_i^T \beta_j + z_i^T \theta_j \quad (1)$$

where μ_{ij} is the mean response at cell i for indicator j , θ_{0j} is the indicator-specific intercept, x_i and z_i are vectors of the covariates (where used) and LVs (respectively), and β_j and θ_j are their corresponding indicator-specific coefficients (Hui 2016). We estimated coefficients for each indicator from likelihoods appropriate to their distribution with Markov Chain Monte Carlo (MCMC) sampling (Hui 2016); a normal distribution (with identity link) for continuous response variables, and a beta distribution (with logit link) for proportions. To obtain the residual indicator values at each cell, we multiplied the matrix of indicator coefficients for each LV by the matrix of cell LV scores.

We set the length of each MCMC chain to 20,000, discarded 1,000 in the burn-in period, and used a thinning rate of 2. We used weakly informative normal priors (mean = 0 and variance = 10) for MCMC estimation of variable coefficients (Hui 2018) and did not include site effects. We explored the results of a range of LVs (from 2 to 30) and found that higher LV models produced more compact and separated clusters (i.e., typologies). Given the high dimensionality of our dataset (34 indicators and 2,845 cells), we chose to include the maximum number of LVs that was computationally feasible (17 LVs). The use of 17 LVs, rather than just 2–3 LVs typical of most ordinations, means that we could capture the strongest correlations and the subtle patterns.

We log-transformed variables in the LVM where necessary to meet assumptions of normality and homogeneity of variance, and standardized (z-score standardization, mean = 0, standard deviation = 1) covariate and response variables (excluding proportions). We verified

MCMC chain convergence by visually inspecting trace plots and calculating Geweke convergence diagnostics after adjusting for multiple comparisons (Geweke 1992). We also visually inspected autocorrelation plots and used Dunn-Smyth residuals to check model assumptions (Appendix D; Dunn and Smyth 1996). We fit the LV model using the R-package ‘boral’ version 1.81 (Bayesian ordination and regression analysis; Hui 2016; Hui 2018).

2.3.2. Quantifying indicator correlations

Correlations among variables will determine the typologies detected by the clustering algorithms clusters. Where correlations represent an ecological interrelationship, they also suggest opportunities for conservation to simultaneously enhance multiple indicators. We estimated ‘residual correlations’ from the LVM, which are ‘residual correlations’ left-over, after accounting for spatial covariation in indicator values that represent covariance left-over after explaining for the covariates (Hui 2016).

The large number of potential correlations increases the risk of falsely identifying correlations as real interrelationships. We therefore took several steps to avoid falsely interpreting spurious correlations as causal. First, we only interpreted correlations where the 99% Bayesian credible interval did not overlap zero. Second, we identified indicators *a-priori* that shared similar underlying data sources, which we expected to be correlated (e.g., cumulative impacts for different habitat types). Third, we focus our interpretation of casual relationships on relationships identified *a-priori* (O’Connor et al., 2015). Finally, we assumed that any strong correlations that could not be anticipated *a-priori* are suggestive of new hypotheses that could be tested, and we refrained from making causal interpretations of them.

2.3.3. Classifying cells into typologies

We used k-medoid cluster analysis to group cells according to their residual indicator values. To partition cells, k-medoid cluster analysis identifies data points with low dissimilarity to others (i.e., the medoids) and assigns nearby observations to form clusters around the medoid data points. The k-medoid method is less sensitive to outliers than the alternative k-means clustering method, which clusters observations around means rather than medoids (Kaufman and Rousseeuw 2009). K-medoid cluster analysis requires the number of clusters (k) to be specified *a-priori*. The statistically optimal number of clusters in the data can be identified using the average silhouette width. This is a measure of how similar an observation is to its designated cluster in comparison to others (Rousseeuw 1987), with high average silhouette width for a clustering configuration indicating tightly clustered observations (Rousseeuw 1987).

While the number of clusters, and thus typologies, can be a subjective decision that depends on the purpose of the analysis and the end user needs, there are benefits of utilizing a fully data-driven approach to guide selection cluster numbers (e.g., choosing the k that produces the greatest silhouette width). We used a balance between fully data-driven and subjectively constrained. We constrained the clustering to be between 5 and 50, as fewer than 5 global typologies are uninformative for our purposes, and more than 50 are too complex. We subsequently identified separate peaks in silhouette width at 5 and 18 clusters (Appendix E) and explored these two outputs. We then performed k-medoid cluster analysis on a Euclidean distance matrix of residual indicator values at each cell using the partitioning around medoids clustering algorithm (Kaufman and Rousseeuw 2009). We produced a three-dimensional plot indicating the relative position of the clusters in ordination space and used an RGB color palette for the three axes to color the typologies. The three-dimensional ordinations enable the similarities among typologies to be mapped geographically. Cluster analysis was performed using the R package ‘cluster’ (Maechler et al., 2019).

We considered uncertainty in clustering by re-running the cluster analysis across the full posterior conditional distribution of residual

values and calculating a robustness statistic. The robustness statistic represents the consistency that pairs of cells were classified in the same or different typologies (Appendix F).

2.3.4. Diagnosing typologies

To diagnose typologies, we interrogate boxplots of residuals, which show the spread of indicator values within each typology. Residuals reflect indicator values relative to the mean value expected for a cell once covariate effects are removed. By setting a statistical quantitative metric to serve as a threshold, we can identify indicators most useful for diagnosing the distinguishing features of the typologies. We demonstrate the use of quantile thresholds below by using 75th and 95th thresholds for the 5-typology and 18-typology outputs, respectively.

Although all three habitats are not present in every cell, our modeling approach gap-fills for missing data across all indicators, so the indicators used to diagnose typologies can be associated with an ecosystem type that is outside its bioclimatic range at some cells. While this outcome can be counterintuitive, the method is deliberately designed to remove bioclimatic patterns through the covariates, enabling us to examine residual patterns in indicator values. Because the

habitat types do frequently co-occur, we considered this slight interpretation challenge to be better than modelling wetland types individually, which would reduce the model’s power to detect shared trends across habitat types. To avoid illogical diagnoses, we only interpret indicators for wetlands that are present at a particular cell.

3. Results

3.1. Interrelationships among ecosystem indicators

We identified interrelationships among the 34 indicators (Fig. 2). Given the size and complexity of the correlation matrix for 34 indicators, we focus here on several key interrelationships (for more comprehensive descriptions, see Appendix G). There were mostly negative, though weak, relationships between marine- and land-based cumulative impacts and ecological structure and function indicators (Fig. 2). For example, seagrass-affiliated species were more likely to be threatened with extinction in cells with higher seagrass marine-based cumulative impacts; saltmarsh species were more likely to be threatened in cells with higher land-based saltmarsh cumulative impacts, and; mangrove

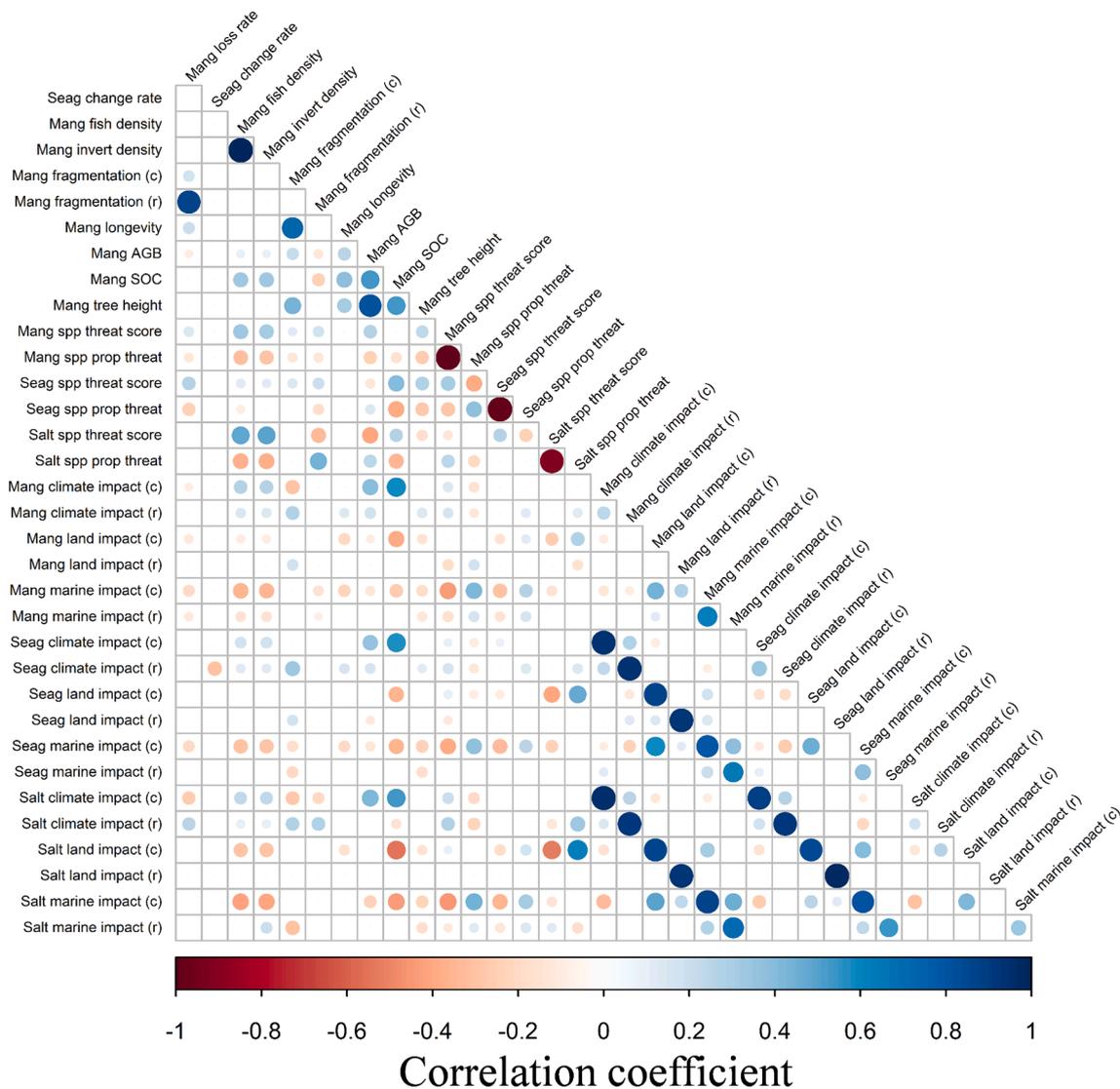


Fig. 2. Residual correlations for interrelationships where the 99% Bayesian credible interval did not overlap zero. Red shades represent negative relationships and blue positive, with the color intensity and dot size indicating relationship strength. Mang: mangrove ecosystem, Seag: seagrass ecosystem, Salt: saltmarsh ecosystem, (c): current status, (r): instantaneous rate of change. For details of indicators, see Table 1; Appendix A. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

fish density, above ground biomass (AGB) and soil organic carbon (SOC) were lower in cells with higher mangrove marine-based cumulative impacts.

Further, mangrove fish and invertebrate density were negatively related to the proportion of threatened species and positively related to the threatened species score in mangrove habitats (Fig. 2). Mangrove loss rate was negatively, though weakly, related to land- and marine-based mangrove cumulative impacts, and seagrass change rate was negatively related to the rate of instantaneous change in seagrass climate-based impacts (Fig. 2). Given that high values for extent change indicators are a positive (i.e., less loss), these relationships mean that areas with the highest rate of loss had higher cumulative impacts. Seagrass change rate was not related to any other cumulative impact indicator (Fig. 2).

The strongest relationships were those between indicators with shared data, such as those between the same cumulative impacts across different habitats (e.g., mangrove climate current impact and saltmarsh climate current impact; Fig. 2). These layers use the same underlying dataset, but with a different habitat-specific severity multiplier based on expert opinion (Halpern et al., 2007). The correlations among indicators reflect correlations in the data, not correlations in interpolated values. We also found an anticipated, strong positive relationship between the fish and invertebrate layers (Fig. 2), which were created with several of the same underlying datasets (e.g., mangrove area, salinity, primary productivity; <https://maps.oceanwealth.org>). Similarly, the strongest negative relationships were those between the two threatened species indicators (Fig. 2). For these, the proportion of threatened species (i.e., Vulnerable, Endangered, or Critically Endangered) is negatively correlated with the weighted average of the species status. Apart from these relationships, interrelationships were generally weak or non-existent (i.e., had low correlation coefficients) for most globally comprehensive

datasets.

3.2. Typologies for the world's coastal wetlands

We next defined typologies that characterize clusters of cells with similar condition in their coastal wetland indicators. The typologies are driven by the two-way interrelationships (Fig. 2), but also capture higher order correlations among indicators that are not apparent from analysis of two-way correlations alone. A silhouette analysis identified two sets of typology clusters at different spatial scales: one with 5 and another with 18. We describe these outputs below and have developed an interactive application allowing users to select individual cells, evaluate cell-specific indicator values, alter quantile thresholds, and filter out cells that do not contain specific habitat types: <http://github.com/globalwetlands/glowdex-app>.

For the 5-typology output (Fig. 3), Typology 1 (33.7% of cells; 959 cells) exists throughout much of the world, has no indicators that are distinctive at the threshold, and can be interpreted as a 'catchall' for sites that vary without any strongly consistent patterns (Fig. 3). Typology 2 (29.7%; 844) largely exists throughout Europe, central-west Africa, Asia, and New Zealand (Fig. 3). Cells within Typology 2 are characterized as having high land- (e.g., organic chemical and nutrient pollution) and marine-based threats (e.g., fishing and shipping) in all three habitats, and a low species threat score for saltmarsh and seagrass, meaning there these habitats have a high number of threatened species (Fig. 3). Typology 3 (13.5%; 383) largely exists throughout southeast Asia, Madagascar, parts of central Europe and northeast USA (Fig. 3). This typology is typified by all three habitats experiencing high climate-based impacts (e.g., ocean acidification, sea level rise and warming; Fig. 3). Typology 4 (13.6%; 386) largely exists throughout west coast USA and Canada, and the Caribbean (Fig. 3). This typology is typified by

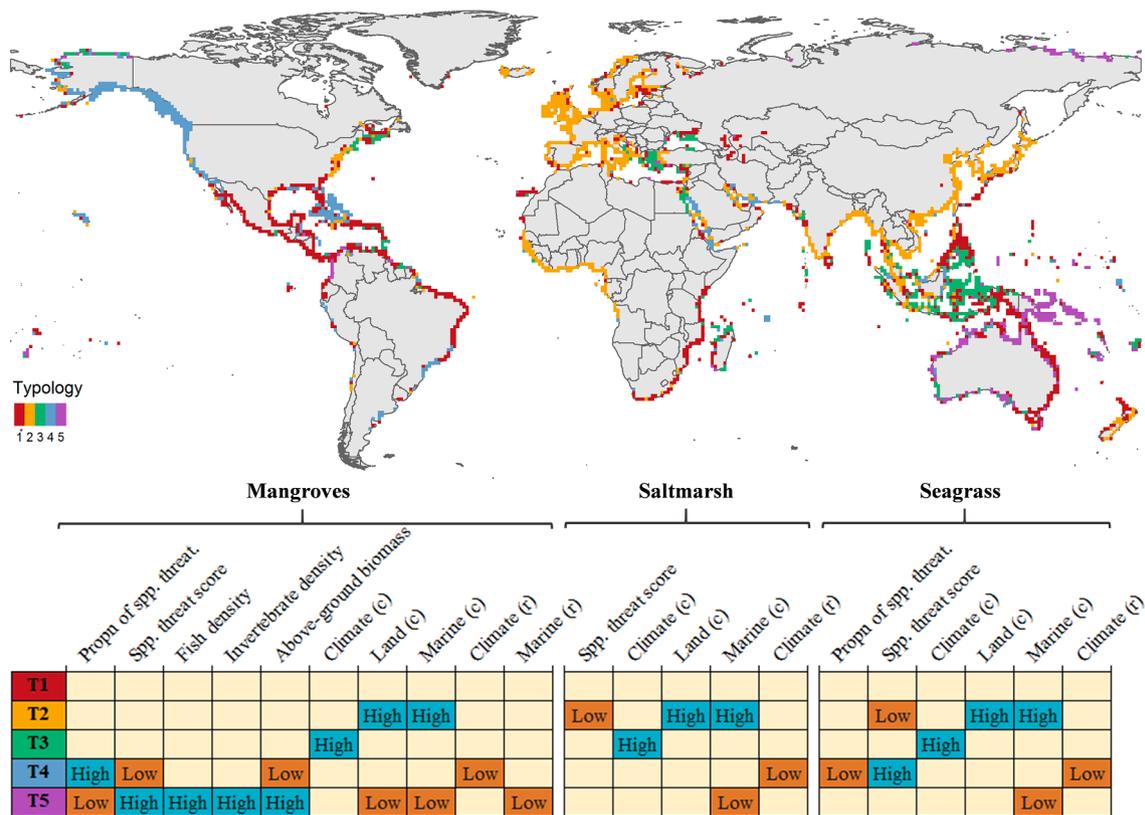


Fig. 3. Coastal wetland typologies for 5-typology output with diagnostic attributes. 'High' and 'low' refer to absolute indicator values being above or below the global average, based on residuals and using 75th quantiles (for boxplots of all indicators, see Appendix J). Given this threshold, Typology 1 has no distinguishing indicators. '(c)' is current status, and '(r)' is instantaneous rate of change. Only indicators for habitats which occur for a given cell should be used to diagnose and describe that typology.

a low rate of increase in climate-based impacts across all habitats, low mangrove AGB, seagrass habitats with a low proportion of threatened species, but mangrove habitats with a high proportion of threatened species (Fig. 3). Typology 5 (9.6%; 273) covers Australia, Papua New Guinea, and Colombia (Fig. 3). Cells within Typology 5 are characterized by low marine-based impacts in all habitats, and low land-based impacts in mangroves. Further, cells with mangroves in typology 5 have high AGB, fish and invertebrate density and a high species threat score (i.e., few threatened species; Fig. 3). For a country-level breakdown of cell numbers within each typology, see Appendix H. For global maps displaying individual typologies, see Appendix I.

The classification of cells into typologies could be affected by uncertainty in the strength of indicator interrelationships, so we calculated an indicator of the robustness of the typologies (Appendix F). Robustness was consistent with the diagnoses, in that the typologies with clearer diagnoses also had higher robustness than typologies that lacked distinguishing indicators. For example, Typology 1, the 'catchall' had low robustness, whereas typology 3 was clearly distinguished by climate threats and had high robustness.

The second output is the 18-typology output (Fig. 4). To illustrate its application, we describe four regional case studies that span different typologies and geographical settings, and typologies with relatively high robustness (Appendix F). We follow a framework for diagnosing and describing case studies, which can be applied to all cells: (1) describing the key coastal wetland habitat types present, (2) identifying the typology, (3) using indicators to describe the typology characteristics for the habitat types present (given the chosen threshold), (4) validate and conceptualize these using evidence from the literature, and (5) identify other case study locations within the typology. It is important to note that the habitat extent estimates given below are based on the best available global data layers but are not always accurate at the local scale, particularly for seagrass and saltmarsh.

3.2.1. West coast Canada

The coastal wetlands of Canada are saltmarsh (111,228 ha) and seagrass (30,154 ha) habitats (extent estimates based on whole of Canada), and the west coast is primarily in Typology 11 (Fig. 5). Typology 11 is characterized by a low rate of increase in climate-based impacts across all habitat types, and a low proportion of saltmarsh-affiliated species threatened by extinction. These cells represent relative saltmarsh refuges where, like PNG, should be protected whilst considering needs for local resources. Other cells within Typology 11

occur along the coast of western USA, especially Alaska, and Saudi Arabia and Iran (Fig. 4).

3.2.2. Papua New Guinea

The coastal wetlands of Papua New Guinea (PNG) are largely mangroves (486,137 ha) and seagrass (934,739 ha), and are primarily within Typology 8 (Fig. 5). Typology 8 is characterized by low marine-based cumulative impacts to mangroves and seagrass, and low land-based impacts to mangroves. Further, mangroves face a low rate of increase in marine-based impacts, have a low proportion of threatened species, and a high density of fish and invertebrates (Fig. 5). Cells within this typology appear to be important coastal wetland refuges from human impacts, suggesting management could focus on protection, whilst considering the needs of the local human population that rely on mangroves for their livelihoods. Parts of PNG, such as the Gulf of Papua in the south, are also classified as wilderness areas with low human impact (Jones et al., 2018). Other cells within Typology 8 occur along the coast of Solomon Islands, Tonga, and some scattered areas in southwest Australia (Fig. 4).

3.2.3. East Africa

The coastal wetlands of East Africa, from Kenya to central Mozambique and including northwest Madagascar, are largely mangroves (729,011 ha) and seagrass (664,763 ha), and are primarily within Typology 4 (Fig. 5). Typology 4 is characterized by a high rate of increase in climate-based impacts across all habitat types. Identifying areas where climate-based impacts, such as increasing sea-level rise, ocean acidification and water temperature, are rapidly accelerating is critical for informing climate specific, adaptable management responses (e.g., ecosystem-based adaptation; Giffin et al., in press). Our findings confirm work identifying East African mangroves – which are largely fringing mangroves – as being particularly vulnerable to sea-level rise (Sasmitho et al., 2016). Other cells within Typology 4 occur along the coast of western India, Pakistan, and Sri Lanka (Fig. 4).

3.2.4. United Kingdom

The coastal wetlands of the United Kingdom are saltmarsh (56,113 ha) and seagrass (13,157 ha), and are primarily in Typology 12 (Fig. 5). Typology 12 is characterized by high marine-based impacts to seagrass, and a low rate of increase in climate-based impacts across all habitat types. Given historical losses in seagrass (Green et al., 2021), management and conservation should prioritize efforts towards reducing marine

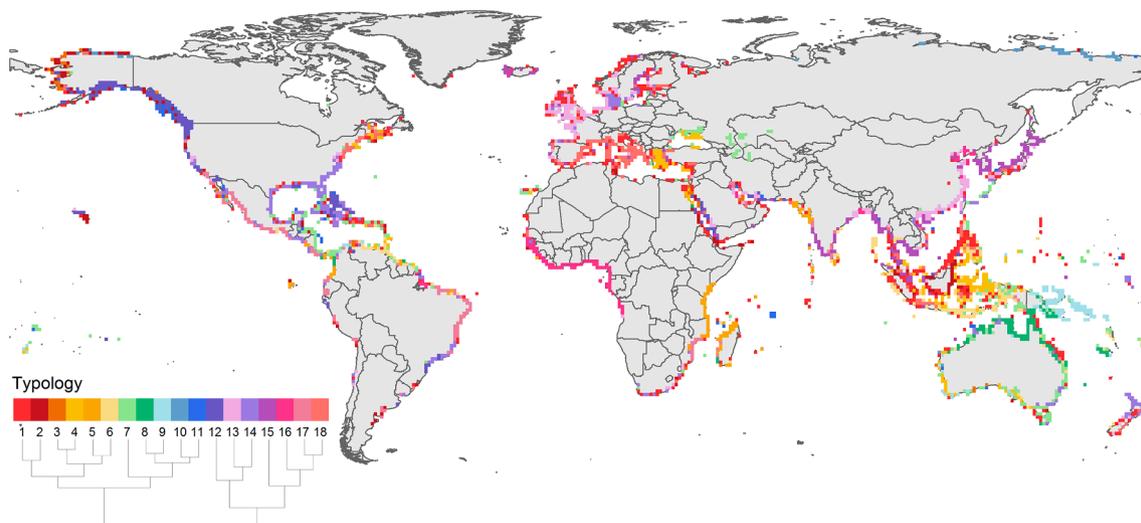


Fig. 4. Coastal wetland typologies for the 18-typology output. Typology colors were based on a three-dimensional ordination of intergroup similarity, so similar colors reflect similar typologies. For boxplots of indicators values that diagnose and define the typologies, see Appendix J. For regional case study examples, see Fig. 5.

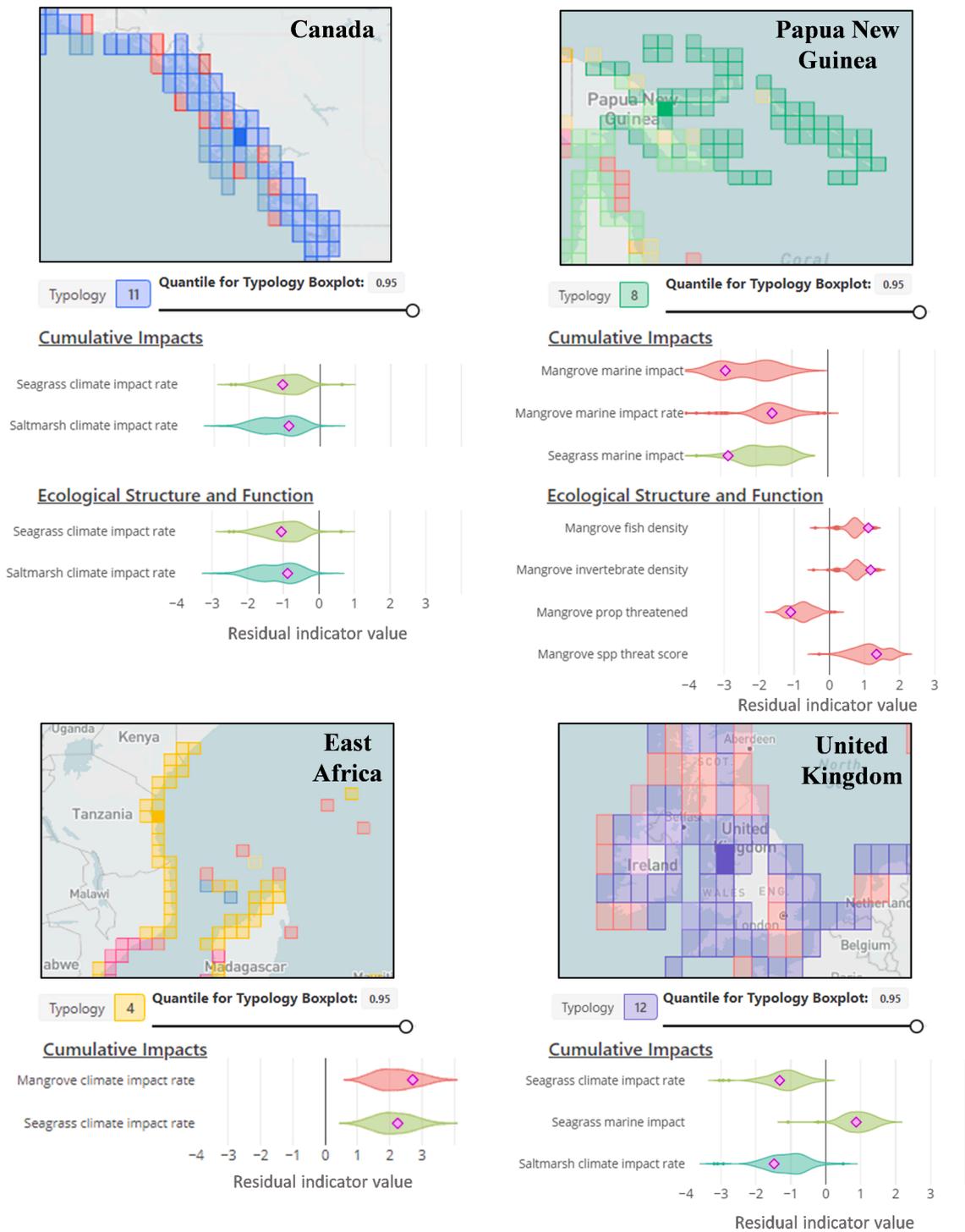


Fig. 5. Case studies for the 18-typology output. Violin plots show the residual indicator values for indicators that are most useful for diagnosing key differences among typologies, defined as those that sit outside a threshold (here, 95th quantiles). Only indicators for habitats which occur for a given cell are shown. The indicator value for the highlighted cell (darkened cell) in each map is shown as a pink diamond in the violin plot. Imagery is taken from the online application: <http://github.com/globalwetlands/glowdex-app>. For plots of all indicators, see Appendix J. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(e.g., fishing and shipping) pressures in the immediate term, as these are related to losses in seagrass extent. Other cells within Typology 12 occur along the coast of France, Ireland, Norway, and China (Fig. 4).

4. Discussion

We described interrelationships among coastal wetland indicators

and used these to develop spatially explicit typologies of ecosystem status. These typologies represent the diverse conservation needs of coastal ecosystems, from managing the increasing threat of climate change (e.g., in east Africa), to protecting globally significant ecosystem refuges (e.g., mangrove forests in Papua New Guinea), to managing intensive conflicting uses of the coastal zone (e.g., in Bangladesh).

A key strength of our methodology is that it can identify the unique

challenges facing different regions and suggest regions that could share similar conservation and management approaches. For instance, our typologies highlighted areas where marine- and land-based impacts are joint issues (e.g. China, France, Bangladesh, and central-west USA), which need joint actions that extend beyond place-based management, such as integrated coastal zone management (Carter et al., 2015). Conservation and management actions to conserve and preserve coastal ecosystems need to mitigate multiple pressures simultaneously (Bates et al., 2019; Tulloch et al., 2020), and our typology framework can inform which combinations of regional pressures can be addressed to optimally reduce cumulative impacts. By identifying how cells vary in pressures and historical rates of loss, the typologies can inform how management is prioritized among restoration and protection actions on the land and in the sea (Saunders et al., 2017). For example, restoration of catchments will be more beneficial in regions that have historically had high rates of land-use conversion (e.g., Europe), whereas protection of wetlands from deforestation will be more beneficial in regions that have low historical rates of loss (e.g., West Papua) (Saunders et al., 2017).

Our results are bolstered by two components of our approach. First, we account for variability amongst cells hypothesized to be due to environmental variation or the size of habitats prior to quantifying interrelationships and developing typologies. Second, our data-driven approach identifies similarities between geographically disjunct areas, highlighting a key difference between our approach and integrated survey approaches that often delineate large regions with few if any outliers (e.g., bioregionalizations based on expert opinion; Mackey et al., 2008). By first accounting for contextual effects using covariates and gap-filling missing data based on interrelationships, our approach differs from existing ones (see Appendix K for comparison with other ecosystem assessment methods). Our approach provides complementary information that can be used in conjunction with existing, score-based approaches such as the Ocean Health Index or the Nested Environmental Assessment Tool (NEAT) (Borja et al., 2016), or univariate ecosystem level indicators (Rowland et al., 2020). Combined, spatial typologies of condition based on indicator interrelationships and score-based indices can provide powerful insights to inform global conservation and management initiatives.

Although we identified a series of significant indicator interrelationships, several expected relationships were weak, particularly between indicators across dimensions ('interdimensional relationships'). For example, the rate of seagrass loss was not related to most seagrass cumulative impacts, while relationships between rate of change in cumulative impacts and habitat extent change and ecological structure and function indicators were very weak. Further, climate-based impacts were generally less strongly related to high rates of habitat loss or low ecological structure and function, compared to land- and marine-based pressures. Weak correlations could exist because temporal or spatial mismatches exist in the global datasets, global pressure layers miss important threatening processes and causal relationships, or if directional effects are context dependent.

A lack of interdimensional relationships suggests that caution is needed when interpreting global cumulative impact maps designed to represent large-scale patterns in ecological processes and ecosystem status (Tulloch et al., 2020). Such cumulative impact maps are often created with a combination of data and models to map pressures, and expert opinion scores are elicited to determine how those pressures are weighted for specific ecosystems (Halpern et al., 2007). Given our findings, we suggest that cumulative impact maps should not be used on their own as large-scale indicators for evaluating the outcomes of conservation policy for coastal wetlands, such as for setting management targets as thresholds.

Global scale analysis of cumulative impacts and ecosystem trends has become a prevalent way to inform on large-scale conservation analyses, which typically simplify global data into two or three categories that relate to specific conservation policy needs. Some examples include

identifying marine wilderness areas (Jones et al., 2018) and marine conservation priority areas (Selig et al., 2014), implementation of MPAs and fisheries restrictions (Cinner et al., 2020), and expansion *versus* management of protected areas (Adams et al., 2019). While there are tradeoffs between producing interpretable science to guide broad investment and diving into the fine details, we found that at least 18 distinct groups (typologies) is the most statistically robust number to globally categorize coastal wetlands, based on our set of indicators. Existing global scale analyses might thus be oversimplified. While we acknowledge the communication benefits of this simplification, our results highlight the need for diverse management and policy solutions for coastal ecosystems that include integrated management and conservation efforts (Griffiths et al., 2020; Tulloch et al., 2020).

Identifying opportunities for developing policy responses and globally coordinated conservation actions in different locations in which similar governing mechanisms operate is particularly useful for developing countries, where resources are thin, and data is generally scarcer. Within the East African cluster, for example, organizations such as the Western Indian Ocean Marine Science Association (WIOMSA) are well suited to drive opportunities that can achieve multiple objectives simultaneously. In these regions, and indeed globally, governance plays a key role in effectively carrying out conservation action and protecting coastal ecosystems (Cinner et al., 2016; Griffiths et al., 2020). The effects of cumulative impacts on rates of mangrove loss, for example, depends on national context and indicators of governance (i.e., National Regulatory Quality from the World Governance Indicators; Turschwell et al., 2020). International initiatives that drive global funding priorities are thus challenged by the need to set broad scale goals while acknowledging that local conservation actions must be tailored to suit local contexts (Waldron et al., 2013). Therefore, future work to identify and overlay opportunities for conservation and management with our diagnostic typologies of ecosystem condition would help to set the scene for globally coordinated conservation actions that are effective and feasible.

4.1. Caveats, questions, considerations, and future directions

A future research priority is to expand the set of indicators for seagrass and saltmarsh (Brown et al., 2021). Among the 34 indicators within our analysis there were fewer for saltmarsh and seagrass than mangroves, and indicators of ecological structure and function were limited primarily to mangroves. While mangroves are better studied at the global scale (Worthington et al., 2020), the likelihood of global indicator development for seagrass and saltmarsh ecosystems is increasing as global *meta*-analyses and experiments are conducted (e.g., quantifying consumption rates in seagrass ecosystems worldwide; Whalen et al., 2020). Gaps in our current suite of indicators do not invalidate our results, but mean that the typologies may not represent interrelationships among unmeasured indicators, particularly for seagrass and saltmarsh, that would be helpful for informing conservation actions. However, all existing global analyses of seagrass and saltmarsh trends are subject to the same caveat (Duffy et al., 2019; Dunic et al., 2021). As more global-scale datasets become available, and the accuracy of others improves, these can be included in future iterations of our methodology.

An interesting question is the extent to which our approach can be applied at different spatial scales, either utilizing a different grid cell size or higher resolution analyses for specific regions of the world. All options are theoretically possible, but high resolution data are seldom available at the global scale, which has limited past efforts to create accurate high resolution global analyses of ecosystem impacts (Halpern and Fujita 2013). Regardless, our typologies are likely to be robust to scaling issues; a sensitivity analysis of cumulative impact maps found that changing the resolution of the data was the least influential source of uncertainty (Stock and Micheli 2016). Future studies should, however, still consider how differences in the scale of indicator measurements affects the classification of locations into typologies.

We present a new method for investigating interrelationships among global indicators of coastal wetlands and for developing spatially explicit typologies of ecosystem condition. Future iterations could improve outputs by: (1) tracking change through time and maintaining ongoing calculations of typologies using dynamic LVMS (Thorson et al., 2016); (2) considering future scenarios such as using predictive modelling of climate change and how that might influence the typologies (especially sea level rise, shoreline recession, coastal erosion and accretion, and coastal flooding), and; (3) creating interpretable action maps that incorporate conservation-relevant variables (e.g., feasibility) and turn the complex outputs from our analyses into management-ready information (e.g., guidelines), and thus more tangible, real-world benefits.

5. Data and materials availability

All data needed to evaluate the conclusions in the paper are present in the paper and the Supplementary Materials. Additional data related to this paper may be requested from the authors.

CRediT authorship contribution statement

Michael Sievers: Methodology, Investigation, Visualization, Writing - original draft, Writing - review & editing. **Christopher J. Brown:** Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Christina A. Buelow:** Methodology, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Ryan M. Pearson:** Methodology, Investigation, Writing - original draft, Writing - review & editing. **Mischa P. Turschwell:** Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Maria Fernanda Adame:** Methodology, Investigation, Writing - review & editing. **Laura Griffiths:** Methodology, Investigation, Writing - review & editing. **Briana Holgate:** Methodology, Investigation, Formal analysis, Writing - review & editing. **Thomas S. Rayner:** Methodology, Investigation, Writing - review & editing. **Vivitskaia JD. Tulloch:** Methodology, Investigation, Writing - review & editing. **Mahua Roy Chowdhury:** Methodology, Investigation, Writing - review & editing. **Philine SE Ermgassen:** Methodology, Investigation, Writing - review & editing. **Shing Yip Lee:** Methodology, Investigation, Writing - review & editing. **Ana I. Lillebø:** Methodology, Investigation, Writing - review & editing. **Brendan G. Mackey:** Methodology, Investigation, Writing - review & editing. **Paul S. Maxwell:** Methodology, Investigation, Writing - review & editing. **Anusha Rajkaran:** Methodology, Investigation, Writing - review & editing. **Ana I. Sousa:** Methodology, Investigation, Writing - review & editing. **Rod M. Connolly:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2021.108141>.

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