Remote Sensing in Ecology and Conservation
Open Access

ORIGINAL RESEARCH

Monitoring shallow coral reef exposure to environmental stressors using satellite earth observation: the reef environmental stress exposure toolbox (RESET)

Michael J. Williamson[1,2], Emma J. Tebbs[1], Terence P. Dawson[1], Henry J. Thompson[1], Catherine E. I. Head[2,3] & David M. P. Jacoby[4]

[1]Department of Geography, Bush House (NE), King's College London, 40 Aldwych, London WC2B 4BG, UK
[2]Institute of Zoology, Zoological Society of London, Outer Circle, Regent's Park, London NW1 4RY, UK
[3]Department of Zoology, University of Oxford, Zoology Research and Administration Building, 11a Mansfield Road, Oxford OX1 3SZ, UK
[4]Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK

Keywords
Bleaching, coral reef, environmental stress, Google Earth Engine, remote sensing, satellite

Correspondence
Michael J. Williamson, Institute of Zoology, Zoological Society of London, Outer Circle, Regents Park, London NW1 4RY, UK. Tel: +44 020 7749 6620; Fax: +44 020 7586 2870; E-mail: michael.williamson@ioz.ac.uk

Editor: Kylie Scales
Associate Editor: Jacquomo Monk

Received: 15 November 2021; Revised: 8 April 2022; Accepted: 9 May 2022

doi: 10.1002/rse2.286

Remote Sensing in Ecology and Conservation 2022;**8** (6):855–874

Abstract

Coral reefs are significantly threatened by multiple environmental stressors associated with climate change. While there is growing recognition of the importance of interacting stressors on coral reefs, so far this has been primarily limited to in situ studies. Satellite remote sensing has potential for investigating coral reef exposure to multiple environmental stressors at a global scale over multiple years; however, current satellite monitoring is primarily focused on thermal stress. Here we collate nine environmental variables (cloud cover, current, depth, salinity, wind, and four sea surface temperature-based metrics) from readily available satellite datasets using the Google Earth Engine geospatial processing platform. Using ecological and health-based thresholds obtained from the literature, we developed, using fuzzy logic (discontinuous functions), a Reef Environmental Stress Exposure Toolbox (RESET) for monitoring environmental stress exposure at multiple scales. Stress exposure scores for 3157 reefs were generated and mapped globally across 12 coral reef ecosystem regions. RESET was also applied to three case-study reefs, previously well monitored for stress and disturbance using other methods. PCA analysis indicated that depth, current, sea surface temperature (SST) and SST anomaly accounted for the greatest contribution to the variance in environmental stress exposure in these three regions. Depth, degree heating weeks, and SST anomaly were identified as the potential drivers of inter- and intra-region variation in environmental stress exposure. Individual variables were then integrated into a multi-metric index of combined stress exposure which corroborated temporal and spatial differences due to known disturbance events. RESET provides a open access, easily interpretable set of tools and associated indices for monitoring environmental stress exposure on coral reefs, designed to inform conservation and management decisions. As such RESET has broad potential to assist in the monitoring of our increasingly imperilled coral ecosystems, in particular, those that are remote or inaccessible.

Introduction

Coral reefs are important ecosystems for a wide range of marine fauna and biodiversity (Jones et al., 2004; Sala & Knowlton, 2006; Scheffer et al., 2001). Over the past 20 years, there has been a significant decline in coral cover across the world's reef systems (Bellwood et al., 2019; Bruno & Selig, 2007; De'ath et al., 2012). These coral losses, caused by disease or bleaching, are often triggered by environmental stressors, such as elevated sea surface temperature (SST), which may directly impact coral reef health or influence how reef ecosystems are affected by, or recover from, other disturbances (Eakin et al., 2019; Harvell et al., 2007; Head et al., 2019; Hughes et al., 2017; Hughes et al., 2018). Although certain variables may be significant stressors to coral reefs on their own, many are compounded, amplified or offset through syntheses with others (Ban et al., 2014; Ellis et al., 2019; Goergen et al., 2019; Veron et al., 2009). Recently, approaches that utilize multiple variables for assessing coral reef exposure to stress and other threats have been proposed as a better method of identifying reefs that are most under threat, as well as those that are limited in their resilience to recover from disturbance events (Maynard et al., 2015; Obura et al., 2009).

Monitoring is a fundamental part of ecosystem conservation and management (Flower et al., 2017; Stem et al., 2005), and regular assessment of the impacts of stressors on declines in coral cover, in both space and time, has become increasingly important for understanding just how vulnerable coral reefs are (Burke et al., 2011; Hedley et al., 2016; Obura et al., 2019). In recent years, there has been increased emphasis on the use of satellite remote sensing to monitor coral reef ecosystems, as satellites can provide greater coverage and take less time than traditional field surveys, and with ever increasing accuracy (Hedley et al., 2016; Hedley et al., 2018). Recently, a global coral reef map of unprecedented thematic detail has been created using Planet and Sentinel-2 imagery processed in Google Earth Engine (Lyons et al., 2020), available together with a bleaching monitoring system at www.allencoralatlas.org (Xu et al., 2020). Sentinel 2 imagery was also recently used to develop a relative depth dataset for each reef globally up to 15 m depth (Li et al., 2021).

Currently, existing tools that utilize remotely sensed data to assess environmental stress exposure on coral reef ecosystems, such as the U.S. National Oceanic and Atmospheric Administration's (NOAA) Coral Reef Watch (https://coralreefwatch.noaa.gov/satellite/index.php), focus on thermal stressors, such as SST, SST anomaly, SST hotspots and degree heating weeks (DHW). Increasingly though, the importance of integrating multiple drivers of reef stress into analyses has been recognized (Cannon et al., 2021; Gibbs & West, 2019; Maina et al., 2011; Maynard et al., 2017). However, in situ, rather than satellite, data are often the primary source for these investigations and those studies that do use remotely sensed data may not consider temporal dynamics (Maina et al., 2011). In addition, some studies use commercial satellite data or develop their own products as part of their analyses, which may be beyond the budgets and technical expertize of some coral reef ecologists or conservation NGOs.

In this study, we used Earth Observation (EO) data and the Google Earth Engine (GEE) cloud-based geoprocessing platform to develop a toolbox for monitoring, mapping and investigating shallow coral reef exposure to environmental stress (as opposed to purely anthropogenic stressors such as fishing), mediated through a combination of interacting variables. Our aims were to (1) identify, from the literature, the main variables that influence coral reef stress and to identify quantitative thresholds to distinguish 'normal' and stressed conditions; (2) develop a user-friendly, open access, spatially and temporally explicit, shallow coral reef stress exposure monitoring tool, in GEE, to assign a stress exposure score to each variable, which are also integrated into a combined multi-metric environmental stress exposure index; and (3) demonstrate the utility of this tool for investigating spatial and temporal variability in shallow reef environmental stress exposure, both globally (across 3157 reefs) and in three well-documented case study regions with high coral cover in relatively clear waters: the Chagos Archipelago; the central Saudi Arabian Red Sea; and the Gilbert Islands of the Republic of Kiribati. We discuss the uses for this toolbox for coral reef conservation and management.

Materials and Methods

The overall workflow used for developing the Reef Environmental Stress Exposure Toolbox (RESET) is summarized in Figure 1.

Study sites

To develop RESET and demonstrate its utility, we used a sample of 3157 globally distributed coral reef locations, including representation across 12 ocean ecosystem regions that cover the major coral reef regions (Burke et al., 2011) (Fig. 2). Coordinates were taken from Maina et al. (2011), which included data from Reef Base (http://reefgis.reefbase.org/) and the Wildlife Conservation Society monitoring sites in the western Indian Ocean, as well as from Ateweberhan and McClanahan (2010).

In addition, we chose three local case study regions with available in situ records of bleaching events over multiple years (2003–2016): the Chagos Archipelago; the central Saudi Arabian Red Sea; and the Gilbert Islands of the Republic of Kiribati (Fig. 2). These three regions represent a range of ocean and environmental conditions and have experienced significant environmentally induced stress events (bleaching) over the past 20 years. Detailed

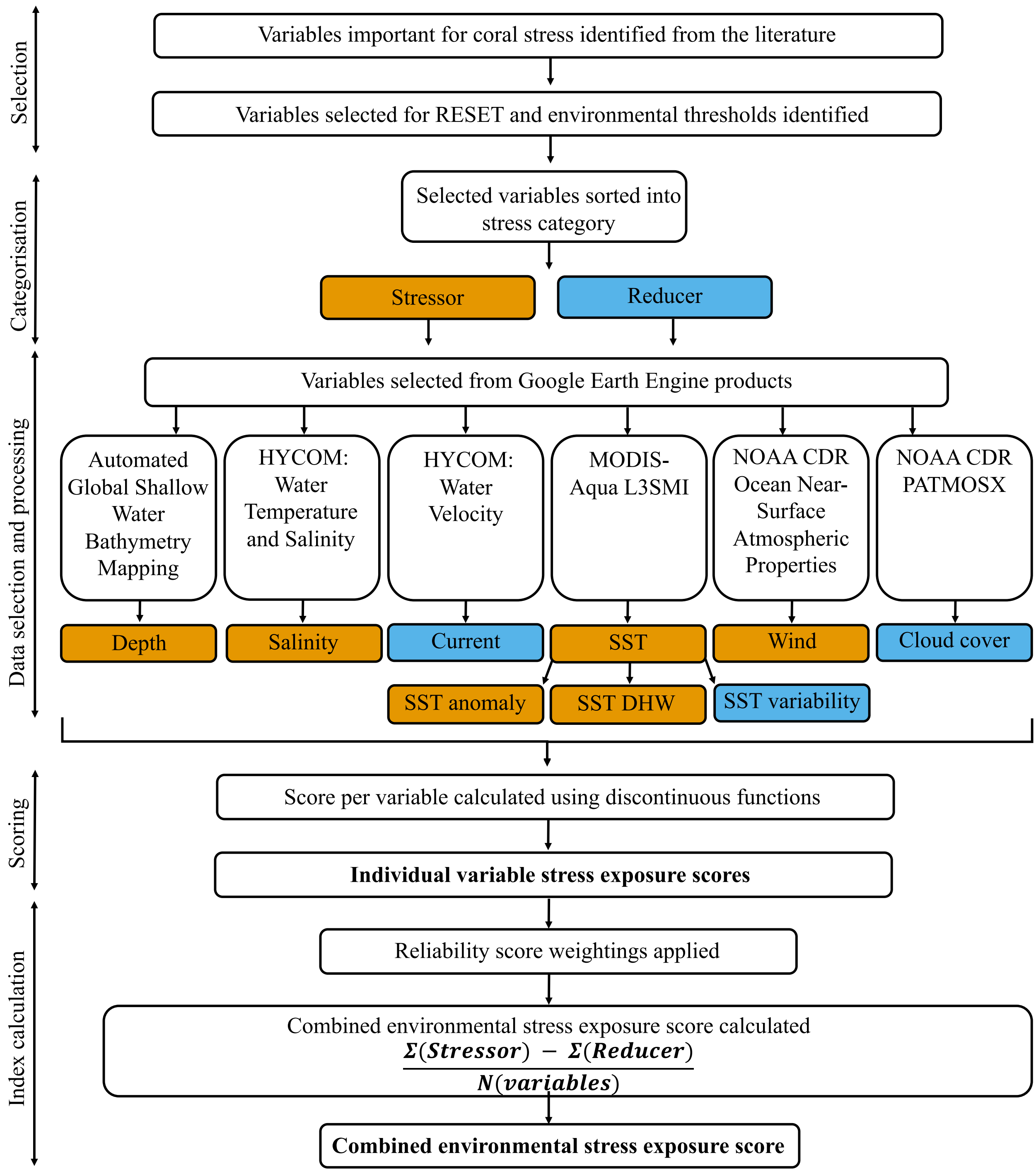


Figure 1. Workflow used to develop the reef environmental stress exposure toolbox (RESET). Stressors are highlighted in oranges, reducers in blue.

in situ data on coral responses to environmental stress (such as bleaching events) is available from 2003 to 2016 at several sample sites in these regions from investigations undertaken by Head et al. (2019) at the Chagos Archipelago, Furby et al. (2013) and Monroe et al. (2018) at the central Saudi Arabian Red Sea; and Carilli et al. (2012) and Donner and Carilli (2019) at the Gilbert Islands of the Republic of Kiribati.

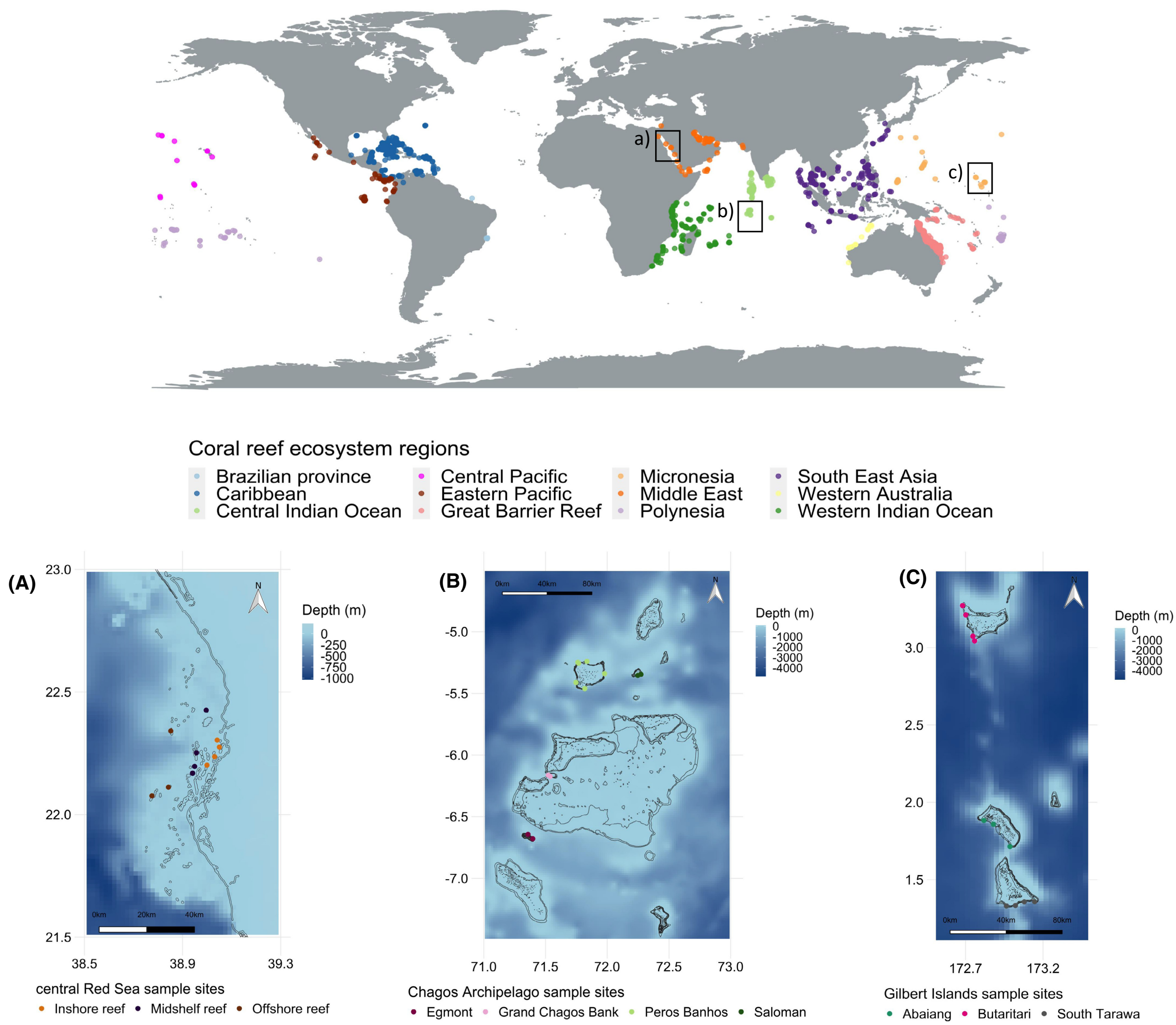


Figure 2. Study sites maps showing the 3157 shallow coral reef sites from 12 coral ecosytem regions, coordinates taken from Maina et al. (2011) and three study regions; (A) the central Saudi Arabian Red Sea; (B) the Chagos Archipelago; (C) the Gilbert Islands of the Republic of Kiribati, used for sampling, with shallow reef areas outlined in black and sample sites identified. Reef data obtained from https://data.unep-wcmc.org/datasets/1 (UNEP-WCMC et al., 2021).

Environmental variable selection and threshold definition

Variables that influence stress in coral reef ecosystems were identified from two reviews: West and Salm (2003) and Sokolow (2009), as summarized in Table 1.

Variables were chosen for inclusion in RESET if they were (1) of environmental, as opposed to purely anthropogenic, origin, (2) had previously shown to have an effect, positive or negative, on stress on coral reef ecosystems, (3) had defined ecological health-based thresholds that allow for discrimination between healthy and unhealthy reefs, and (4) were available as products in GEE. For each environmental variable, thresholds (i.e., limiting values, which, if exceeded, can cause stress and health deterioration for coral reef ecosystems) were extracted during the literature review to parametrize the inputs for the RESET. Nine variables were selected and the thresholds identified, including references, for these variables can be found in Table 2. Although these thresholds can be region specific (Bridge et al., 2013; Lesser et al., 1990; Mumby et al., 2001; Spencer et al., 2000), wherever possible, globally applicable thresholds were identified from the literature. However, where these could

Table 1. Environmental variables identified by West and Salm (2003) and Sokolow (2009) as important environmental coral reef stressors.

Environmental coral stressor
Chlorophyll-a
Cloud cover
Current
Depth
DHW
Photosynthetically active radiance (PAR)
Salinity
Sea surface height
SST
SST anomaly
SST variability
Turbidity
Upwelling
Wind

not be found, thresholds based on regional studies were used and assumed to be applicable at a global scale. Correlation analyses conducted using the 'cor' function in *stats* in R indicated that Pearson correlation values between all variables were all under the commonly used cut off threshold of 0.7 (Dormann et al., 2013; Farrell et al., 2019). As such all selected variables were included in the analyses.

Following the method proposed by Maina et al. (2011), variables were assigned into two categories: environmental stressors (hereafter termed 'stressors') and environmental stress reducers (hereafter 'reducers'), using data from West and Salm (2003) and Maina et al. (2011) (Table 2). Stressors were considered the primary negative drivers of coral reef stress. Reducers can play an important role in improving coral reef resilience (Obura et al., 2009; Rowlands et al., 2012) and mitigate the primary effects of stressor impact on coral reef ecosystems. Variables were weighted according to reliability (Table 2), which was defined as whether a variable was considered predictable and persistent in its impacts on coral reef stress, taken from West and Salm (2003). Although not featured in West and Salm (2003), salinity was deemed low reliability, due to the variability in impact and salinity tolerance in many species (Coles & Jokiel, 1992; Guan et al., 2015; Röthig et al., 2016). Those variables that had low reliability were weighted 50% less than high reliability weightings.

Remote sensing data

The remote sensing datasets used in this study are summarized in Table 3.

Although depth does not directly cause stress on coral reef systems, it is an important mediating factor in how corals react to other environmental stressors (Graham et al., 2015; Head et al., 2019; West & Salm, 2003). The only bathymetry product available in GEE, ETOPO1, had a spatial resolution of 1 arc-minute that was too coarse for this study. Instead we used Li et al. (2021)'s automatic global shallow water depth mapping method, which utilizes Sentinel-2 reflectance data (from 1st January 2019 to

Table 2. Variables used for the assessment of shallow coral reef stress identified by West and Salm (2003) and Sokolow (2009). Variables were grouped by stressors (primary drivers of shallow coral reef stress) and reducers (those that mitigate the primary effects of stressors) informed by data from Maina et al. (2011). Upper and lower thresholds obtained from the literature are provided with variable units and threshold references. Variables were given values of 0 and 1 for lower and upper thresholds, respectively. Reliability factor was informed by data from West and Salm (2003), and was an indicator of how reliably this variable impacts coral stress at a global scale. Scale indicates whether the threshold is seen at a regional or global scale. Details of the journal article where the thresholds for each variable were obtained are given.

Environmental stress variable	Unit	Stress category	Lower threshold	Upper threshold	Reliability factor	Scale	References
Variables included in RESET							
Cloud cover	oktas	Reducer	3.0	7.0	low	Regional	(Mumby et al., 2001)
Current	m/s[1]	Reducer	0.13	0.15	high	Regional	(Maina et al., 2008)
Depth	m[1]	Stressor	<10	>20	high	Regional	(Graham et al., 2015; Wagner et al., 2010)
DHW	weeks	Stressor	4.0	8.0	high	Regional	(Kayanne, 2017)
Salinity	ppt	Stressor	32.0–38.0	< 26.0 or > 45.0	low	Regional	(Li et al., 2009)
SST	°C	Stressor	21.0–27.0	>30.0 or < 18.0	high	Global	(Hoegh-Guldberg, 1999; Maina et al., 2011)
SST anomaly	°C	Stressor	1.0	2.0	high	Global	(Eakin et al., 2009)
SST variability	°C	Reducer	4.0	10.0	high	Regional	(Maina et al., 2008)
Wind	m/s[1]	Stressor	8.0–28.0	< 5.0 or > 33.0	low	Regional	(Fabricius et al., 2008; Maina et al., 2008)

Table 3. Variables used for the assessment of shallow coral reef stress, including source and temporal and spatial resolution. All information on variable products can be found in the Earth Engine Data Catalogue (https://developers.google.com/earth-engine/datasets/).

Environmental stress variable	Temporal resolution (hour)	Spatial resolution (km)	Start year	End year	Data source (https://developers.google.com/earth-engine/datasets/catalog/)
Cloud cover	3	11	1978	Present	NOAA Climate Data Record (CDR) of Cloud Properties from AVHRR Pathfinder Atmospheres – Extended (PATMOS-x), Version 5.35.3 (Heidinger et al., 2014)
Current, salinity	24	9	1992	Present	HYCOM: Hybrid Coordinate Ocean Model, Water Velocity (Cummings & Smedstad, 2013)
Depth	NA	0.1	2017	Present	Sentinel-2 MSI: MultiSpectral Instrument, Level-2A (Li et al., 2021)
SST, DHW, SST anomaly, SST variability	24	4.6	2002	Present	Moderate-resolution Imaging Spectroradiometer (MODIS) Aqua Data (NASA Goddard Space Flight Center, Ocean Ecology Laboratory, & Group, O.B.P, 2018)
Wind	24	27	1988	Present	NOAA Ocean Surface Bundle (OSB) Climate Data Record (CDR) of Near-surface Atmospheric Properties, Version 2 (Clayson et al., 2016)

31st December 2020) to obtain shallow water bathymetry at a resolution of 10 m. The method is applicable up to a maximum depth of 20 m (Li et al., 2021), which is consistent with the upper threshold for depth of 20 m identified in the literature (Table 2). However, the method is most appropriate in clear waters of 15 m depth or less, and its reliability drops between 15 and 20 m and in turbid waters (Li et al., 2021).

Overall ocean current speed was calculated from HYCOM Sea Water Velocity in eastward and northward directions using the formula: overall current = $\sqrt{\text{northward}^2 + \text{eastward}^2}$. To avoid wind driven surface processes, we used current values at 10 m depth.

MODIS Aqua SST data were used to obtain SST anomaly, DHW and SST variability. For SST anomaly, the monthly mean of 10 years (2002–2012) of SST values for the region was calculated and subtracted from the SST value for each pixel for the corresponding month, following the method by Eakin et al. (2009). DHW was calculated following the method of Eakin et al. (2009) by averaging the SST anomaly for each 7-day time frame to create a weekly mean for 12, 7-day periods prior to the final date of the period of interest. The number of weeks where the weekly mean was 1°C above the 10-year mean was counted to give DHW for each region of interest. For SST variability, the minimum SST value was subtracted from the maximum SST value for each pixel. The accuracy of the variables used in RESET, where available, can be found in Table S2.

Reef environmental stress exposure toolbox (RESET)

RESET was written in the Google Earth Engine (GEE) JavaScript API. Launched in 2010, GEE is a cloud-based geoprocessing platform, which enables access to a wide variety of satellite remote sensing data sets for analysis either within GEE or to download and analyse externally with other software (Gorelick et al., 2017).

GEE also enables users to publish their own apps (https://www.earthengine.app/), which allows for dynamic user interfaces and increases accessibility to GEE products for non-experts (Tamiminia et al., 2020). As such, to increase the utility of the RESET, a RESET app was developed (https://mjw1280.users.earthengine.app/view/reef-environmental-stress-exposure-toolbox) as part of this study.

Stress exposure scores

To facilitate comparison of different stress variables, and their integration into a multimetric index, a stress exposure (SE) score for each variable was assigned using a common scale (Ruaro et al., 2020; Stoddard et al., 2008). Threshold values from Table 1 were used to assign a value for each variable between 0 (indicating no stress) and 1 (indicating maximum stress) using discontinuous functions (fuzzy logic) (Fig. 3). For both stressor and reducer variables, values below the lower threshold are assigned a score of 0 and values above the upper threshold are assigned a score of 1. Values between the thresholds were assigned a score defined by a linear function of the form $y = mx + c$, where m is the gradient and c is the intercept. To reduce missing data due to cloud cover but still allow analysis of seasonal variability, a time period of 1 month was selected to aggregate the SE score for each variable, except for DHW where 12 weeks were used to match the calculation period from NOAA Coral Reef Watch (Eakin et al., 2009).

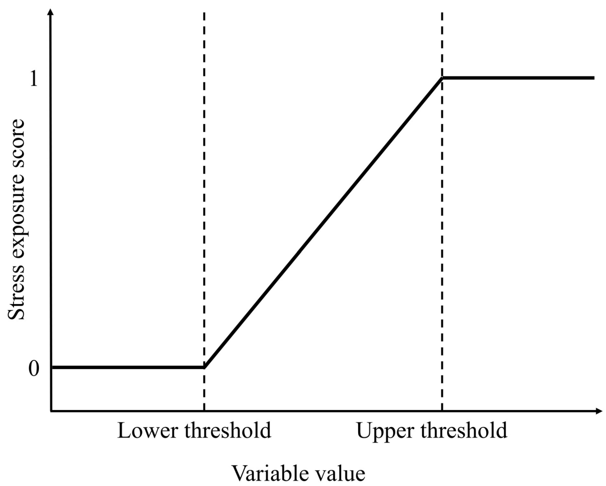


Figure 3. Discontinuous functions, including thresholds for 0 and 1 values, for defining stress exposure scores or each variable stressor and reducer variable.

The combined environmental stress exposure index

Indices are frequently used to aggregate a suite of variables known to have either a positive or negative influence on ecosystem health (Bunn et al., 2010; Sheldon et al., 2012; Williams et al., 2009). They provide an interpretable reference point for evaluating health and stress exposure and are a common tool for assessing ecosystem health within aquatic communities (Longo et al., 2017; Robertson et al., 2016; Ruaro et al., 2020; Schoolmaster et al., 2013; Williams et al., 2009). Therefore, we integrated individual variable SE scores into a combined environmental stress exposure index.

The reliability weightings from Table 1 were applied to each variable SE score, and results were exported from GEE. The combined environmental SE index was then calculated in R version 4.0.3 (R Core Team, 2020) as:

$$\text{Combined Environmental Stress Exposure} = \frac{\Sigma(\text{Stressor}) - \Sigma(\text{Reducer})}{N(\text{Variables})}$$

where Σ(Stressor) is the sum of the SE score of the stressor variables (including weightings), Σ(Reducer) is the sum of the reducer variables (including weightings) and N(Variables) is the total number of variables. Instances where negative SE scores occurred from low stressor values but high reducer values indicate low stress exposure and were therefore converted to 0. Remote sensing data can be unavailable during certain periods (e.g., long periods of cloud cover). Whenever data for a specific variable was missing for a specific time period and site, this variable was omitted from the combined environmental SE score. If two or more variables were missing for the entire study period at a site, this site was removed from the analysis (see Case Study Data Collection for further details).

Evaluating RESET

Due to the often remote locations of coral reef ecosystems and the typically high cost of surveys, long term in situ datasets on reef environmental stress exposure are not readily available. Therefore, we used El Niño periods to evaluate the ability of RESET to capture spatial and temporal variability during known disturbance events, such as coral bleaching. El Niño events were chosen as they can cause detectable changes in several environmental variables, such as SST, wind, current and salinity (Harrison & Larkin, 1998; Johnson et al., 2000), which can lead to altered environmental stress exposure to reef systems (Claar et al., 2018; Lix et al., 2016; Stone et al., 1999). In addition, they can have large area impacts over ocean basin and even global scales (Fedorov & Philander, 2000; Latif & Keenlyside, 2009) and temporal, spatial and strength data on these events are readily available (e.g., https://ggweather.com/enso/oni.htm).

Global analysis of reef stress exposure

To demonstrate the use of RESET at a global scale, and to investigate spatial differences in environmental stress exposure, an SE score (with weightings) was calculated for each variable for 3157 reefs from 12 shallow coral reef ecosystem regions (Fig. 2). In addition, to investigate temporal differences in environmental stress exposure, SE scores were calculated for two periods with different levels of environmental stress: April 2012, a non-El Niño period, and April 2016, a strong non-El Niño period. Here, we define a reef as a single connected reef, a site as a collection of different localized reefs and a region as a collection of sites within the same area. To calculate SE scores at each reef, a 500 m buffer was created around the latitude and longitude position of each reef, to match the resolution of many of the products selected, and to avoid overlap with other nearby reefs where data was also to be extracted. SE scores for each variable, the combined environmental SE index and summary statistics for each ecosystem region were calculated. All analyses were conducted using R version 4.0.3 (R Core Team, 2020).

Case study

To demonstrate the utility of RESET at finer spatial scales, SE scores were calculated and used to investigate spatial and temporal patterns in stress exposure at our case study sites (Fig. 2). Following the El Niño events of 2015/16, coral reefs in the Chagos Archipelago experienced extensive bleaching and declines in coral cover in the region (Head et al., 2019; Sheppard et al., 2017). Coral reefs of the Gilbert Islands of the Republic of Kiribati and the central Saudi Arabian Red Sea also experienced El Niño-linked bleaching and declines in 2004 and 2010 (Carilli et al., 2012; Donner & Carilli, 2019), and 2010 and 2015 (Furby et al., 2013; Monroe et al., 2018), respectively.

Mean monthly SE scores for each variable were calculated quarterly (January, April, July, October) from 2003 to 2016 for 34 different sites across the three regions (Chagos Archipelago = 12, Gilbert Islands = 11, central Red Sea = 11) (Table S2), to match the study regions from Head et al. (2019), Carilli et al. (2012) and Furby et al. (2013), respectively. This time period covers six El Niño events (2002/2003, 2004/2005, 2006/2007, 2009/2010, 2014/2015, 2015/2016) some of which coincided with bleaching events in these regions.

Principal Component Analysis (PCA) was used to detect spatial differences in the SE scores between the case study regions in the individual drivers of stress exposure using the 'prcomp' function in the *stats* package in R (R Core Team, 2020), emphasizing and revealing the extent to which integrated variables contribute to environmental stress. Box plots were used to investigate temporal differences in SE scores of the individual environmental variables between regions (non-El Niño events, El Niño events, and El Niño events coinciding with bleaching events). In addition, because regional differences in bleaching have been found across all three case study regions (Carilli et al., 2012; Donner et al., 2010; Furby et al., 2013; Head et al., 2019; Monroe et al., 2018) box plots were plotted to investigate spatial differences between the RESET variables within these three regions.

Finally, the combined environmental SE index was calculated quarterly from 2003 to 2016 for each case study region to investigate changes in environmental stress over time relative to known bleaching and El Niño events. Linear regression was used to identify temporal trends using the 'lm' function in the *stats* package (R Core Team, 2020).

Results

The final GEE JavaScript code for the RESET can be found at: https://github.com/mjw-marine/Reef-Environmental-Stress-Exposure-Toolbox.git and the RESET GEE App can be found at https://mjw1280.users.earthengine.app/view/reef-environmental-stress-exposure-toolbox. This RESET App provides a Guided User Interface (GUI) that requires no prior knowledge of GEE. However, the script can also be adapted directly in the JavaScript code if required.

Environmental coral reef stress exposure at a global scale

SE values from the RESET were calculated across 3157 sites from 12 different global shallow coral reef ecosystem regions between two different monthly periods. Boxplots of each variable from 2012 and 2016 from reefs in the Central Indian Ocean, Western Indian Ocean and Great Barrier Reef can be found in Figure 4. DHW was far greater in 2016 compared with 2012 in all three regions, which, as DHW is a significant driver of bleaching events, is consistent with findings of extensive bleaching in these regions in 2016 compared with 2012. Additional summary statistics of SE scores from all RESET variables across the 12 regions can be found in Table S3.

The spatial distribution of the combined environmental SE index values across the 12 global shallow coral reef ecosystem regions during El Niño and non-El Niño periods is summarized in Figures 5, and 6 shows the difference in combined environmental SE score across the 12 coral reef ecosystem regions. This illustrates the scalability of the RESET and the combined environmental SE score and shows the potential of the RESET for investigating spatial and temporal variability in coral reef exposure to environmental stressors across multiple reef regions.

General inter-region variance

PCA analysis allowed variance of individual SE variables to be compared across the three regions. Figure 7 shows the score of each site for the first two principal components with SE scores and the loading of each environmental variable on the first two principal components (PC), which together accounted for 92.5% of the total variance. Depth and current made the greatest contribution to the variance of the first PC. SST variability and SST anomaly were the most important contributors to the second PC. Current and cloud were all highly correlated in the first PC, and SST, SST anomaly and DHW highly correlated in the second PC. Depth was the most uncorrelated with the other variables. Sites within the same region had variable SE scores most similar to each other, but there were outliers within the regions (e.g., OS1 and TRW002), indicating that there is also variance in how variables may contribute to overall stress within a region. The central Red Sea had considerably different variable SE scores compared with the Chagos Archipelago and the Gilbert Islands which were more similar to one another. This is most likely due to the Red Sea being sheltered and shallow, with a lack of freshwater input from rivers and streams, resulting in a unique region of shallow depths, increased salinity and low current speeds (Daqamseh et al., 2019; Tragou & Garrett, 1997).

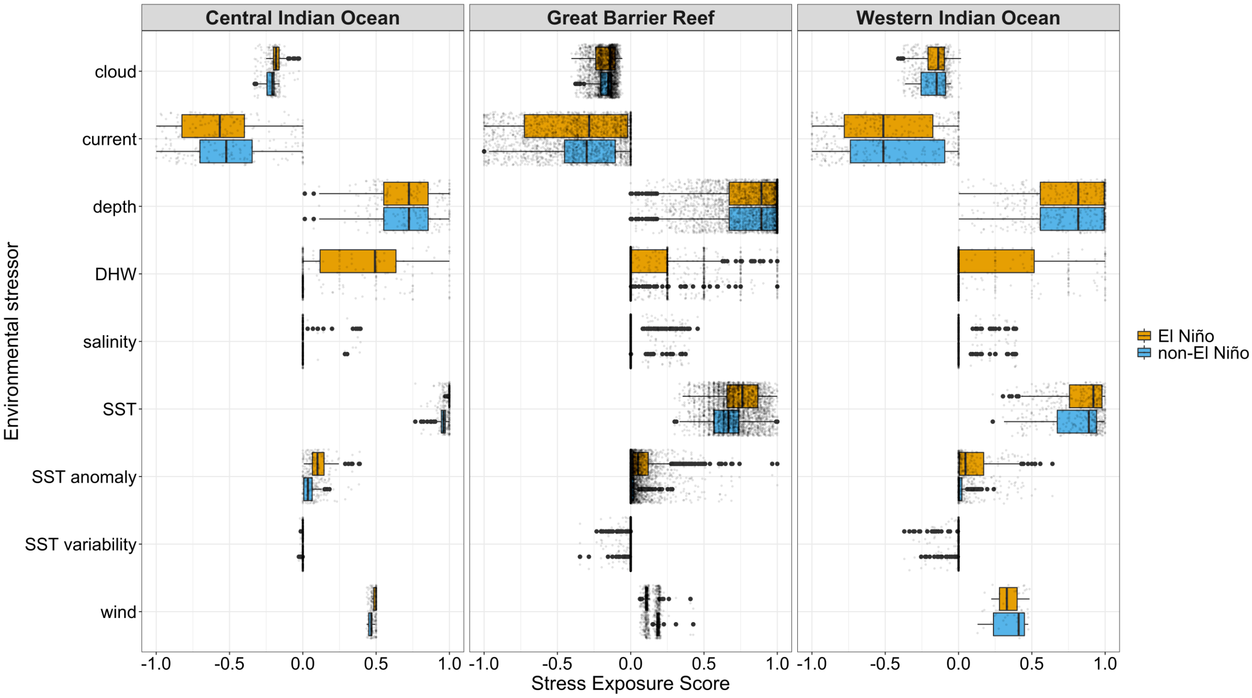


Figure 4. Box plots of the distribution of SE scores of RESET variables between non-El Niño periods (April 2012), and strong El Niño periods (April 2016) from three coral reef ecosystem regions. Box plot represents median SE score and the interquartile range. Whiskers extend from the hinge to the highest and lowest values within 1.5× the interquartile range. Any values outside that are indicated as outliers.

Temporal intra-region variance

Figure 8 illustrates how RESET can be used to investigate temporal variance in SE scores between regions. Greater temporal variance was observed in the Chagos Archipelago and the Gilbert Islands than in the central Red Sea. In the Chagos Archipelago, much higher DHW and SST anomaly scores were observed during the El Niño bleaching event compared with the non-El Niño and El Niño years, with no obvious differences in the other variable SE scores. In the Gilbert Islands, non-El Niño years had lower variable SE scores for SST, DHW, and SST anomaly, and greater variable SE values for current, with no obvious difference in stress variable distribution between El Niño years and El Niño years with a bleaching event. In the central Saudi Arabian Red Sea, there was a slight increase in the SE score for SST anomaly and SST between El Niño years with a bleaching event and El Niño and non- El Niño years, but no obvious differences in the other variables.

Spatial intra-region variance

RESET was able to capture intra-region spatial differences in stress (Fig. 9) in agreement with previous studies in the Chagos Archipelago (Head et al., 2019), Gilbert Islands (Carilli et al., 2012; Donner & Carilli, 2019) and the central Red Sea (Furby et al., 2013; Monroe et al., 2018). SE scores for DHW were low at Butaritari in the Gilbert Islands compared with Abaiang, and South Tarawa. South Tarawa had greater SE scores for depth, salinity and current than Abaiang and Butaritari. In the central Red Sea, depth and current SE scores were larger in Offshore than Midshelf and Inshore sites. The primary difference between sites in the Chagos Archipelago was depth, with SE scores at Egmont and Peros Banhos much more variable than at Grand Chagos Bank and Saloman which had consistently high and low SE scores for depth, respectively.

The combined environmental stress exposure index

The combined environmental SE index was used to investigate long-term trends for each case study region over a 14-year period (2003–2016) (Fig. 10), which covered six El Niño events in these regions. The Chagos Archipelago showed fluctuations in combined environmental SE around a stable value. The combined environmental SE index captured peaks in stress that coincided with bleaching events in Chagos Archipelago. There were peaks for

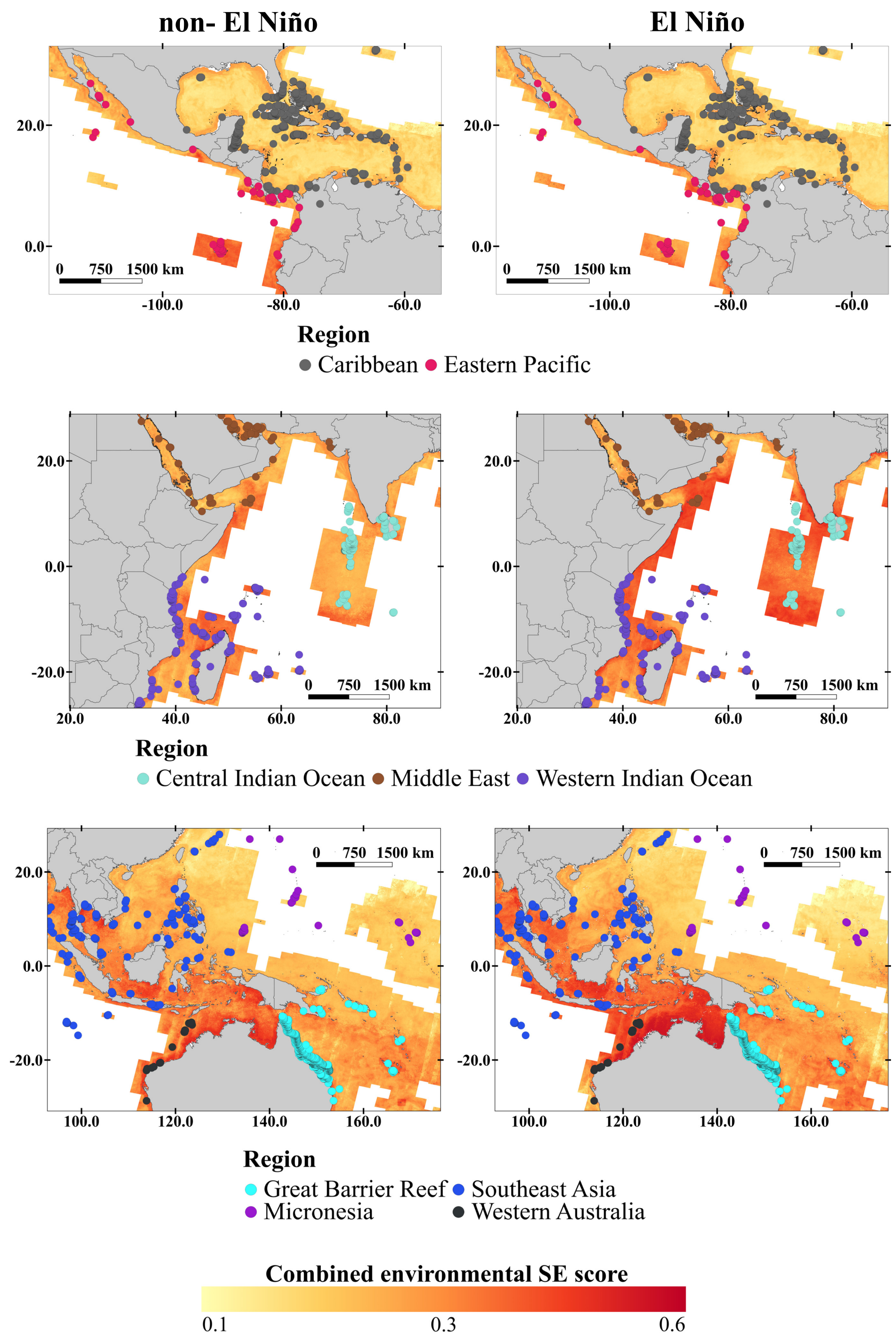


Figure 5. Global combined environmental SE maps from a non-El Niño period (April 2012) and a strong El Niño period (April 2016) for the Caribbean and Eastern Pacific (top), Indian Ocean and Middle East (middle), Southeast Asia, Indonesia, and Australiasia (bottom). Location data for all sites can be found in Appendix S1. White areas show data gaps due to a lack of Sentinel-2 data used for shallow water bathymetry.

the Gilbert Islands during bleaching events, but peaks were also present during El Niño years that did not result in bleaching events. The combined environmental SE index for the central Saudi Arabian Red Sea showed a regular periodic cycle, with no clear peaks in El Niño years. Results from linear models indicate that there was significant change over time in combined environmental SE index, with stress increasing gradually in the central Red Sea (estimate = 0.006, $F_1 = 16.90$, $p < 0.001$), Chagos Archipelago (estimate = 0.009, $F_1 = 46.13$, $p < 0.001$) and Gilbert Islands (estimate = 0.008, $F_1 = 15.24$, $p = 0.001$) (Fig. 10).

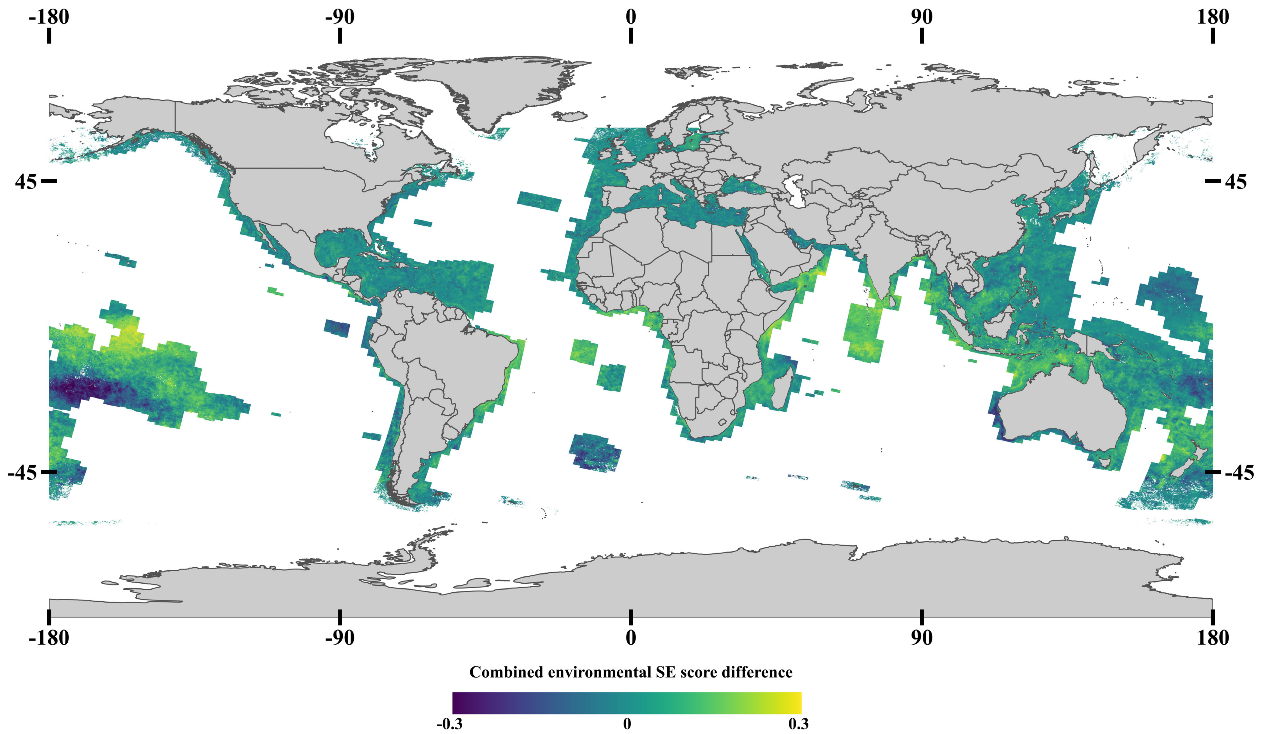


Figure 6. Combined environmental SE score difference map differences calculated by subtracting April 2012 scores from April 2016 scores. Areas in orange and red highlight areas where environmental stress was greater in 2016 than 2012. Areas in green and blue highlight areas where environmental stress was less in 2016 than 2012. White areas show data gaps due to a lack of Sentinel-2 data used for obtaining shallow water bathymetry.

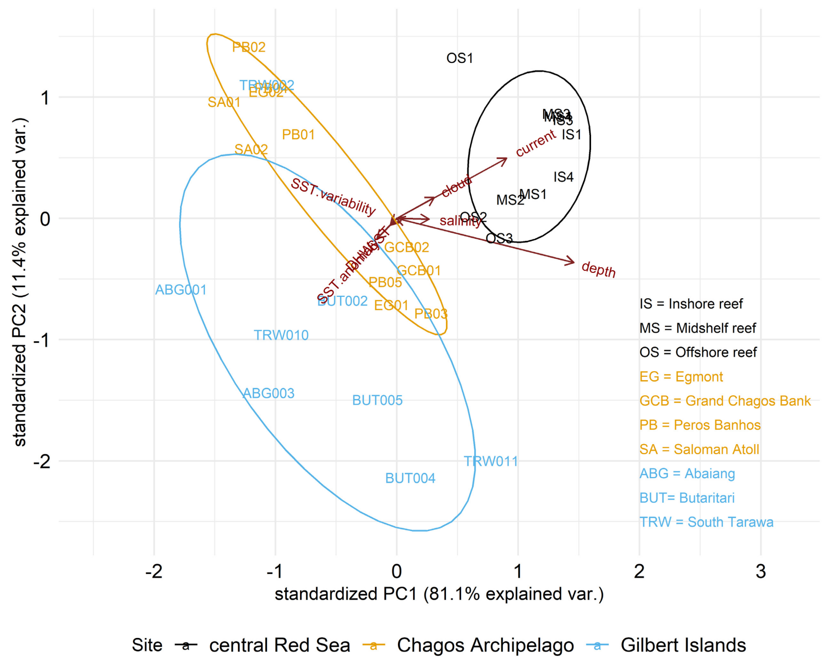


Figure 7. Biplots of the different samples of reefs and regions from PCA of SE scores for environmental variables used in the RESET. X and Y axes show normalized principal component scores.

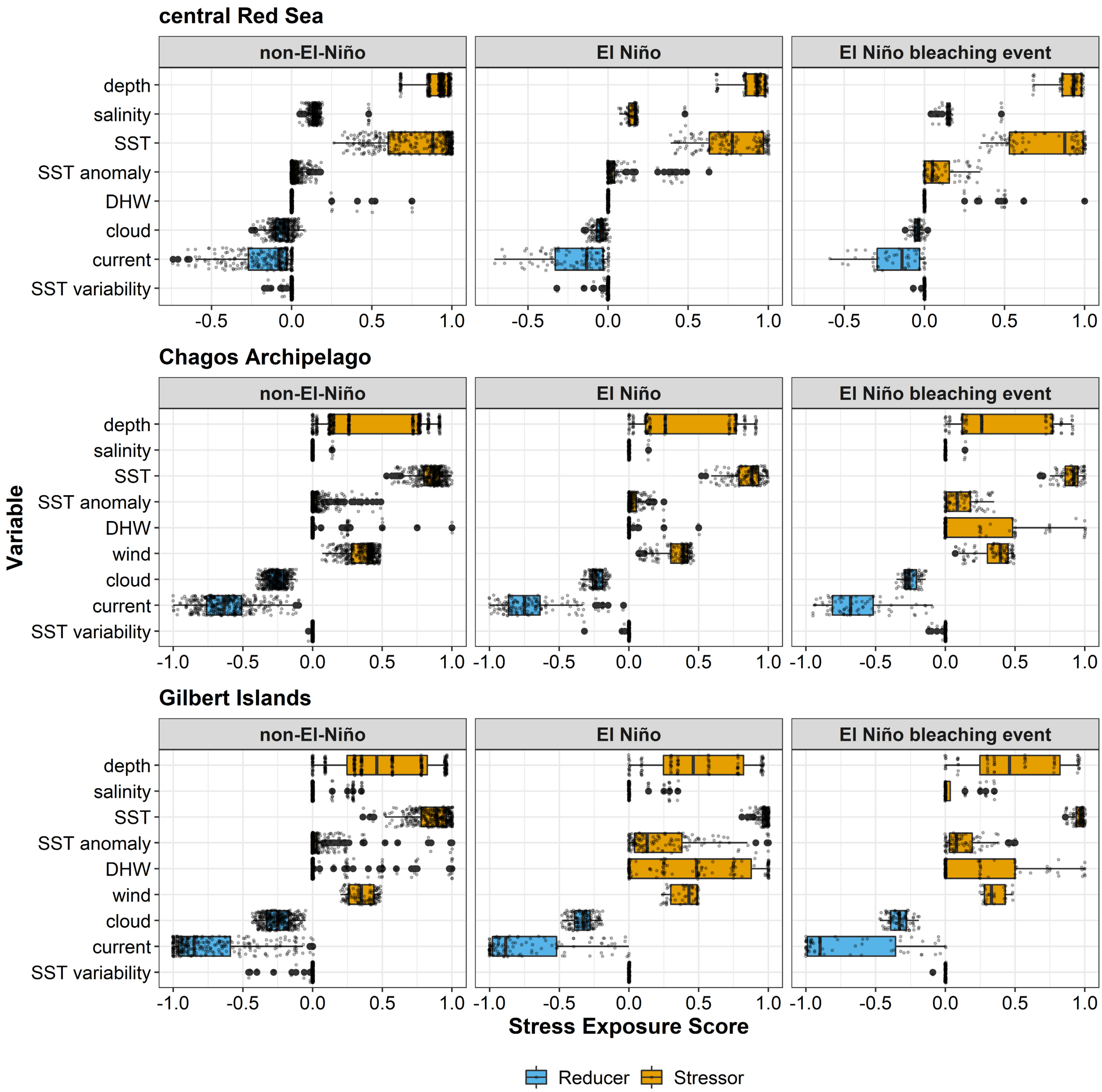
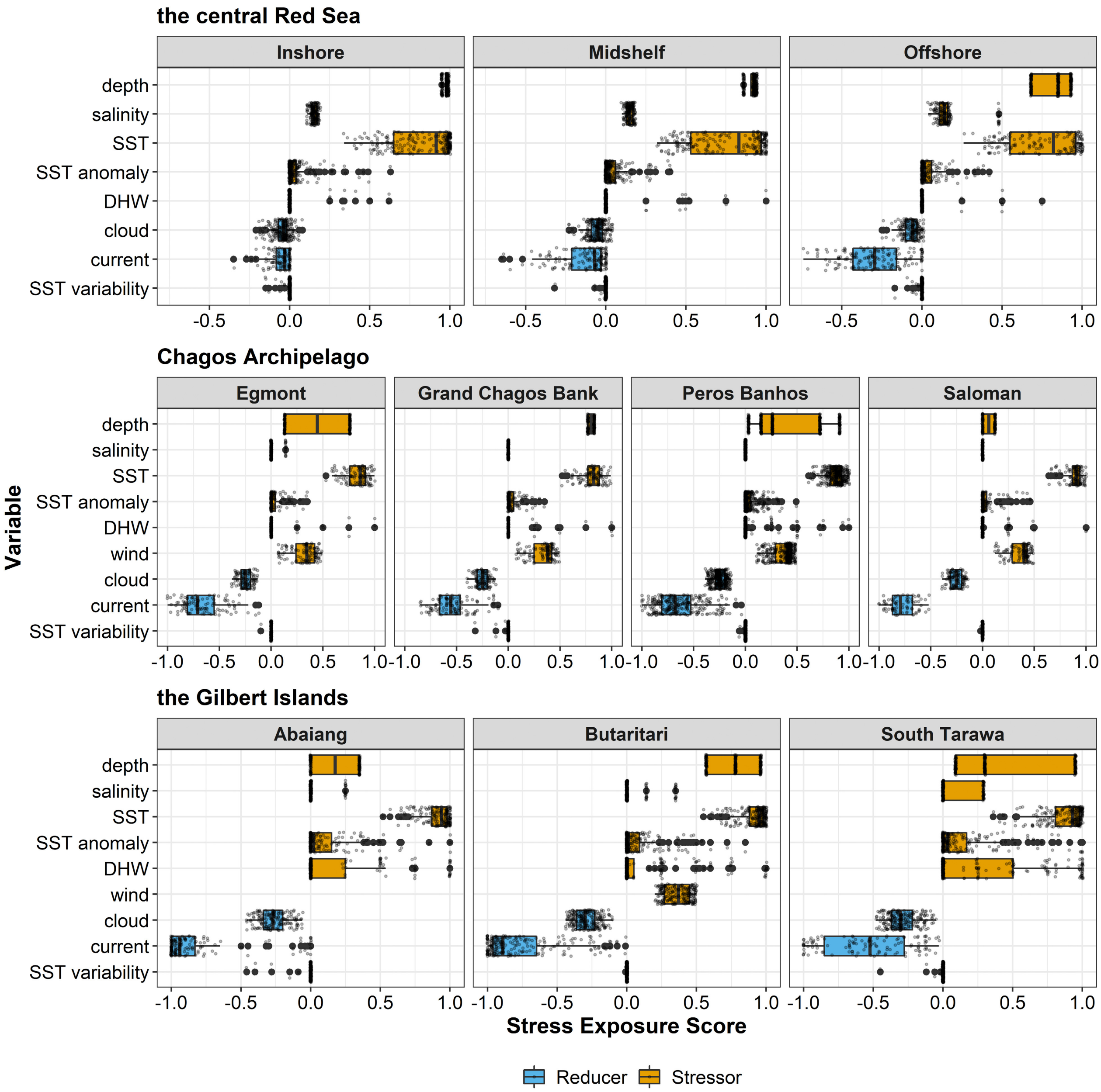


Figure 8. Boxplots of the distribution of variable SE scores between El Niño years, El Niño years with bleaching events and non-El Niño years by different region. Reducers are represented as negatives in the figure to show that they reduce the stress on coral reefs. Note that cloud, salinity and wind are weighted at 50% of the other stressors and as such, can only have a max SE score of 0.5 (or −0.5 for cloud which is a reducer). Note that each sampling period (non-El Niño, El Niño and El Niño years bleaching event) may have different sample sizes [central Red Sea; non-El Niño (n = 2838), El Niño (n = 1158), El Niño bleaching event (n = 636); Chagos Archipelago; non-El Niño (n = 3555), El Niño (n = 1458), El Niño bleaching event (n = 816); Gilbert Islands; non-El Niño (n = 2894), El Niño (n = 1159), El Niño bleaching event (n = 664)].

Discussion

Prior to this study, remote sensing approaches for evaluating the environmental stress exposure of coral reefs primarily focused on one or two variables, principally metrics of SST. However, stress events on reefs are not limited exclusively to thermal stress. In this study, we developed a toolbox, RESET, using GEE, which incorporates multiple shallow coral reef environmental stressors, from freely available remote sensing datasets, into a publicly available and easy-to-use GEE App (the JavaScript code is also available for users to adapt to their own



9. Box plots of the distribution of variable SE scores between different sites in the central Red Sea, the Chagos Archipelago and the Gilbert Islands.

needs). Thus, RESET will make monitoring environmental stress exposure of shallow coral reefs more accessible to researchers, conservationists and managers, particularly for remote locations. The toolbox provides spatially and temporally explicit data that can be applied to investigate the various components of shallow coral reef environmental stress exposure, either individually or through a combined multi-metric index (Williams et al., 2009). Therefore, RESET has the potential, in conjunction with fine-scale in situ monitoring approaches, to be a widely applicable tool for monitoring spatial and temporal change and long-term trends in environmental stress exposure on shallow coral reefs, from local to global scales.

RESET was able to identify temporal and spatial differences in stress exposure from known disturbances within three case study regions. In the Chagos Archipelago, El Niño years in which bleaching events took place had

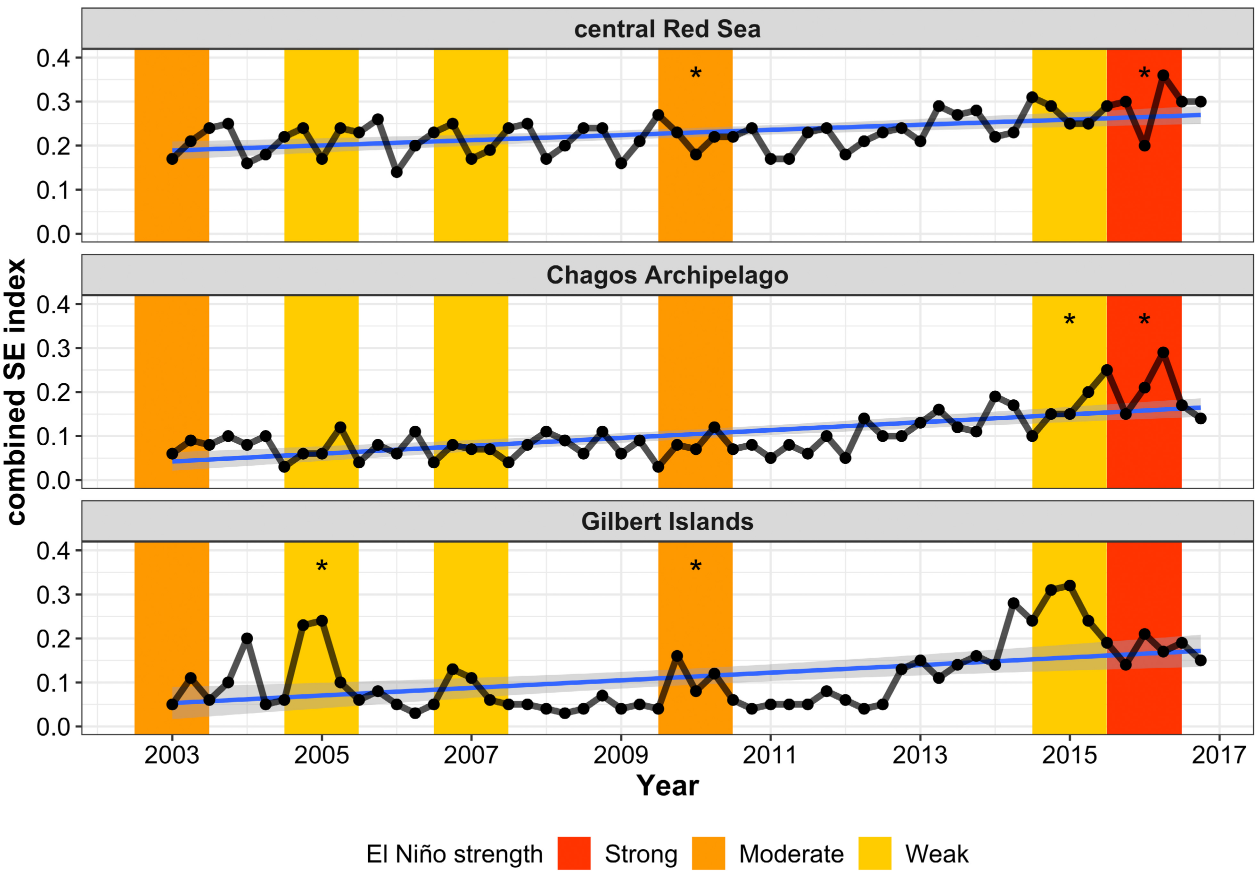


Figure 10. Mean monthly combined environmental SE scores taken quarterly from all sites (January, April, July and October) from the central Saudi Arabian Red Sea, the Chagos Archipelago and the Gilbert Islands in the Republic of Kiribati; and from 01/01/2003 to 31/12/2016. Trend line in blue with 95% standard error in grey. El Niño events are highlighted by strength; strong = red; moderate = orange; and yellow = weak. Asterisks note El Niño years where bleaching events occurred during this period.

much higher DHW and SST anomaly scores compared with non-El Niño and El Niño years (without bleaching), supporting previous findings by Head et al. (2019). In the Gilbert Islands, drivers of stress between non-El Niño years and El Niño years and El Niño years with a bleaching event were identified. However, no obvious difference in stress variable distribution was detected between El Niño years and El Niño years with a bleaching event, which is consistent with findings by Cannon et al. (2021) who reported resilience following previous bleaching events at reefs in this region. The RESET also supports previous work on intra-regional differences in bleaching in these regions, with inshore reefs more susceptible to bleaching events in the central Red Sea (Furby et al., 2013; Monroe et al., 2018), reefs at the Great Chagos Bank having greatest coral declines in the Chagos Archipelago (Head et al., 2019), and South Tarawara experiencing the greatest heat stress compared with other sites in the Gilbert Islands (Carilli et al., 2012; Donner et al., 2010). The case study sites were either in offshore regions, or, in the case of the central Red Sea, had minimal terrestrial runoff (Daqamseh et al., 2019; Tragou & Garrett, 1997). (Daqamseh et al., 2019; Tragou & Garrett, 1997). As such, further evaluation of RESET should be carried out in other regions, closer to shore with higher turbidity.

RESET has been designed for researchers to be able to adapt the toolbox and the GEE JavaScript code to their own applications. All variables identified for the RESET were included because variation in these factors away from the optimal has been shown to cause significant environmental stress on coral reefs, and the thresholds provide the requisite reference conditions and information on naturally occurring variance. However, should a variable be determined as not important to stress exposure for a given region, not have the appropriate reference conditions, or new products become available, RESET is designed so users can alter thresholds and add or remove variables/products to increase the accuracy and applicability of the toolbox for specific regions. In addition, we developed the RESET GEE App to provide an accessible GUI so that interested parties can utilize the RESET without any prior experience of GEE or JavaScript (Tamiminia et al., 2020). Hence, the RESET toolbox, and particularly the combined environmental SE index, has potential to provide valuable information to aid policy makers and managers, and compare and inform management interventions, as well as highlighting particular regions that have high risk or low resilience to disturbance.

It should be noted that RESET is not an exhaustive toolbox of environmental stressors and stress thresholds. Several environmental variables known to have an impact on coral cover, such as pH, UV, photosynthetically active radiance (PAR), chlorophyll-*a* and turbidity (Hoegh-Guldberg, 1999; Mason et al., 2020; Sokolow, 2009), were not included in RESET due to a lack of suitable products in GEE. pH, PAR and UV (or appropriate proxies) were unavailable in GEE. In addition, current chlorophyll-*a*, turbidity and POC products in GEE have low accuracy in shallow coastal areas (Le et al., 2013; Reichstetter et al., 2015; Wattelez et al., 2017). Algorithms for the detection of chlorophyll-*a* and turbidity in shallow waters do exist (Abbas et al., 2019; Dogliotti et al., 2015; Wattelez et al., 2017), but these are not sensitive enough to the levels that influence coral and not specific to coral regions, and, as such, would likely have low accuracy in the clear and shallow waters typical of coral reefs. In addition, products unavailable in GEE may be accessed through other sources, such as European Centre for Medium-Range Weather Forecasts or Copernicus Marine Service; the integration and testing of these algorithms and products into GEE was outside the scope of this current study. Measuring variables such as chlorophyll-*a* and PAR can be undertaken in situ but require expensive equipment and, therefore, are often missing from in situ monitoring also. As such, in future, further development of these products, and their integration into GEE, as well as the addition of products currently not available in GEE, would improve RESET and provide a better understanding of the full range of stressors to coral reefs. In addition, new benthic and geomorphic maps derived from satellite remote sensing are now available in GEE (Kennedy et al., 2021) as well as additional long-term datasets on coral cover [e.g., Roelfsema et al., (2021)] which could be an interesting avenue for further refinement of the RESET.

For our case study regions, wind values were regularly unavailable for some sites, which were therefore excluded from PCA analysis. This indicates that, despite their global coverage, certain products and variables may not be available for all coral reef ecosystems. This can be a particular problem close to coastlines (Cracknell, 1999; Malthus & Mumby, 2003). However, only 14.7% (5/34) of sites had data missing for a single variable throughout the entire study period, and only one site had data missing from multiple variables (Table S3). Missing data will influence the combined environmental SE scores, particularly if those missing variables are important stressors to the reef system. Therefore, spatial and temporal biases introduced by missing data should be considered when interpreting the results.

The combined environmental SE index identified peaks in environment stress exposure that match known periods of bleaching in our three study areas (e.g., 2005 and 2010 in the Gilbert Islands, and 2015 and 2016 in the Chagos Archipelago). Therefore, the combined environmental SE index could provide a benchmark with which to aid policy makers and managers, and compare and inform management interventions, as well as highlighting particular regions that have high risk or low resilience to disturbance. However, multimetric indices can be problematic as they may mask important contributions for a single variable in the index and as such may lack sensitivity (Souza & Vianna, 2020). Validating the index against a regular time series of different in situ metrics of coral reef stress, for example live coral cover loss, three-dimensional complexity or recent mortality and algal growth, across different regions, would be an important next step for the future development of the RESET. In lieu of this, direct comparisons with other available stress indices, such as SST anomalies and trends, such as data from NOAA coral reef watch, could be undertaken in the future.

Although this study focused on environmental stressors, subsequent work might consider biotic and anthropogenic impacts, such as fishing pressure and community composition. Variables such as fishing pressure (e.g., Global Fishing Watch, https://globalfishingwatch.org/, available in GEE), distance from human populations, or population density could be integrated into the toolbox to explore the interplay between climate-driven changes and human disturbance. To achieve this, specific thresholds for each of these variables would need to be identified based on information available in the literature (e.g., maximum sustainable yields) or determined through new empirical studies. This will be particularly important for understanding stressors on reefs close to coastal communities.

With the continued decline and degradation of the world's coral reefs, monitoring and management of these valuable ecosystems are vital. Increasingly, the importance of understanding the influence of multiple interacting environmental stressors on reef ecosystems is being recognized (Cannon et al., 2021; Gibbs & West, 2019; Maina et al., 2011), but, despite this, most current EO-based coral reef monitoring approaches focus predominantly on thermal stress. Therefore, we developed the Reef Environmental Stress Exposure Toolbox (RESET), which incorporates multiple environmental variables known to influence shallow coral reef stress. We demonstrate the utility of this approach by mapping the stress exposure across 3157 reefs globally. This method can be utilized to investigate spatial and temporal trends globally in shallow coral reefs, applied here in three well-documented coral reef ecosystems in the Indian and Pacific Oceans and the Red Sea. RESET is, therefore, a widely applicable tool for investigating environmental stressors of shallow coral reefs, from local to global scales, that will make monitoring stress on shallow coral reef ecosystems more accessible for NGOs, managers and researchers, supporting the conservation of these vital ecosystems.

Acknowledgements

This work was supported by the Natural Environment Research Council (Grant No. NE/L002485/1) to MJW, as part of the London NERC Doctoral Training Partnership. Funding to DMPJ was provided by the Bertarelli Foundation and contributed to the Bertarelli Programme in Marine Science and by Research England. We would also like to thank Martin Birks for his help optimizing the final RESET code in the Google Earth Engine API. Finally, we would like to thank the two reviewers for their comments to help improve the manuscript.

References

Abbas, M.M., Melesse, A.M., Scinto, L.J. & Rehage, J.S. (2019) Satellite estimation of chlorophyll-a using moderate resolution imaging spectroradiometer (MODIS) sensor in shallow coastal water bodies: validation and improvement. *Water*, **11**(8), 1621. https://doi.org/10.3390/w11081621

Ateweberhan, M. & McClanahan, T.R. (2010) Relationship between historical sea-surface temperature variability and climate change-induced coral mortality in the western Indian Ocean. *Marine Pollution Bulletin*, **60**(7), 964–970. https://doi.org/10.1016/j.marpolbul.2010.03.033

Ban, S.S., Graham, N.A.J. & Connolly, S.R. (2014) Evidence for multiple stressor interactions and effects on coral reefs. *Global Change Biology*, **20**(3), 681–697. https://doi.org/10.1111/gcb.12453

Bellwood, D.R., Pratchett, M.S., Morrison, T.H., Gurney, G.G., Hughes, T.P., Álvarez-Romero, J.G. et al. (2019) Coral reef conservation in the Anthropocene: confronting spatial mismatches and prioritizing functions. *Biological Conservation*, **236**, 604–615. https://doi.org/10.1016/j.biocon.2019.05.056

Bridge, T.C.L., Hoey, A.S., Campbell, S.J., Muttaqin, E., Rudi, E., Fadli, N. et al. (2013) Depth-dependent mortality of reef corals following a severe bleaching event: implications for thermal refuges and population recovery. *F1000Research*, **2**, 187. https://doi.org/10.12688/f1000research.2-187.v3

Bruno, J.F. & Selig, E.R. (2007) Regional decline of coral cover in the Indo-Pacific: timing, extent, and subregional comparisons. *PLoS One*, **2**(8), e711. https://doi.org/10.1371/journal.pone.0000711

Bunn, S.E., Abal, E.G., Smith, M.J., Choy, S.C., Fellows, C.S., Harch, B.D. et al. (2010) Integration of science and monitoring of river ecosystem health to guide investments in catchment protection and rehabilitation. *Freshwater Biology*, **55**(s1), 223–240. https://doi.org/10.1111/j.1365-2427.2009.02375.x

Burke, L., Reytar, K., Spalding, M. & Perry, A. (2011) *Reefs at risk revisited*. Washington, D.C.: World Resources Institute, The Nature Conservancy, WorldFish Center, International Coral Reef Action Network, UNEP World Conservation Monitoring Centre and Global Coral Reef Monitoring Network.

Cannon, S.E., Aram, E., Beiateuea, T., Kiareti, A., Peter, M. & Donner, S.D. (2021) Coral reefs in the Gilbert Islands of Kiribati: resistance, resilience, and recovery after more than a decade of multiple stressors. *PLoS One*, **16**(8), e0255304. https://doi.org/10.1371/journal.pone.0255304

Carilli, J., Donner, S.D. & Hartmann, A.C. (2012) Historical temperature variability affects coral response to heat stress. *PLoS One*, **7**(3), e34418. https://doi.org/10.1371/journal.pone.0034418

Claar, D.C., Szostek, L., McDevitt-Irwin, J.M., Schanze, J.J. & Baum, J.K. (2018) Global patterns and impacts of El Niño events on coral reefs: a meta-analysis. *PLoS One*, **13**(2), e0190957. https://doi.org/10.1371/journal.pone.0190957

Clayson, C.A., Brown, J.; NOAA CDR Program. (2016) *NOAA climate data Record Ocean surface bundle (OSB) climate data record (CDR) of ocean near surface atmospheric properties, version 2*. NOAA National Center for Environmental Information. https://doi.org/10.7289/V55T3HH0

Coles, S.L. & Jokiel, P.L. (1992) Effects of salinity on coral reefs. In: Connell, D.W. & Hawker, D.W. (Eds.) *Pollution in tropical aquatic systems*. Boca Raton, FL: CRC Press, pp. 147–166.

Cracknell, A.P. (1999) Remote sensing techniques in estuaries and coastal zones an update. *International Journal of Remote Sensing*, **20**(3), 485–496. https://doi.org/10.1080/014311699213280

Cummings, J.A. & Smedstad, O.M. (2013) Variational data assimilation for the global ocean. In: Park, S.K. & Xu, L. (Eds.) *Data assimilation for atmospheric, oceanic and hydrologic applications (vol. II)*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 303–343.

Daqamseh, S.T., Al-Fugara, A.K., Pradhan, B., Al-Oraiqat, A. & Habib, M. (2019) MODIS derived sea surface salinity, temperature, and chlorophyll-a data for potential fish zone mapping: West Red Sea coastal areas, Saudi Arabia. *Sensors*, **19**(9), 2069.

De'ath, G., Fabricius, K.E., Sweatman, H. & Puotinen, M. (2012) The 27–year decline of coral cover on the great barrier reef and its causes. *Proceedings. National Academy of Sciences. United States of America*, **109**(44), 17995–17999. https://doi.org/10.1073/pnas.1208909109

Dogliotti, A.I., Ruddick, K.G., Nechad, B., Doxaran, D. & Knaeps, E. (2015) A single algorithm to retrieve turbidity from remotely-sensed data in all coastal and estuarine waters. *Remote Sensing of Environment*, **156**, 157–168. https://doi.org/10.1016/j.rse.2014.09.020

Donner, S.D. & Carilli, J. (2019) Resilience of Central Pacific reefs subject to frequent heat stress and human disturbance. *Scientific Reports*, **9**, 3484. https://doi.org/10.1038/s41598-019-40150-3

Donner, S.D., Kirata, T. & Vieux, C. (2010) Recovery from the 2004 coral bleaching event in the Gilbert Islands, Kiribati. *Atoll Research Bulletin Bulletin*, **587**.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G. et al. (2013) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, **36**(1), 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

Eakin, C.M., Lough, J.M. & Heron, S.F. (2009) Climate variability and change: monitoring data and evidence for increased coral bleaching stress. In: van Oppen, M.J.H. & Lough, J.M. (Eds.) *Coral bleaching: patterns, processes, causes and consequences*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 41–67.

Eakin, C.M., Sweatman, H.P.A. & Brainard, R.E. (2019) The 2014–2017 global-scale coral bleaching event: insights and impacts. *Coral Reefs*, **38**(4), 539–545. https://doi.org/10.1007/s00338-019-01844-2

Ellis, J.I., Jamil, T., Anlauf, H., Coker, D.J., Curdia, J., Hewitt, J. et al. (2019) Multiple stressor effects on coral reef ecosystems. *Global Change Biology*, **25**(12), 4131–4146. https://doi.org/10.1111/gcb.14819

Fabricius, K.E., De'ath, G., Puotinen, M.L., Done, T., Cooper, T.F. & Burgess, S.C. (2008) Disturbance gradients on inshore and offshore coral reefs caused by a severe tropical cyclone. *Limnology and Oceanography*, **53**(2), 690–704. https://doi.org/10.4319/lo.2008.53.2.0690

Farrell, A., Wang, G., Rush, S.A., Martin, J.A., Belant, J.L., Butler, A.B. et al. (2019) Machine learning of large-scale spatial distributions of wild turkeys with high-dimensional environmental data. *Ecology and Evolution*, **9**(10), 5938–5949. https://doi.org/10.1002/ece3.5177

Fedorov, A.V. & Philander, S.G. (2000) Is El Niño changing? *Science*, **288**(5473), 1997–2002. https://doi.org/10.1126/science.288.5473.1997

Flower, J., Ortiz, J.C., Chollett, I., Abdullah, S., Castro-Sanguino, C., Hock, K. et al. (2017) Interpreting coral reef monitoring data: a guide for improved management decisions. *Ecological Indicators*, **72**, 848–869. https://doi.org/10.1016/j.ecolind.2016.09.003

Furby, K.A., Bouwmeester, J. & Berumen, M.L. (2013) Susceptibility of Central Red Sea corals during a major bleaching event. *Coral Reefs*, **32**(2), 505–513. https://doi.org/10.1007/s00338-012-0998-5

Gibbs, D.A. & West, J.M. (2019) Resilience assessment of Puerto Rico's coral reefs to inform reef management. *PLoS One*, **14**(11), e0224360. https://doi.org/10.1371/journal.pone.0224360

Goergen, E.A., Moulding, A.L., Walker, B.K. & Gilliam, D.S. (2019) Identifying causes of temporal changes in *Acropora cervicornis* populations and the potential for recovery. *Frontiers in Marine Science*, **6**(36). https://doi.org/10.3389/fmars.2019.00036

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. & Moore, R. (2017) Google earth engine: planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, **202**, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Graham, N.A.J., Jennings, S., MacNeil, M.A., Mouillot, D. & Wilson, S.K. (2015) Predicting climate-driven regime shifts versus rebound potential in coral reefs. *Nature*, **518**, 94. https://doi.org/10.1038/nature14140

Guan, Y., Hohn, S. & Merico, A. (2015) Suitable environmental ranges for potential coral reef habitats in the tropical ocean. *PLoS One*, **10**(6), e0128831. https://doi.org/10.1371/journal.pone.0128831

Harrison, D.E. & Larkin, N.K. (1998) El Niño-southern Oscillation Sea surface temperature and wind anomalies, 1946–1993. *Reviews of Geophysics*, **36**(3), 353–399. https://doi.org/10.1029/98RG00715

Harvell, D., Jordán-Dahlgren, E., Merkel, S., Rosenberg, E., Raymundo, L., Smith, G. et al. (2007) Coral disease, environmental drivers, and the balance between coral and microbial associates. *Oceanography*, **20**, 172–195.

Head, C.E.I., Bayley, D.T.I., Rowlands, G., Roche, R.C., Tickler, D.M., Rogers, A.D. et al. (2019) Coral bleaching impacts from back-to-back 2015–2016 thermal anomalies in the remote Central Indian Ocean. *Coral Reefs*. https://doi.org/10.1007/s00338-019-01821-9

Hedley, D.J., Roelfsema, M.C., Chollett, I., Harborne, R.A., Heron, F.S., Weeks, S. et al. (2016) Remote sensing of coral reefs for monitoring and management: a review. *Remote Sensing*, **8**(2). https://doi.org/10.3390/rs8020118

Hedley, J.D., Roelfsema, C., Brando, V., Giardino, C., Kutser, T., Phinn, S. et al. (2018) Coral reef applications of Sentinel-2: coverage, characteristics, bathymetry and benthic mapping with comparison to Landsat 8. *Remote Sensing of Environment*, **216**, 598–614. https://doi.org/10.1016/j.rse.2018.07.014

Heidinger, A.K., Foster, M.J., Walther, A., Zhao, X.; NOAA CDR Program. (2014) *NOAA climate data record (CDR) of cloud properties from AVHRR pathfinder atmospheres - extended (PATMOS-x), version 5.3*. NOAA National Centers for Environmental Information. https://doi.org/10.7289/V5348HCK

Hoegh-Guldberg, O. (1999) Climate change, coral bleaching and the future of the world's coral reefs. *Marine and Freshwater Research*, **50**(8), 839–866. https://doi.org/10.1071/MF99078

Hughes, T.P., Barnes, M.L., Bellwood, D.R., Cinner, J.E., Cumming, G.S., Jackson, J.B.C. et al. (2017) Coral reefs in the Anthropocene. *Nature*, **546**(7656), 82–90. https://doi.org/10.1038/nature22901

Hughes, T.P., Kerry, J.T., Baird, A.H., Connolly, S.R., Dietzel, A., Eakin, C.M. et al. (2018) Global warming transforms coral reef assemblages. *Nature*, **556**(7702), 492–496. https://doi.org/10.1038/s41586-018-0041-2

Johnson, G.C., McPhaden, M.J., Rowe, G.D. & McTaggart, K.E. (2000) Upper equatorial Pacific Ocean current and salinity variability during the 1996–1998 El Niño–La Niña cycle. *Journal of Geophysical Research, Oceans*, **105**(C1), 1037–1053. https://doi.org/10.1029/1999JC900280

Jones, G.P., McCormick, M.I., Srinivasan, M. & Eagle, J.V. (2004) Coral decline threatens fish biodiversity in marine reserves. *Proceedings of the National Academy of Sciences of the United States of America*, **101**(21), 8251–8253. https://doi.org/10.1073/pnas.0401277101

Kayanne, H. (2017) Validation of degree heating weeks as a coral bleaching index in the northwestern Pacific. *Coral Reefs*, **36**(1), 63–70. https://doi.org/10.1007/s00338-016-1524-y

Kennedy, E.V., Roelfsema, C.M., Lyons, M.B., Kovacs, E.M., Borrego-Acevedo, R., Roe, M. et al. (2021) Reef cover, a coral reef classification for global habitat mapping from remote sensing. *Scientific Data*, **8**(1), 196. https://doi.org/10.1038/s41597-021-00958-z

Latif, M. & Keenlyside, N.S. (2009) El Niño/southern oscillation response to global warming. *Proceedings. National Academy of Sciences. United States of America*, **106**(49), 20578–20583. https://doi.org/10.1073/pnas.0710860105

Le, C., Hu, C., Cannizzaro, J., English, D., Muller-Karger, F. & Lee, Z. (2013) Evaluation of chlorophyll-a remote sensing algorithms for an optically complex estuary. *Remote Sensing of Environment*, **129**, 75–89. https://doi.org/10.1016/j.rse.2012.11.001

Lesser, M.P., Stochaj, W.R., Tapley, D.W. & Shick, J.M. (1990) Bleaching in coral reef anthozoans: effects of irradiance, ultraviolet radiation, and temperature on the activities of protective enzymes against active oxygen. *Coral Reefs*, **8**(4), 225–232. https://doi.org/10.1007/bf00265015

Li, J., Knapp, D.E., Lyons, M., Roelfsema, C., Phinn, S., Schill, S.R. et al. (2021) Automated global shallow water bathymetry mapping using Google earth engine. *Remote Sensing*, **13**(8), 1469. https://doi.org/10.3390/rs13081469

Li, X., Huang, H., Lian, J., Huang, L. & Dong, J. (2009) Effects of the multiple stressors high temperature and reduced salinity on the photosynthesis of the hermatypic coral *Galaxea fascicularis*. *Acta Ecologica Sinica*, **29**(3), 155–159. https://doi.org/10.1016/j.chnaes.2009.07.002

Lix, J.K., Venkatesan, R., Grinson, G., Rao, R.R., Jineesh, V.K., Arul, M.M. et al. (2016) Differential bleaching of corals based on El Niño type and intensity in the Andaman Sea, southeast bay of Bengal. *Environmental Monitoring and Assessment*, **188**(3), 175. https://doi.org/10.1007/s10661-016-5176-8

Longo, C.S., Frazier, M., Doney, S.C., Rheuban, J.E., Humberstone, J.M. & Halpern, B.S. (2017) Using the ocean health index to identify opportunities and challenges to improving Southern Ocean ecosystem health. *Frontiers in Marine Science*, **4**(20). https://doi.org/10.3389/fmars.2017.00020

Lyons, B.M., Roelfsema, C.M., Kennedy, E.V., Kovacs, E.M., Borrego-Acevedo, R., Markey, K. et al. (2020) Mapping the world's coral reefs using a global multiscale earth observation framework. *Remote Sensing in Ecology and Conservation*, **6**(4), 557–568. https://doi.org/10.1002/rse2.157

Maina, J., McClanahan, T.R., Venus, V., Ateweberhan, M. & Madin, J. (2011) Global gradients of coral exposure to environmental stresses and implications for local management. *PLoS One*, **6**(8), e23064. https://doi.org/10.1371/journal.pone.0023064

Maina, J., Venus, V., McClanahan, T.R. & Ateweberhan, M. (2008) Modelling susceptibility of coral reefs to environmental stress using remote sensing data and GIS models. *Ecological Modelling*, **212**(3), 180–199. https://doi.org/10.1016/j.ecolmodel.2007.10.033

Malthus, T.J. & Mumby, P.J. (2003) Remote sensing of the coastal zone: an overview and priorities for future research. *International Journal of Remote Sensing*, **24**(13), 2805–2815. https://doi.org/10.1080/0143116031000066954

Mason, R.A.B., Skirving, W.J. & Dove, S.G. (2020) Integrating physiology with remote sensing to advance the prediction of coral bleaching events. *Remote Sensing of Environment*, **246**, 111794. https://doi.org/10.1016/j.rse.2020.111794

Maynard, J.A., Marshall, P.A., Parker, B., Mcleod, E., Ahmadia, G., van Hooidonk, R. et al. (2017) *A guide to assessing coral reef resilience for decision support*. Nairobi, Kenya: UN Environment.

Maynard, J.A., McKagan, S., Raymundo, L., Johnson, S., Ahmadia, G.N., Johnston, L. et al. (2015) Assessing relative resilience potential of coral reefs to inform management. *Biological Conservation*, **192**, 109–119. https://doi.org/10.1016/j.biocon.2015.09.001

Monroe, A.A., Ziegler, M., Roik, A., Röthig, T., Hardenstine, R.S., Emms, M.A. et al. (2018) *In situ* observations of coral bleaching in the central Saudi Arabian Red Sea during the 2015/2016 global coral bleaching event. *PLoS One*, **13**(4), e0195814. https://doi.org/10.1371/journal.pone.0195814

Mumby, P., Chisholm, J., Edwards, A., Clark, C., Roark, E., Andrefouet, S. et al. (2001) Unprecedented bleaching-induced mortality in *Porites* spp. at Rangiroa atoll, French Polynesia. *Marine Biology*, **139**(1), 183–189. https://doi.org/10.1007/s002270100575

NASA Goddard Space Flight Center, Ocean Ecology Laboratory, & Group, O.B.P. (2018) *Moderate-resolution Imaging Spectroradiometer (MODIS) aqua remote-sensing reflectance data*. 2018 Reprocessing. Greenbelt, MD, USA: NASA OB.DAAC. https://doi.org/10.5067/AQUA/MODIS/L3M/RRS/2018.

Obura, D., Grimsditch, G., Marshall, P., Setiasih, N., Aeby, G., McLeod, L. et al. (2009) Resilience assessment of coral reefs: assessment protocol for coral reefs, focusing on coral bleaching and thermal stress. In: *IUCN working group on climate change and coral reefs*. Gland, Switzerland: IUCN.

Obura, D.O., Aeby, G., Amornthammarong, N., Appeltans, W., Bax, N., Bishop, J. et al. (2019) Coral reef monitoring, reef assessment technologies, and ecosystem-based management. *Frontiers in Marine Science*, **6**(580). https://doi.org/10.3389/fmars.2019.00580

R Core Team. (2020) *R: a language and environment for statistical computing. In*. Vienna, Austria: R Foundation for Statistical Computing.

Reichstetter, M., Fearns, P.R.C.S., Weeks, S.J., McKinna, L.I.W., Roelfsema, C. & Furnas, M. (2015) Bottom reflectance in ocean color satellite remote sensing for coral reef environments. *Remote Sensing*, **7**(12), 16756–16777. https://doi.org/10.3390/rs71215852

Robertson, B.P., Savage, C., Gardner, J.P.A., Robertson, B.M. & Stevens, L.M. (2016) Optimising a widely-used coastal health index through quantitative ecological group classifications and associated thresholds. *Ecological Indicators*, **69**, 595–605. https://doi.org/10.1016/j.ecolind.2016.04.003

Roelfsema, C., Kovacs, E.M., Vercelloni, J., Markey, K., Rodriguez-Ramirez, A., Lopez-Marcano, S. et al. (2021) Fine-scale time series surveys reveal new insights into spatio-temporal trends in coral cover (2002–2018), of a coral reef on the southern great barrier reef. *Coral Reefs*, **40**(4), 1055–1067. https://doi.org/10.1007/s00338-021-02104-y

Röthig, T., Ochsenkühn, M.A., Roik, A., van der Merwe, R. & Voolstra, C.R. (2016) Long-term salinity tolerance is accompanied by major restructuring of the coral bacterial microbiome. *Molecular Ecology*, **25**(6), 1308–1323. https://doi.org/10.1111/mec.13567

Rowlands, G., Purkis, S., Riegl, B., Metsamaa, L., Bruckner, A. & Renaud, P. (2012) Satellite imaging coral reef resilience at regional scale. A case-study from Saudi Arabia. *Marine Pollution Bulletin*, **64**(6), 1222–1237. https://doi.org/10.1016/j.marpolbul.2012.03.003

Ruaro, R., Gubiani, É.A., Hughes, R.M. & Mormul, R.P. (2020) Global trends and challenges in multimetric indices of biological condition. *Ecological Indicators*, **110**, 105862. https://doi.org/10.1016/j.ecolind.2019.105862

Sala, E. & Knowlton, N. (2006) Global marine biodiversity trends. *Annual Review of Environment and Resources*, **31**(1), 93–122. https://doi.org/10.1146/annurev.energy.31.020105.100235

Scheffer, M., Carpenter, S., Foley, J.A., Folke, C. & Walker, B. (2001) Catastrophic shifts in ecosystems. *Nature*, **413**, 591. https://doi.org/10.1038/35098000

Schoolmaster, D.R., Grace, J.B., Schweiger, E.W., Guntenspergen, G.R., Mitchell, B.R., Miller, K.M. et al. (2013) An algorithmic and information-theoretic approach to multimetric index construction. *Ecological Indicators*, **26**, 14–23. https://doi.org/10.1016/j.ecolind.2012.10.016

Sheldon, F., Peterson, E.E., Boone, E.L., Sippel, S., Bunn, S.E. & Harch, B.D. (2012) Identifying the spatial scale of land use that most strongly influences overall river ecosystem health score. *Ecological Applications*, **22**(8), 2188–2203. https://doi.org/10.1890/11-1792.1

Sheppard, C., Sheppard, A., Mogg, A., Bayley, D., Dempsey, A., Roche, R. et al. (2017) Coral bleaching and mortality in the Chagos archipelago to 2017. *Atoll Research Bulletin*, **613**, 1–25. https://doi.org/10.5479/si.0077-5630.613

Sokolow, S. (2009) Effects of a changing climate on the dynamics of coral infectious disease: a review of the evidence. *Diseases of Aquatic Organisms*, **87**(1–2), 5–18. https://doi.org/10.3354/dao02099

Souza, G.B.G. & Vianna, M. (2020) Fish-based indices for assessing ecological quality and biotic integrity in transitional waters: a systematic review. *Ecological Indicators*, **109**, 105665. https://doi.org/10.1016/j.ecolind.2019.105665

Spencer, T., Teleki, K.A., Bradshaw, C. & Spalding, M.D. (2000) Coral bleaching in the southern Seychelles during the 1997–1998 Indian Ocean warm event. *Marine Pollution Bulletin*, **40**(7), 569–586. https://doi.org/10.1016/S0025-326X(00)00026-6

Stem, C., Margoluis, R., Salafsky, N. & Brown, M. (2005) Monitoring and evaluation in conservation: a review of trends and approaches. *Conservation Biology*, **19**(2), 295–309. https://doi.org/10.1111/j.1523-1739.2005.00594.x

Stoddard, J.L., Herlihy, A.T., Peck, D.V., Hughes, R.M., Whittier, T.R. & Tarquinio, E. (2008) A process for creating multimetric indices for large-scale aquatic surveys. *Journal of the North American Benthological Society*, **27**(4), 878–891. https://doi.org/10.1899/08-053.1

Stone, L., Rajagopalan, B., Bhasin, H. & Loya, Y. (1999) Mass coral reef bleaching: a recent outcome of increased El Niño activity? *Ecology Letters*, **2**(5), 325–330. https://doi.org/10.1046/j.1461-0248.1999.00092.x

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S. & Brisco, B. (2020) Google earth engine for geo-big data applications: a meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, **164**, 152–170. https://doi.org/10.1016/j.isprsjprs.2020.04.001

Tragou, E. & Garrett, C. (1997) The shallow thermohaline circulation of the Red Sea. *Deep Sea Research Part I: Oceanographic Research Papers*, **44**(8), 1355–1376. https://doi.org/10.1016/S0967-0637(97)00026-5

UNEP-WCMC, WorldFish Centre, WRI & TNC (2021) *Global distribution of warm-water coral reefs, compiled from multiple* *sources including the Millennium Coral Reef Mapping Project*. Version 4.1. Includes contributions from IMaRS-USF and IRD (2005), IMaRS-USF (2005) and Spalding et al. (2001). Cambridge, UK: UN Environment World Conservation Monitoring Centre. Data. https://doi.org/https://doi.org/10.34892/t2wk-5t34

Veron, J.E.N., Hoegh-Guldberg, O., Lenton, T.M., Lough, J.M., Obura, D.O., Pearce-Kelly, P. et al. (2009) The coral reef crisis: the critical importance of <350ppm CO_2. *Marine Pollution Bulletin*, **58**(10), 1428–1436. https://doi.org/10.1016/j.marpolbul.2009.09.009

Wagner, D.E., Kramer, P. & van Woesik, R. (2010) Species composition, habitat, and water quality influence coral bleaching in southern Florida. *Marine Ecology Progress Series*, **408**, 65–78. https://doi.org/10.3354/meps08584

Wattelez, G., Dupouy, C., Lefèvre, J., Ouillon, S., Fernandez, J.-M. & Juillot, F. (2017) Application of the support vector regression method for turbidity assessment with MODIS on a shallow coral reef lagoon (Voh-Koné-Pouembout, New Caledonia). *Water*, **9**(10), 737. https://doi.org/10.3390/w9100737

West, J.M. & Salm, R.V. (2003) Resistance and resilience to coral bleaching: implications for coral reef conservation and management. *Conservation Biology*, **17**(4), 956–967. https://doi.org/10.1046/j.1523-1739.2003.02055.x

Williams, M., Longstaff, B., Buchanan, C., Llansó, R. & Dennison, W. (2009) Development and evaluation of a spatially-explicit index of Chesapeake Bay health. *Marine Pollution Bulletin*, **59**(1–3), 14–25. https://doi.org/10.1016/j.marpolbul.2008.11.018

Xu, Y., Vaughn, N.R., Knapp, D.E., Martin, R.E., Balzotti, C., Li, J. et al. (2020) Coral bleaching detection in the Hawaiian Islands using spatio-temporal standardized bottom reflectance and Planet Dove satellites. *Remote Sensing*, **12**(19), 3219. https://doi.org/10.3390/rs12193219

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Accuracy and uncertainty of environmental variables from GG products used for the CRSEI.
Table S2. Region, sites and reef names used for calculating Reef Environmental Stress Exposure Toolbox (RESET). Latitude and longitude in decimal degrees is included.
Table S3. Summary statistics for SE scores for the RESET per region by non-El Niño period (April 2012) and strong El Niño period (April 2016).
Figure S1. Scree plot of PCA of CRSEI stress variables.

Appendix S1. Location data of 3157 shallow coral reef sites, used for global analysis.

