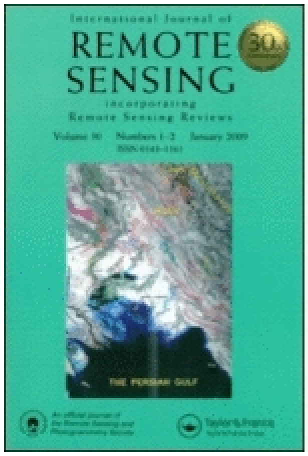

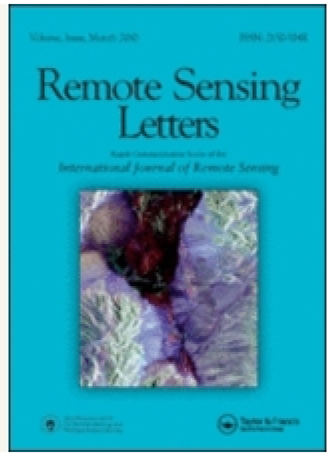

Modelling and forecasting the effects of increasing sea surface temperature on coral bleaching in the Indo-Pacific region

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Modelling and forecasting the effects of increasing sea surface temperature on coral bleaching in the Indo-Pacific region

Idham Khalil[a], Aidy M-Muslim[b], Mohammad Shawkat Hossain[b]* and Peter M. Atkinson[c]

[a] Faculty of Science and Marine Environment, Universiti Malaysia Terengganu (UMT), 21030 Kuala Terengganu, Terengganu, Malaysia

[b] Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu (UMT), 21030 Kuala Terengganu, Terengganu, Malaysia

[c] Faculty of Science and Technology, Lancaster University, Lancaster, LA1 4YR, United Kingdom

*Corresponding author: shawkat@umt.edu.my; Tel.: +6096683527

Modelling and forecasting the effects of increasing sea surface temperature on coral bleaching in the Indo-Pacific region

Abstract

The Coral Triangle (CT) and the South China Sea (SCS) are the world's great tropical seas, located in the Indo-Pacific (IP) region. It is home to the richest marine ecosystem on Earth with a total of 76% reef-building coral species as well as 37% coral reef fish species. Unfortunately, this sensitive area is now vulnerable to Sea Surface Temperature (SST) warming. In relation to this, a considerable number of studies covering larger areas have suggested that warming trends are likely in the ~~South China Sea~~CT and the ~~Coral Triangle~~SCS. This research explored the possible consequences of SST warming on the rich ecosystems of the IP region, specifically on bleaching of its coral reefs. Reefbase provided coral bleaching records together with the daily NOAA AVHRR Optimum Interpolation (OI) SST V2 dataset (OISSTv2) with a spatial resolution of 25 km were used to explore the relationship between coral bleaching and SST in the IP region. Three different categories of monthly mean SST were tested as potential covariates: minimum SST, mean SST and maximum SST, obtained from the OISSTv2 (1982 to 2016). The fitted logistic regression (LR) model revealed a significant and large correlation between coral bleaching and annual maximum monthly mean SST in the study area using the extensive and spatially well-distributed bleaching data from an online database and the time-series of AVHRR images. Predicted maps of coral bleaching based on the LR model were highly consistent with NOAA Coral Reef Watch (CRW) Degree heating Weeks (DHW) maps. However, some important discrepancies resulted from the more specific local fitting used in the LR model. The maximum SST was forecasted from 2020 to 2100 based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) dataset under the Representative Concentration Pathways (RCP2.6) scenario. The fitted logistic regression model was employed to transform the forecasted maximum SST values into maps of the probability of coral bleaching from 2020 to 2100. The results provide considerable cause for concern, including the likelihood of widespread coral bleaching in many places in the IP region over the next 30 years.

Key words: SST; space-time; coral bleaching; Coral Triangle; South China Sea

Introduction

Coral reefs play a well-recognized role in maintaining the biodiversity of the world's most productive coastal ecosystems (Connell 1978; Knowlton et al. 2010), protecting the shoreline and supporting the food chain, tourism, fishery resources, protein production and a great range of ecosystem services to coastal communities (Costanza et al. 1997; Moberg and Folke 1999; Adey 2000; Hossain et al. 2016). They have been increasingly exploited and threatened by human beings (Hossain et al. 2016), and impacted by the elevated sea surface temperatures (SSTs) associated with global warming and climate change in recent decades (van Hooidonk, Maynard, and Planes 2013; Moustafa et al. 2014; Spalding and Brown 2015; Sully et al. 2019). Rapid increases in SSTs of 1-2 °C beyond a threshold (Frieler et al. 2013) reduce oxygen solubility and expel symbiotic interactions between corals and different types of algae (or zooxanthellae) such as red, green and brown algae. The breakdown of these algae resulting in coral bleaching, which becomes apparent from the white skeleton of the corals (B. E. Brown 1997). Mass coral bleaching worldwide occurred first in 1997-98, again in 2010 and recently in 2015-16 due to mainly changes in SSTs (Arora et al. 2021; Arthur 2000; De et al. 2022). Over the past two decades (~~2014~~1998-2017), global bleaching episodes destroyed 75% of tropical corals and other reef-associated organisms (Hughes et al. 2017; Lough, Anderson, and Hughes 2018; Stuart-Smith et al. 2018). Ocean modelers forecast that only a few tropical corals will survive in the upcoming eight decades if SST anomalies persist (Frieler et al. 2013). Hence, management and conservation of corals is of great global importance for coastal managers and government policy regulators, with the specific challenge being to manage ocean warming while protecting the many reef organisms and fishery resources supported by coral habitats (Mumby and Steneck 2008; Keller et al. 2009; Abe et al. 2021).

Conserving corals requires a reliable model to forecast spatially extensive coral bleaching events. The heterogenous patterns of bleaching intensity and magnitude at the regional and global scales arising, due to differential adaptation, acclimation to thermal stresses, recovery after stresses by species-specific corals with spatial and temporal differences, make generating a reliable SST-induced bleaching model challenging (Pittock 1999; Gates and Edmunds 1999; Douglas 2003; Dunne, Eakin, and Donner 2012).

Traditionally, degree heating weeks (DHWs) (measured in °C weeks) is used as an indicator of SST anomalies from which to forecast coral bleaching (Liu, Strong, and Skirving 2003). The popular National Oceanic and Atmospheric Administration (NOAA) Coral Reef Watch programme ~~used not only local field observations, but also~~ relied on SST anomalies derived from remote sensing data to make coral bleaching warnings globally, such as for the bleaching that occurred in the North Pacific in 2014, in the South Pacific and Indian oceans in 2015 (McPhaden 2015), the Great Barrier Reef in 2016 (Normile 2016), and in the Indo-Pacific (IP) region in 2010, 2014, and 2016~~, and 2014~~ (Arora et al. 2021; Arthur 2000; De et al. 2022). The NOAA defined the onset of coral bleaching as when the weekly SST anomalies exceeds the climatological maxima (maximum monthly mean) by 1°C for a 12-week period~~month or more~~ (Liu, Strong, and Skirving 2003; Eakin, Lough, and Heron 2009; Arora et al. 2019), that results in DHW. Bleaching is ~~almost certain~~expected to occur after 1-3 weeks when reefs are exposed to the DHW ≥~~reaches~~ 4°C-weeks (Bleaching Alert (BA) 1~~I~~ is announced).~~, while m~~Mass bleaching is almost certain to occur when reefs are exposed to the DHW ~~reaches~~ ≥8°C-weeks (BA ~~II~~ 2 is announced) (Eakin, Lough, and Heron 2009; Arora et al. 2021). The likelihood of bleaching can also be predicted using degree heating months (DHM developed for historical SST data) suggested by Donner et al. (2005). However, SST-induced bleaching probability maps across many regions are scarce, such that the current, and most commonly followed, DHW-based satellite models suffer from both over- and under-prediction compared to field data (S. D. Donner 2011; Frieler et al. 2013; Sully et al. 2019) and, hence, finding an alternative metric to DHW is imperative.

Despite a link existing between onset of bleaching event and thermal thresholds, researchers failed to suggest a local climatological maxima. Rather to understand coral resilience and mortality, researchers have relied on thermal history (S. D. Donner 2011; Heron et al. 2016). McClanahan et al. (2007) demonstrated that DHW has a tendency to over- or under-predict coral bleaching in locations where thermal stress changes over time (Oliver and Palumbi 2011). Corals occurring in thermally changing environments are more resistant to bleaching events. In contrast, some studies (Goreau and Hayes 1994; B. Brown et al. 2002; J. E. Carilli et al. 2009; S. D. Donner 2011) revealed that the mean of the warmest month of the year could be the best predictor of coral bleaching in the equatorial Pacific, in part, because the seasonal peak in SST occurs in different years. It is critical, however, to fit models that are specific to the Indo-Pacific (IP) region rather than depending on globally fitted models that may be inadequately adapted to local regions.

Different models have been fitted to retroactively quantify the thermal threshold and the corresponding bleaching events at global coral reefs using multitemporal SST data. To forecast reef fates, coupled ocean-atmosphere circulation models (GCMs) were used (Frieler et al. 2013; van Hooidonk, Maynard, and Planes 2013) and model biases were corrected by adjusting the mean and annual cycle of the model in previous studies (Sheppard 2003; Hoeke et al. 2011). Ensemble analysis of GCMs, Coupled Model Intercomparison Project Phases (CMIPs) forced with the Representative Concentration Pathways (RCPs) were used in earlier studies to predict bleaching environments (Taylor, Stouffer, and Meehl 2012). However, models suffer from over- or under-projection of the variability in the coral bleaching conditions and the annual bleaching cycle in some cases (Andrews et al. 2012; van Hooidonk, Maynard, and Planes 2013). Together with inherent model sensitivities, different models have different uncertainties introduced by time-dependent biases (onset of bleaching) and geographic biases, (Dunne, Eakin, and Donner 2012; van Hooidonk, Maynard, and Planes 2013; S. D. Donner, Rickbeil, and Heron 2017), and all of these make model calibration challenging.

The objectives of this research were to: (1) examine the empirical relationships between coral bleaching and sea surface temperature in the Indo-Pacific region, covering the Coral Triangle (CT)~~South China Sea (SCS)~~ and the South China Sea (SCS) ~~Coral Triangle (CT)~~ sea surfaces, and (2) forecast the maximum monthly mean SST from 2020 to 2100 using the latest Coupled Model Intercomparison Project Phase 5 (CMIP5) dataset under the RCP2.6 scenario. Additionally, the research focuses on developing and implementing monitoring systems that can be used in marine management operations that are based on satellite-derived SST.

Materials

Study sites

The coral reef area selected for this study is part of the IP region between latitudes 16.5° S - 26.5° N and longitudes 96.5° E - 165.5° E, covering the ~~SCS~~ CT and ~~CT~~SCS, an area of 9 million km^2 (Fig. 1). Corals (571 species) and associated fish species (3,794) have made the SCS extremely rich in biodiversity (Huang et al. 2016). In contrast, the CT has the world's largest concentration of corals (more than 500 species; >76% of the world) (Veron et al. 2009) and 2,228 (37% of the world) reef fishes (Allen 2008) comprising parts of the Western Pacific and South-East Asia (Fig. 1). Although this IP region is rich in marine biodiversity (contains 75% of the world's corals; (Bruno and Selig 2007)), it is experiencing high levels of threat to biodiversity and coral habitat degradation, mainly due to SST-induced coral bleaching (Riegl et al. 2015).

The El Niño-Southern Oscillation (ENSO) is the dominant feature among different ocean-atmosphere modes (Zheng 2019), resulting in warmer than normal SST and, consequently, increasing the probability of severe bleaching in the tropical IP. Due to monsoonal climate variabilities, SSTs remain warm and humid throughout the year (Saha 2010). The North-East and South-West monsoons occur typically during October-to-February and June-to-September, respectively. Based on monthly Optimum Interpolation Sea Surface Temperature (OISST)V2 SST datasets spanning more than three decades (1982-2016), the warmest month was found to be May over the IP region. SSTs ranged between 2~~6~~4.~~5~~7 and 31~~0~~.2~~8~~ °C, while the coldest month (ranged between 1~~5~~7.5 and 31.0~~3~~ °C) was January (Fig. 2).

SST data

The SST data used in this research were NOAA OISSTv2 data with a spatial resolution of 25 km (0.25°) (Banzon et al. 2016) obtained from the NOAA Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html). Although this SST dataset is produced primarily based on satellite sensor AVHRR data, NOAA filled data gaps using field-based data collected from ships and buoys in the areas where the AVHRR data were contaminated with cloud cover. The final collation of the available SST data is hosted in the International Comprehensive Ocean–Atmosphere Data Set (ICOADS). The monthly OISSTv2 datasets have a bias of -0.03°C, processed by NOAA using linear interpolation. The interpolation technique is optimized using weekly field and satellite sensor datasets (Reynolds et al. 2002). The temporal resolution of the OISSTv2 datasets is one day and data available from January 1982 to present. However, SST data of 35 years (specifically from January 1982 - December 2016), covering pixels 276 x 172 (columns x rows) in the World Geodetic System (WGS) projection used for this study area considering availability of coral bleaching records for the same time span. Of the total of 1260 SST datasets, 420 were derived for each of the maximum (the maximum daily value among all the daily values in a month), minimum (the minimum daily value among all the daily values in a month) and mean (the mean daily value of all the daily values in a month) SST to evaluate the most predictive of bleaching occurrences.

Coral bleaching data

Coral bleaching records, from 1982 to 2016, were obtained from the ReefBase Online Geographic Information System (ReefGIS), developed and managed by the WorldFish Center. A search query to the ReefGIS database provided 390 bleaching or no bleaching records for the IP region. Since ReefGIS was not updated at the time of this research, bleaching records used here were updated with the records of Donner (2017) (hereafter termed Donner), available at http://simondonner.com/bleachingdatabase/. The new bleaching database, developed by Donner, is the compilation of ReefGIS and data extracted from published papers and data provided reef managers (especially those involved in managing marine parks). The records of ReefGIS and Donner were merged to remove redundant records. Donner's records contributed 15% additional data, especially those where bleaching events occurred in parts of Papua New Guinea and the SCS. Finally, 460 bleaching records were used for further analysis. Later, bleaching records were categorized into five types: no-bleaching (147 records), low (55 records), medium (96 records), high (104 records), and unknown severity (58). Note, records belonging to the unknown bleaching-type (bleaching observed, however, no severity status reported) were considered as bleaching occurrences (313 records).

Climate model datasets

Based on historical datasets, future sea surface temperatures (SSTs) were forecasted using the latest Coupled Model Intercomparison Project Phase 5 (CMIP5), which was developed from 22 constituent climate models (Table 1). The Royal Netherlands Meteorological Institute (KNMI) Climate Explorer (http://climexp.knmi.nl/CMIP5/monthly/tos/index.cgi) provides the data inputs required for the model.

The multi-model mean SST was simulated from 1861-to-2100 for the study sites. A total of 2,880 global monthly CMIP5 mean SST forecasts were downloaded and analysed. Preliminary analysis of the CMIP5 models revealed that the forecasted temperatures were always below the OISSTv2 temperatures (Fig. 3).

NOAA's DHW

NOAA has used satellite sensor data with a spatial resolution of 50 km to generate Degree Heating Week (DHW) products to identify bleaching affected areas under the Coral Reef Watch (CRW) programme and announce bleaching alerts (BA) to the public across the world since the 1990s. DHW refers to the thermal stress accumulated over a 12-week period and ranges from 0-to-16 °C-weeks. In general, significant coral bleaching is expected to occur when DHW values reach 4 °C-weeks, while mass coral bleaching is predicted when DHW values reach 8 °C-weeks. DHW data are available from 2001 onwards at: https://data.nodc.noaa.gov/crw/tsps50km/dhw/.

Methods

Logistic regression

Logistic regression (LR) is a generalised linear model (GLM) suitable for predicting the probability of bleaching events in the IP region from SST. The fitted model utilizes the standard GLM approach involving specification of a link function on the left-hand side of the linear model and maximum likelihood inference (McCullagh and Nelder 1989). LR allows the identification of a linear relationship between a binary outcome variable (occurrence and non-occurrences of coral bleaching) and a group of covariates (based on SSTs). For this research, the annual maximum (MaxSST), minimum (MinSST) and mean SST (MeanSST) were explored as possible covariates with which to predict the probability of bleaching occurrence at specific locations (i.e., per image pixel). The main purpose of modelling was to produce the logit-transformed probability. LR also estimates the logistic model parameters, standard errors and levels of significance. The LR function is defined as:

$$Logit(p) = log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \quad (1)$$

where x_1, x_2, … x_k are the SST-based covariates and p represents the binary bleaching occurrence (dependent variable). The $Logit(p)$ can be back-transformed to probability, p using the Equation (2).

$$p = \frac{1}{1 + e^{-logit(p)}} \quad (2)$$

Accuracy assessment

The best fitting model was chosen based on accuracy assessment using the Akaike information criterion (AIC) (Akaike 1992) and Area Under the Curve (AUC).

The AIC was used to select the best fitting LR model (Equation 3).

$$AIC = 2K - 2log(L) \quad (3)$$

where K is the number of covariates in the fit and L is the likelihood. Generally, the AIC can be considered as a means of *ranking* the models in terms of fit rather than measuring the level of significance. The smallest AIC value indicates the best fitting model, using the relative Kullback-Leibler distance between a model probability distribution and the truth.

The AUC of the receiver operating characteristic (ROC) curve from a single cross-validation and bootstrapping exercise was also reported. A random sample of 322 (70%) data pairs was drawn from the 460 data pairs, while the remaining 138 (30%) data points were held back for model validation. An area under the ROC curve (AUC) of more than 0.7 indicates that the model has good predictive ability.

Coral bleaching probability map

The best fitting model was used in prediction to generate bleaching probability maps, with the probability for each pixel ranging from 0 to 1. The probability maps generated by LR for 2001 were compared qualitatively with maps of NOAA's DHW alert areas. This visual comparative analysis is not intended to validate the capability of the proposed LR-based prediction technique or NOAA's DHW alert areas. Additionally, the correlation was calculated between the LR-based probability maps and the NOAA DHW maps for the IP region in 2010 to assess quantitatively the association between the two maps. Finally, coral bleaching maps, forecasted for the years between 2020 and 2100, were produced by combining the LR model with the CMIP5 model monthly MaxSST datasets.

Results

LR-based prediction of coral bleaching

To compare between the Max, Min and Mean SST as covariates in the LR model, the AIC (Table 2), fitted LR model parameters (Fig. 4) and ROC curves (Fig. 5) were produced. Identifying which SST stress distribution best explains bleaching occurrence is a necessary step in generating a generic model suitable for application to coral ecosystems. Different coral species may be affected by different SST regimes. The relative goodness-of-fit results showed that MaxSST (443.~~8~~2; the lowest AIC) produced a better fit than MeanSST (492.6) and MinSST (504.5) and this is consistent with expectation (Table 2). Thus, MaxSST was used in the LR-based model development as the SST stress metric for the IP region.

As evident in the LR curve in Fig. 4, the MaxSST relationship produces an S-like sigmoid shape and produces the best fitting model for predicting coral bleaching probability. The AUC)was 0.75 (Fig. 5), indicating again that MaxSST provides a reliable bleaching probability model.

Coral bleaching probability map

This study used the two bleaching years 2001 and 2010. During the La Niña year 2001, the incoming hot water moved towards the IP region, while during the El Niño year 2010, hot surface water moved away from the IP region. The LR-based bleaching prediction map and the NOAA's Coral BA map are provided in Figs. 6 and 7, respectively, for the IP region in 2001. A comparison between them can be made based specifically on the similarities and differences between locations showing bleaching severity.

This study used to describe bleaching severity in five categories: No stress, Watch, Warning, Alert Level-1, and Alert Level-2 based on the level of the bleaching probability in the magnitude of lower to higher respectively for IP region (Figs. 6 and 7). According to the LR maps of May and June 2001, the south-eastern parts of the SCS were predicted to be most severely affected by bleaching occurrences (left panel, the 5th and 6th rows, respectively, in Fig. 6) compared to other months. In comparison, bleaching severity with 'watch' and 'warning' levels were the largest for the same months of 2001 in the BA. This indicates that both mapping techniques were consistent to some degree in predicting coral bleaching events in the IP region, with differences in the representation of the scale of bleaching severity.

The LR provided bleaching probability values for each pixel and bleaching a probability map for each month; illustrated in the left panel of Figs. 6 (January-to-June 2001) and 7 (July-to-December 2001). NOAA's BA maps provided values for each pixel in a subjective fashion, with bleaching severity stages ranging from 'watch' to 'alert level 2', illustrated in the right panel of Figs. 6 (January – June 2001) and 7 (July – December 2001). Therefore, the later maps were unable to inform about bleaching severity across the scale gradients unlike the probability values in the LR maps. Overall, the maps were in good agreement at demonstrating bleaching areas and were able to separate bleaching from non-bleaching areas (no stress for NOAA and 0-0.1 for LR prediction).

A few discrepancies between the maps were observed, mainly when identifying areas with high bleaching probability (January-to-April 2001) and 'watch' alert areas (January-to-April 2001). From January-to-April 2001, when the simple severity alertness scale 'watch' is shown in the NOAA maps (green areas), bleaching probabilities of 0.6-1.0 were produced on a continuous scale (discretized for visualization into four shades of yellow-to-dark red in the LR maps; 1st to 4th rows) indicating that LR provided more informative and numerically precise maps compared to the BA maps.

Further comparison was made between the 2010 bleaching probability map and NOAA BA map product using correlation analysis. Both datasets were first normalised and a total of 396 pairwise pixels were selected. The scatterplot (Fig. 8) and associated coefficient of determination derived from the 2010 bleaching occurrences imply that they have moderate (r = 0.65) correlation (Fig. 8). Note, that a strong El Nino event occurred in that year.

Forecasted coral bleaching probability maps

Fig. 9 shows the decadal LR-based bleaching forecast maps for the IP region generated using CMIP5 models for 2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090 and 2100.

The LR model utilizing the forecasted maximum SST predicts severe bleaching probabilities, starting from the year 2040 and continuing until 2060, especially in the central part of the IP region, covering the coasts of the CT region, while the northern parts of the SCS are forecasted to experience no bleaching events in those critical years. Comparatively, a low bleaching probability is forecasted from 2070-to-2100, also reported as the percentage area of bleaching in Table 3.

It is clear from the spatiotemporal assessment of bleaching probability extent (Table 3) that more than half of the IP region will be affected by bleaching events, with bleaching severity indices of greater than 0.5 common across the region. The greatest extent of bleaching (23% of the total) is forecasted to occur in 2080, with a severity of 0.8-0.9. The year 2050 is forecasted to be the most critical (about 58% of the total), followed by bleaching with little variation in coverage in the years between 2060 and 2100 (57% in 2060, 56% in 2070 and in 2080, 55% in 2090 and 56% in 2100, respectively; calculated from Table 3).

Discussion

Coral bleaching and maximum SST

Coral bleaching can be attributed to a variety of individual and environmental factors, including changes in light intensity and exposure time (Fitt et al. 2001), decreased salinity (Coles and Jokiel 1992) and sedimentation and water quality (Dollar and Grigg 1981) in coral habitats, among others. One of the chief factors affecting the degradation of coral reef ecosystems is increased SST (Foo and Asner 2020). Under typical circumstances, the optimal SST for coral reef life is between 22 ^{0}C and 28 ^{0}C (Birkeland 1997). Previous studies documented the impact of rising SST on bleaching occurrence (Hoegh-Guldberg 1999; Sheppard 2003; S. Donner et al. 2005; S. D. Donner 2009). Halpern et al. (2008) also demonstrated that SST is the most significant factor affecting marine ecosystems such as coral reefs, after examining the effect of 17 contributing factors on 20 marine ecosystems. Although most research supports the understanding that SST is the prime cause of bleaching, it is not certain which measure of SST is most predictive of bleaching. This is due to the dynamic nature of the environment, and variability in adaptation to changes in SST thresholds by coral species. Manzello, Berkelmans, and Hendee (2007) identified maximum monthly SST as the primary factor causing coral reef ecosystem deterioration. Tittensor et al. (2010) confirmed the findings, stating that using spatial regression analysis, SST was found to be the only variable that was significantly important across all 13 major species evaluated. Additionally, the study suggested that warmer waters may be altering the distribution of marine species.

This research found that MaxSST was the best covariate explaining bleaching events for the IP region, consistent with the findings of others. Foo and Asner (2020) also observed a 50% mortality of corals because of bleaching, caused by maximum SST. Compared to MeanSST and MinSST, MaxSST was able to predict bleaching probability with an 11% and 14% greater accuracy, respectively, with also a lower AIC indicative of a better fit taking into account accuracy and parsimony (Table 2).

The thermal sensor(s) of remote sensing systems can provide SST data, but not the presence or absence of bleaching. Bleaching occurrences are predicted from the history of bleaching events (field observations) and thermal anomalies (either from field observations at small spatial scale or from remote sensing observations at large spatial scale). While previous studies used 3-day field observations during the coral bleaching seasons, this short duration of observation is unlikely sufficient for predicting bleaching patterns through statistical correlations (Berkelmans et al. 2004). This research suggests using monthly maximum SST to fit a LR between the ReefBase and AVHRR datasets. Donner (2011) also suggested to employ maximum *annual* SST to gain knowledge of the long-term thermal history of global coral reefs to predict bleaching events in future. Whether coral community assemblages occurring in the study region are either resistant or vulnerable to thermal stress within short or longer periods is an important consideration for the application of SST in predicting bleaching from satellite sensor data. Remote sensing professionals may utilize field-based knowledge of coral biology and ecology that details how spatiotemporal variabilities affect coral bleaching occurrences and their patterns (Sully et al. 2019). Field observations of coral bleaching, once integrated with monthly SST data derived from remote sensing, have the ability to harmonize both short-term and long-term approaches, although in doing so subtle spatiotemporal variabilities should not be lost. For example, some widespread bleaching occurrences in the northwest Pacific during 2001-to-2015 were not well correlated with high SST anomalies, while DHW was found to be an ideal predictor in this case (Kayanne 2017).

Remote sensing has a significant potential contribution to make towards predicting and forecasting bleaching and its impacts on the marine ecosystem, including corals, where fine spatial resolution and complete coverage are almost impossible to achieve in other ways.

The finer the spatial resolution, the greater the potential information on environmental variables such as maximum SST used in predicting bleaching events. Moreover, finer-resolution products have greater consistency with *in situ* bleaching observations and, thus, have greater potential for use in regression models. Interestingly, the LR-based empirical methods, applied in this research, effectively generated detailed spatiotemporal bleaching maps for the IP region utilizing the spatial resolution of AVHRR (i.e., 25 km). This model was found to be suitable for mapping and monitoring bleaching occurrences at the local level, specifically for the vast CT and SCS regions. Using SST derived from 5 km spatial resolution NOAA CRW datasets, bleaching was predicted with greater accuracy in some studies (Heron et al. 2016; Mohammed et al. 2016). Further research should be undertaken to determine the optimum spatial resolution for producing SST variables and to provide high quality remote sensing products for predicting coral bleaching prevalence (Weeks et al. 2008).

MaxSST could potentially provide a more efficient approach than DHW, as previously reported for global bleaching events (Claar et al. 2018). A clear correlation was found between bleaching occurrence and maximum SST during the 1980-to-2020 period of bleaching events globally (van Woesik and Kratochwill 2022). The LR model, proposed in this research, is simple and easy to implement since it requires only SST extremes, while global models fitted within a Bayesian inference framework require many temperature measures, including DHW, depth information and coral diversity (Sully et al. 2019; Lisboa and Kikuchi 2020) which can be difficult to achieve at the local scale due to paucity of data (S. D. Donner, Rickbeil, and Heron 2017).

The LR model may be limited by the water depth assumption. It is assumed that there is no significant variation in SST until 20 m depth. This common assumption might not be true for some regions. However, SST vertical heterogeneity has been addressed in some studies. Castillo and Lima (2010) reported that there were negligible differences between satellite-derived SST and *in situ* observations at different depths and, therefore, it is not an important issue from a biological point-of-view. Besides, McClanahan et al. (2007) identified water depth as less significant when modelled with heat stress from satellite sensor data in predicting coral bleaching.

The adoption of LR allowed the calculation of the rate of change in the odds of bleaching occurring e^b, where b represents the slope of LR for an increase of 1°C in MaxSST. The slope b *is* 1.69 which means that the odds of bleaching increases by a factor of 5.36 for each 1°C increase in MaxSST. Further, the overall baseline probability in the model is 68% bleaching and 32% non-bleaching from 1982 to 2012. The baseline odds are 0.68/1.0-0.68 =

2.13. Hence, it can be concluded that a 1°C increase is associated with an increased odds of 2.13 x 5.36 = 11.42. This corresponds to a probability of 11.42/1+11.42 = 0.91 overall, which emphasises the vulnerability of the region to coral bleaching due to a continuously increasing MaxSST.

Coral bleaching in future based on CMIP5 forecasts

Coral bleaching prevalence has been predicted using GCMs, similar to this study, based on changes in SST (Hoegh-Guldberg 1999; Sheppard 2003; S. Donner et al. 2005). Decadal coral bleaching severity was projected here for 2020-2100, for the first time, for the IP region using CMIP5 data. The fine-resolution CMIP5 forced with the new RCPs was used for the first time in projecting coral bleaching from monthly MaxSST. GCM models used by Donner et al. (2005), specifically the Hadley Centre Coupled Model version 3 (HadCM3) and Parallel Climate Model (PCM), had spatial resolutions of 2.5°× 3.75° and 2.81°× 2.81°, respectively. In contrast, the CMIP5 framework provides a spatial resolution of 1.25° x 1.25°.

The first RCP scenario was simulated to forecast future maximum SST as well as the future probability of coral bleaching (RCP2.6 in CMIP5) (Moss et al. 2010). The CMIP5 model simulates the rate of ocean warming in the study areas from 1982 to 2012 which is found to be less rapid than predicted by satellite sensor data. Forster et al. (2013) reported that the constituent models in CMIP5 tended to overestimate the observed SST, which agrees with the present research. In contrast, most models tested in CMIP5 from the decadal SST projected by Kim, Webster, and Curry (2012) tended to produce cooler SST. The present research supports the findings that when dealing with short time-series, the data produced by CMIP5 tend to underestimate the observed SST.

A gradual increase towards a high probability of bleaching was predicted in this research to dominate the IP region from 2020 to 2050 before reaching a plateau. The CT area was projected to be in a critical situation by as early as 2040 due to severe bleaching with 0.6-0.7 probability values. The decadal maps of coral bleaching presented in Fig. 9 show that the early trend of bleaching is consistent with (van Hooidonk, Maynard, and Planes (2013). They found that the majority of corals in tropical waters will face bleaching between 2040 and 2050. The situation of widespread bleaching in 2050 was also reported by Burke et al. (2012). Moreover, the low probability of bleaching during 2070-2100 is interesting given the general understanding that the Earth is warming. However, this is an outcome of the long-term trend in MaxSST forecasted from CMIP5. Villarini and Vecchi (2012) and Knutti and Sedláček (2013) showed that a flat trend of global meanSST was detected from approximately 2060 until 2100 under the RCP2.6 scenario. From the forecasted maps of coral bleaching it can be seen that the northern part of the SCS (coast of Vietnam and northwards) is projected to remain comparatively safe for corals until the end of 2100. However, it is a matter of serious concern that the CT, the heart of the coral reefs, is threatened by a high probability of bleaching at least between 2040 to 2060.

The present research indicates that serious coral bleaching is forecasted to occur, even in the near future, due to ocean warming. However, this near future scenario is subject to changes depending on the realized patterns of SST as well as the resilience and adaptation of corals (West and Salm 2003) to future ocean warming (J. Carilli, Donner, and Hartmann 2012). Frieler et al. (2013) reported that global mean temperature should be limited to 1.2°C above pre-industrial temperatures to conserve at least 50% of the global coral reefs.

Conclusion

This research used a fitted logistic regression model and climate change scaenarios to forecast coral bleaching events in the IP region up to 2100. Most previous studies produced regression models that are fitted to global data at the expense of local precision. As a result they missed the opportunity to fit to local variation in the world's most important coral reef region. They were also not used to forecast coral bleaching in the future. The LR model fitted here revealed a significant relation between the probability of coral bleaching and annual maximum monthly mean SST in the study area by utilising an extensive and spatially well-distributed bleaching dataset extracted from an online database and a time-series of remotely sensed AVHRR images of maximum sea surface temperature. This empirical relation allowed the prediction of coral bleaching probability across the study area based on historical maximum monthly mean SST. The result obtained was in overall close agreement with the NOAA CRW DHW map albeit with discrepancies arising from the more local fitting conducted in the LR model. Coral bleaching was forecasted over the coming decades up to 2100 based on the locally specific LR model coupled with forecasted maximum SST obtained from the CMIP5 model ensemble. According to the LR model fitted in this research, the expected increase in maximum sea surface temperature in the region forecasted by the CMIP5 model is likely to lead to widespread coral bleaching. This research, thus, highlights The likelihood of devastating impacts on the world's most important coral region even within the next three decades, with most areas experiencing some losses within the next decade.

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Disclosure statement

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Figure captions

Fig. 1. Map showing the spatial boundary of the South China Sea and the Coral Triangle. The dots shown in the map represents coral bleaching events from the year 1982 to 2012 (ReefBase 2012; Donner, 2017).

Fig. 2 The average monthly sea surface temperature (SST) extracted from OISSTv2 for 1982-2016 for IP region.

Fig. 3 The forecasted SSTs for IP region derived from CMIP5 models (1982-2016), illustrating all of them are below values derived from the OISSTv2 (black line).

Fig. 4. The LR plots, illustrating the probability of coral bleaching occurrence versus maximum (MaxSST), minimum (MinSST), and mean (MeanSST) for IP region. The histogram in each of the three plots represent the (upper) occurrence of bleaching and (lower) non-occurrence of bleaching.

Fig. 5 The area under the ROC curve (AUC) for the LR model when maximum SSTs were used as model input for the IP region.

Fig. 6. Coral Bleaching probability map and CRW BA for Jan to June 2001.

Fig. 7. Coral Bleaching probability map and CRW BA for July to December 2001.

Fig. 8. Pearson correlation showing the comparison between 2010 DHW and probability map.

Fig. 9. Coral bleaching probability forecasts from the year 2020 to 2100 shown by decade based on CMIP5-estimated maximum SST. Note that even by 2040 coral bleaching probabilities in excess of 0.6 to 0.7 are spatially extensive in the ~~SCS~~ CT and ~~CT~~SCS.

Table 1. List of climate models used in the CMIP5 simulation.

	Model	Institution
1.	bcc-csm1-1	Beijing Climate Center, China Meteorological Administration
2.	CanESM2	Canadian Centre for Climate Modelling and Analysis
3.	CCSM4	National Center for Atmospheric Research
4.	CESM1-CAM5	National Center for Atmospheric Research
5.	CNRM-CM5	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique
6.	CSIRO-Mk3-6-0	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)
7.	EC-EARTH	EC-EARTH consortium
8.	FIO-ESM	The First Institute of Oceanography, SOA, China
9.	GFDL-CM3	Geophysical Fluid Dynamics Laboratory
10.	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory
11.	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory
12.	GISS-E2-R	Goddard Institute for Space Studies
13.	HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration
14.	HadGEM2-ES	Met Office Hadley Centre
15.	IPSL-CM5A-LR	Institut Pierre-Simon Laplace
16.	IPSL-CM5A-MR	Institut Pierre-Simon Laplace
17.	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
18.	MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M)
19.	MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M)
20.	MRI-CGCM3	Meteorological Research Institute

21.	NorESM1-M	Norwegian Climate Center
22.	NorESM1-ME	Norwegian Climate Center

Table 2. The AIC of the models fitted to MaxSST, MeanSST, and MinSST.

Model	AIC
MaxSST	443.17
MinSST	504.50
MeanSST	492.60

Table 3. Areas predicted to be affected by coral bleaching, forecasted from CIMP5 model outputs for the Indo-Pacific region from 2020-2100.

	Percentage of pixels (%)								
Probability	2020	2030	2040	2050	2060	2070	2080	2090	2100
0.0 - 0.1	5.6	3.8	3.0	2.4	2.4	2.7	2.7	2.9	2.6
0.1 - 0.2	3.9	3.1	2.6	2.1	2.7	2.4	2.2	2.1	2.2
0.2 - 0.3	4.2	3.0	2.7	2.1	2.8	2.4	2.2	2.7	2.0
0.3 - 0.4	8.2	4.0	2.6	2.6	2.3	2.3	2.9	2.4	3.0
0.4 - 0.5	10.8	6.5	3.7	3.1	2.7	3.8	2.6	4.0	3.0
0.5 - 0.6	8.1	12.6	8.5	4.4	4.5	5.2	5.5	5.4	6.2
0.6 - 0.7	9.6	11.3	11.4	10.4	10.1	12.3	8.4	10.1	10.1
0.7 - 0.8	**13.9**	**15.1**	11.8	11.5	11.0	13.2	13.1	13.0	14.2
0.8 - 0.9	6.7	9.9	**16.9**	**22.2**	**21.6**	**19.2**	**23.7**	**20.6**	**21.4**
0.9 - 1.0	3.5	5.2	11.3	13.7	14.4	11.1	11.1	11.2	9.8

Notes: Values are in percentage of total pixels, including only water bodies. Maximum percentages for each decade (column) are given in **bold**.

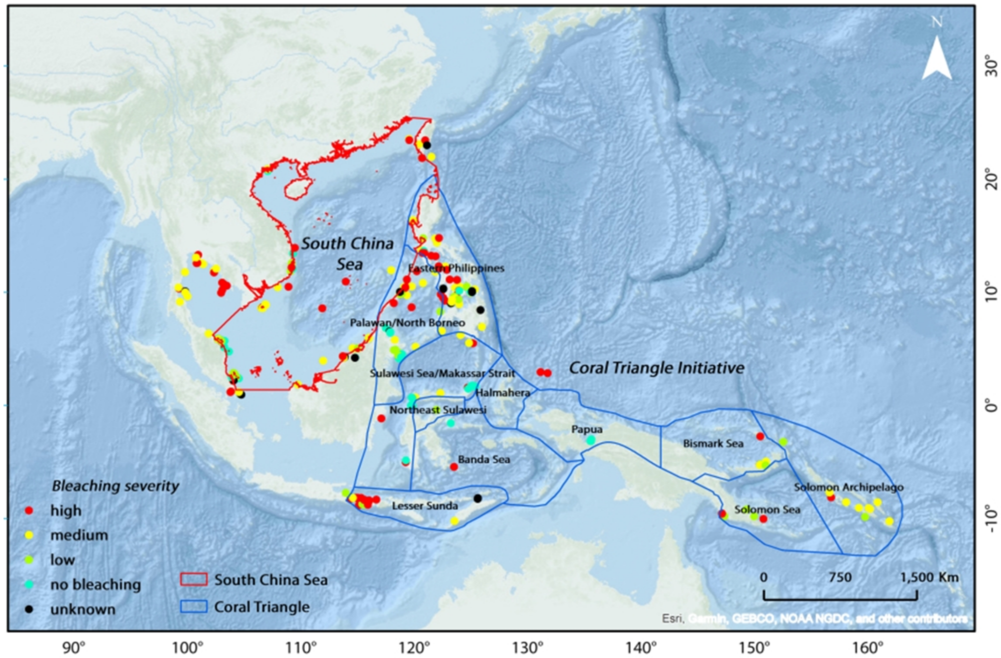

Fig. 1. Map showing the spatial boundary of the South China Sea and the Coral Triangle. The dots shown in the map represents coral bleaching events from the year 1982 to 2012 (ReefBase 2012; Donner, 2017).

874x599mm (72 x 72 DPI)

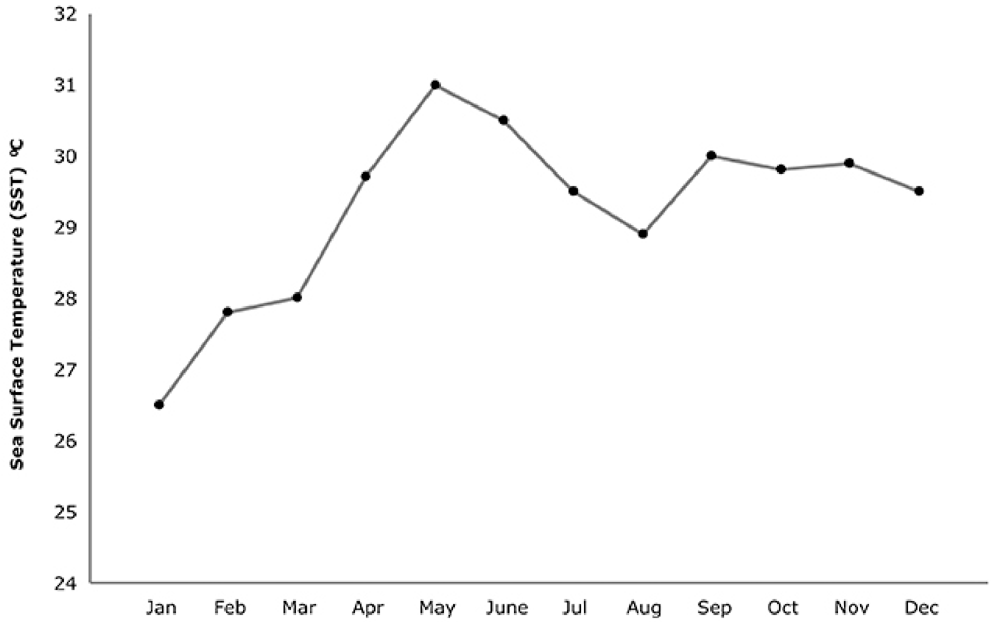

Fig. 2 The average monthly sea surface temperature (SST) extracted from OISSTv2 for 1982-2016 for IP region.

226x144mm (72 x 72 DPI)

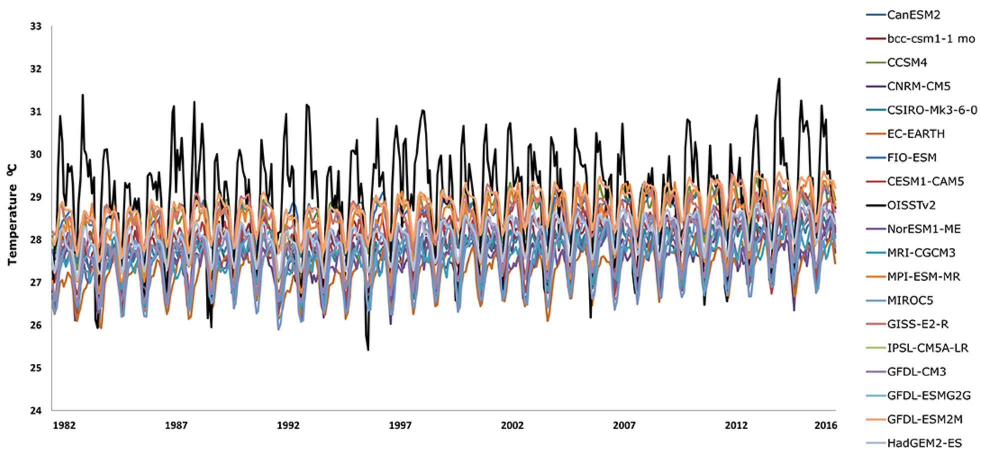

Fig. 3 The forecasted SSTs for IP region derived from CMIP5 models (1982-2016), illustrating all of them are below values derived from the OISSTv2 (black line).

391x181mm (72 x 72 DPI)

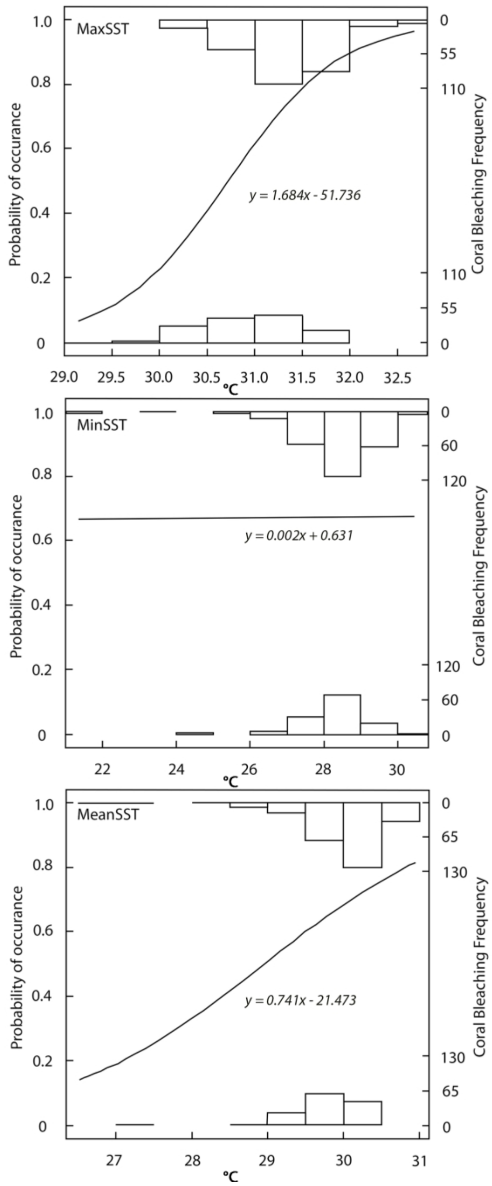

Fig. 4. The LR plots, illustrating the probability of coral bleaching occurrence versus maximum (MaxSST), minimum (MinSST), and mean (MeanSST) for IP region. The histogram in each of the three plots represent the (upper) occurrence of bleaching and (lower) non-occurrence of bleaching.

124x292mm (300 x 300 DPI)

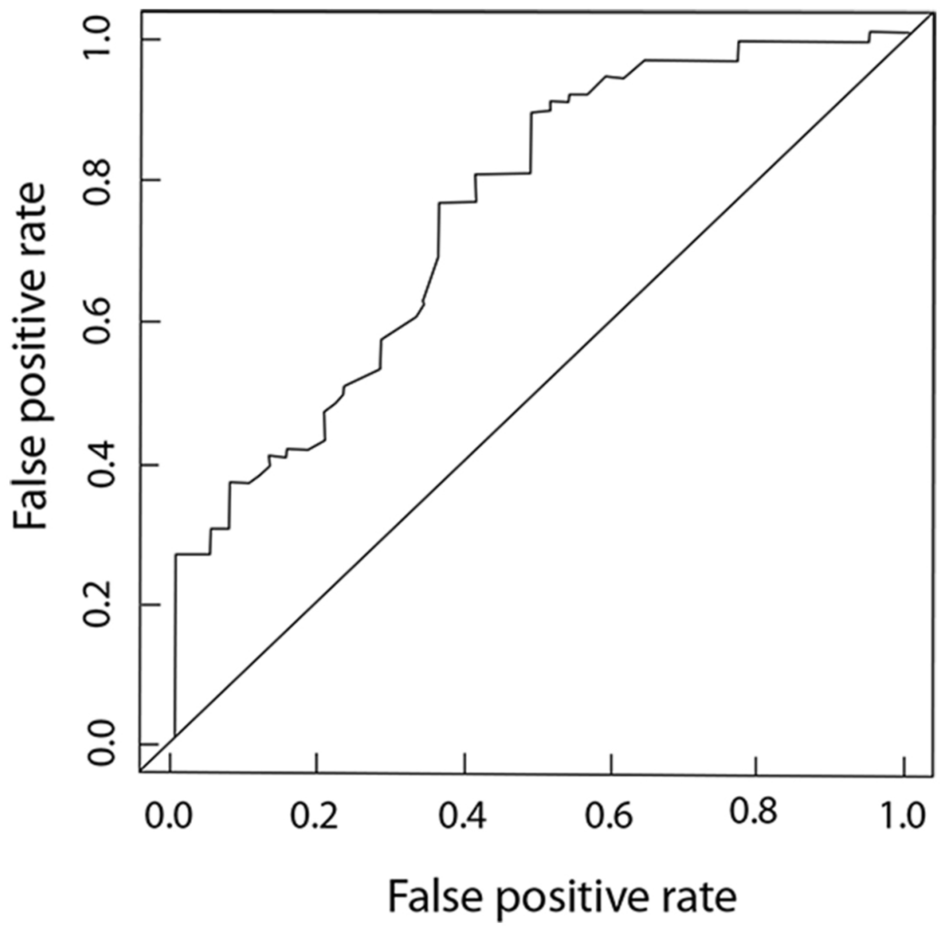

Fig. 5 The area under the ROC curve (AUC) for the LR model when maximum SSTs were used as model input for the IP region.

493x458mm (72 x 72 DPI)

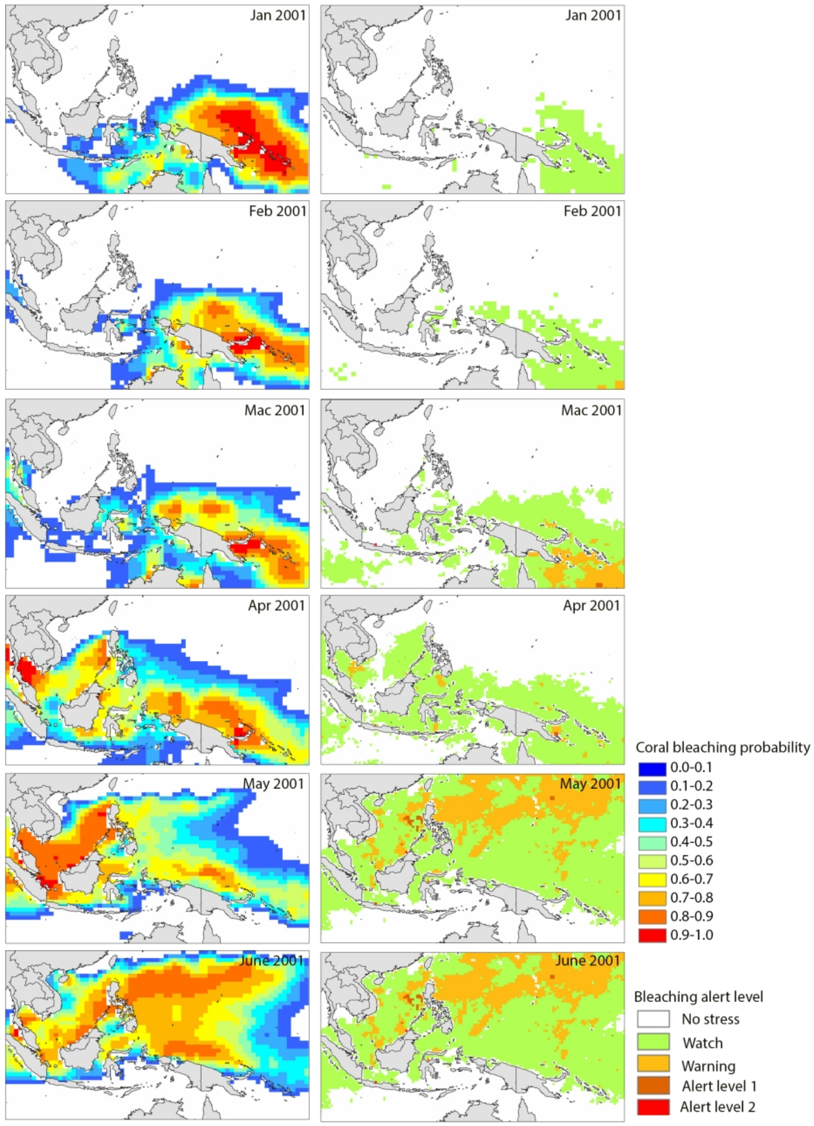

Fig. 6. Coral Bleaching probability map and CRW BA for Jan to June 2001.

874x1249mm (72 x 72 DPI)

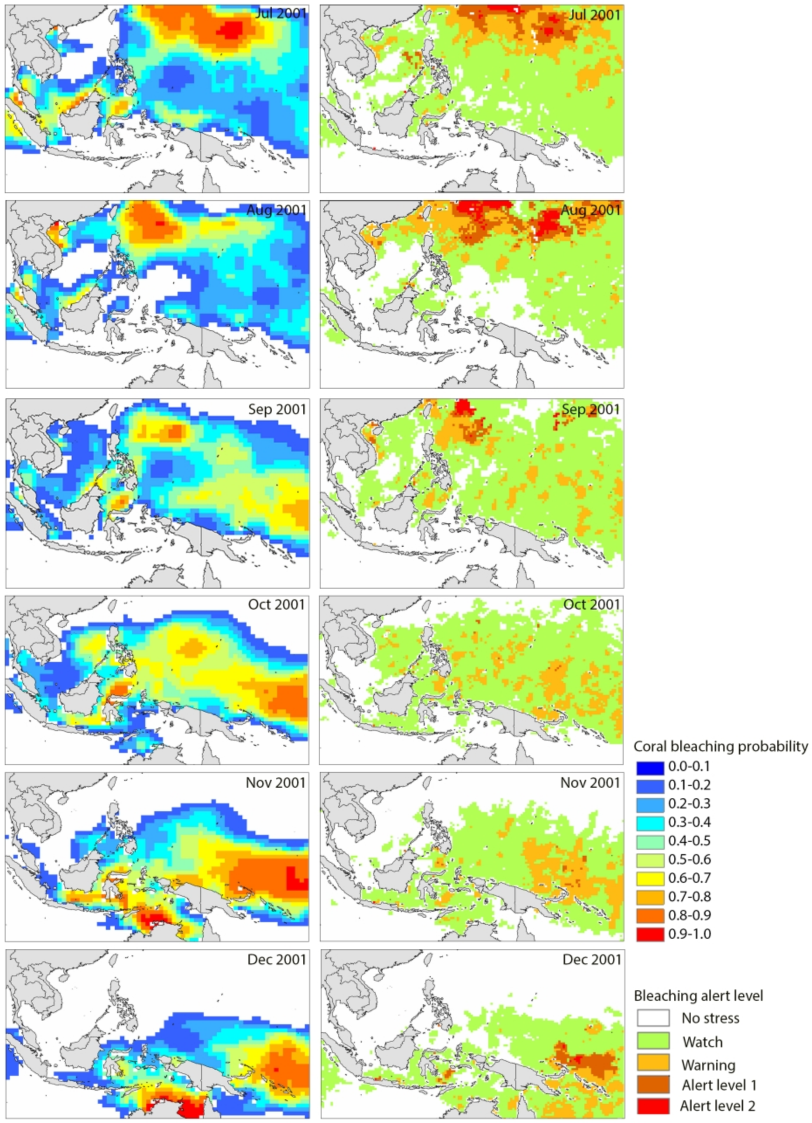

Fig. 7. Coral Bleaching probability map and CRW BA for July to December 2001.

874x1249mm (72 x 72 DPI)

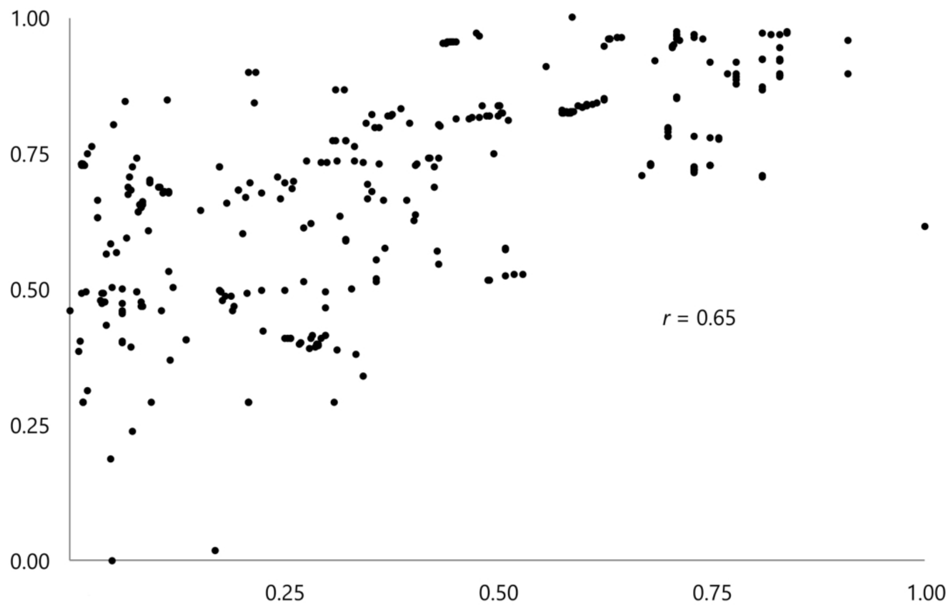

Fig. 8. Pearson correlation showing the comparison between 2010 DHW and probability map.

666x499mm (72 x 72 DPI)

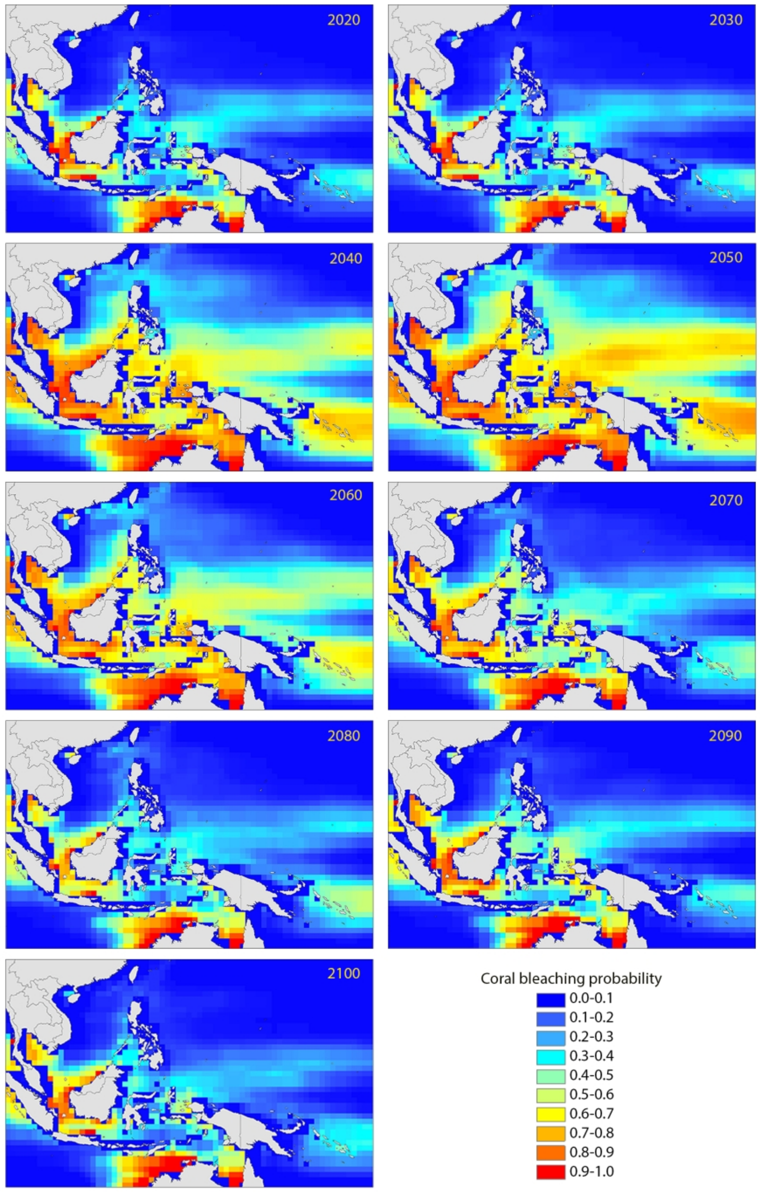

Fig. 9. Coral bleaching probability forecasts from the year 2020 to 2100 shown by decade based on CMIP5-estimated maximum SST. Note that even by 2040 coral bleaching probabilities in excess of 0.6 to 0.7 are spatially extensive in the SCS and CT.

770x1207mm (72 x 72 DPI)