UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENVIRONMENTAL AND LIFE SCIENCES

Geography and Environmental Sciences

Satellite Observation of Trends in Sea Surface Temperature

And Coral Bleaching in the Indo-Pacific Region

By

IDHAM BIN KHALIL

Thesis for the degree of Master of Philosophy

August 2019

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF ENVIRONMENTAL AND LIFE SCIENCES

Geography and Environmental Sciences

Thesis for the

degree of Master of Philosophy

SATELLITE OBSERVATION OF TRENDS IN SEA SURFACE TEMPERATURE AND CORAL BLEACHING IN THE INDO-PACIFIC REGION

Idham bin Khalil

Global warming phenomena have started to gain public attention as the associated impacts are starting to affect human livelihoods. In the marine environment, an increasing ocean temperature is threatening coral reef ecosystems. However, ocean warming across the globe is not uniform. The spatial and temporal trends of ocean temperature need to be characterised. Little is known about the past and future trends in local ocean temperatures, which may be especially important in coral rich areas like the Coral Triangle and the South China Sea. This thesis uses a combination of monthly 1^0 spatial resolution NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2 dataset (OISSTv2) and the Representative Concentration Pathways (RCP2.6) mitigation scenario of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to characterise Sea Surface Temperature (SST) trends in the Indo-Pacific region. This research revealed warming trends detected for three SST variables. In the Coral Triangle warming trends with a rate of 0.013 °C yr^{-1}, 0.017 °C yr^{-1}, and 0.019 °C yr^{-1} were detected over 29 years for MaxSST, MeanSST and MinSST, respectively. In the SCS, the warming rates were 0.011 °C yr^{-1}, (MaxSST), 0.012 °C yr^{-1} (MeanSST) and 0.015 °C yr^{-1} (MinSST) over 29 years. The CMIP5 RCP2.6 forecast suggested a future warming rate to 2100 of 0.004°C yr^{-1} for both areas. Using MaxSST as a proxy for coral bleaching, this thesis attempted to model their relationship using logistic regression. Coral bleaching probability maps for the past and the future were produced. Widespread coral bleaching was predicted within a few decades. Further analysis was undertaken to explore the most appropriate spatial resolution of SST data for modelling coral bleaching. This thesis demonstrated that 4 km spatial resolution MaxSST is the best resolution to model coral bleaching events in the region.

Table of Contents

List of Tables

List of Figures

DECLARATION OF AUTHORSHIP

I, Idham bin Khalil declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

SATELLITE OBSERVATION OF TRENDS IN SEA SURFACE TEMPERATURE AND CORAL BLEACHING IN THE INDO-PACIFIC REGION

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:

Khalil, I., Atkinson, P.M. & Challenor, P., 2016. Looking back and looking forwards: Historical and future trends in sea surface temperature (SST) in the Indo-Pacific region from 1982 to 2100. *International Journal of Applied Earth Observation and Geoinformation*, 45(August), pp.14–26.

Signed:

Date: 21 August 2019

Acknowledgements

Alhamdulillah. To the only God, I am grateful for His blessing.

Sooner or later, there will be an end of each journey. Every journey is different. What is certain in this long journey, there is laughter and sorrow. If we fall, rather than drowning in the misery, we should find the purpose to get back on track. Make a step at a time, with His permission we will eventually reach our utmost destination.

Thanks to Professor Peter Atkinson, a supervisor who is always by my side with his encouragement and words of spirit throughout my Mphil. Even when he moved to University of Lancaster and I had already been in Malaysia, he kept providing me with unceasing advice and technical guidance. Also to Dr Jadu Dash and Professor Peter Challenor, both of you had helped me in the completion of this thesis.

Thanks to all my friends in Geog Hub (Rizal, Sarwar, Sarchil, Prasan and all). To everyone who has filled my life with colours for 4 years in Southampton, thank you. Also, thanks to the 'Keluarga Soton' who had made me realised the true meaning of 'family' in this 'Her Majesty' land.

Thanks to my dad, Tn. Hj. Khalil Yusof and mum, Siti Rohani Yusof Shaikh Abdullah for their incessant prayers. My gratitude also goes to my parents-in-law (Tn. Hj.j Ibrahim Muhammad and Hasnah Baha), siblings and relatives in Pahang and Johor.

Special thanks to Universiti Malaysia Terengganu and the Ministry of Higher Education for the opportunity given to me and colleagues in PPSMS for your undying support.

I reserved the deepest appreciation to my beloved wife, Nor Haslinda Ibrahim. Your never-ending sacrifice, perseverance and patience in accompanying me throughout the PhD journey are priceless. To my children, Muhammad Amnan, Muhammad Abdullah, Muhrizah Humaira' and Muhrizah Huda, this is not the end; this is indeed a beginning in the quest for knowledge.

To Allah, I am nothing without you and everything belongs to You.

Definitions and Abbreviations

AATSR - Advanced Along-Track Scanning Radiometer

AIC - Akaike's Information Criterion

AMSR-E - Advanced Microwave Scanning Radiometer - Earth Observing System

ANN - Artificial Neural Network

AUC – Area Under the Curve

AVHRR - Advanced Very High Resolution Radiometer

Bcc-csm1-1 - Beijing Climate Center, China Meteorological Administration

CanESM2 - Canadian Centre for Climate Modelling and Analysis

CCSM4 - National Center for Atmospheric Research

CESM1-CAM5 - National Center for Atmospheric Research

CMIP5 - Coupled Model Intercomparison Project Phase 5

CNRM-CM5 - Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique

CoRTAD - Coral Reef Temperature Anomaly Database

CRW - Coral Reef Watch

CSIRO-Mk3-6-0 - CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)

CT - Coral Triangle

DHW - Degree Heating Weeks

EC-EARTH - EC-EARTH consortium

ENSO - El Nino-Southern Oscillation

ESA - European Space Agency's

EUMETSAT - European Organisation for the Exploitation of Meteorological Satellites

FIO-ESM - The First Institute of Oceanography, SOA, China

GCM - Global Circulation Models

GCRMN - Global Coral Reef Monitoring Network

GFDL - Geophysical Fluid Dynamics Laboratory

GFDL-CM3 - Geophysical Fluid Dynamics Laboratory

GHRSST - Group for High Resolution Sea Surface Temperature

GISS-E2-R - Goddard Institute for Space Studies

HadCM3 - Hadley Centre Coupled Model, version 3

HadGEM2-AO - National Institute of Meteorological Research/Korea Meteorological Administration

HadGEM2-ES - Met Office Hadley Centre

HadISST1 - Hadley Centre Sea Ice and Sea Surface Temperature

HIV - Human Immunodeficiency Virus

HSV - Herpes Simplex Virus

IPCC - Intergovernmental Panel on Climate Change

IPSL-CM5A-LR - Institut Pierre-Simon Laplace

ITCZ - Intertropical Convergenze Zone

JAXA - Japan Aerospace Exploration Agency

LR - Logistic regression

M-AERI - Marine-Atmospheric Emitted Radiance Interferometer

MIROC5 - Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology

MMM - Maximum Monthly Mean

MMMmax - Maximum Monthly Meanmax

MODIS - Moderate Resolution Imaging Spectrometer

MPI-ESM-LR - Max Planck Institute for Meteorology (MPI-M)

MRI-CGCM3 - Meteorological Research Institute

NASA - National Aeronautics and Space Administration's

NCAR - National Centre for Atmospheric Research

NE - North East

NOAA - National Oceanic and Atmospheric Administration

NODC - National Oceanographic Data Center

NorESM1-ME - Norwegian Climate Center

OISSTv2 - Optimum Interpolation (OI) Sea Surface Temperature (SST) V2

PCHIP - Piecewise Cubic Hermite Interpolation

PCM - Parallel Climate Model

RCP2.6 - Representative Concentration Pathways 2.6

ReefGIS - ReefBase Online Geographic Information System

ROC - Receiver Operating Characteristic

SCS - South China Sea

SEVIRI - Spinning Enhanced Visible and Infrared Imager

SOM - Self-organizing Map

SST - Sea Surface Temperature

SSTdepth - subsurface SST

SSTint - Interface SST

SSTsubskin - Subskin SST

SW - South West

TAR - Third Assessment Report

TMI - Tropical Microwave Image

TRMM - Tropical Rainfall Measuring Mission

U.S. DoD - United States Department of Defense

UNEP - United Nations Environment Programme

WCMC - World Conservation Monitoring Centre

WPWP - Western Pacific Warm Pool

Chapter 1: Introduction

1.1 Research Context

Coral reefs can be described as a combination of limestone formations and a set of associated living organisms (Kleypas et al. 2001). A square kilometre of coral reef might comprise the reef (limestone), the coral itself (small animals, which belong to the group cnidarian), symbiotic algae known as zooxanthellate, other cnidarians such as jellyfish and sea anemones, molluscs such as oysters and clams, crustaceans like crabs, fungi, sponge, and turtles and reef fishes. These marine organisms not only compete for food and space, but also depend on, and are interconnected with, each other. It is not surprising when this ecosystem, which is located between latitude 30° North to 30° South, is considered to be the most diverse marine habitat in the ocean (Nancy et al. 2010). The coral reefs found today are believed to have grown between 50 to 25 million years ago (Bellwood and Wainwright, 2002; Renema et al. 2008). Coral reefs cover approximately 0.1% of the Earth's surface (Reaka-Kudla, 1997) and are often referred to as the 'rainforest of the sea' due to their enormous biodiversity (variety and variability of species). Coral reef diversity has been estimated at approximately 600,000 to 10 million species (Bouchet, 2006; Nancy et al., 2010). Coral reefs benefit people all over the globe in numerous ways as presented in Figure 1-1.

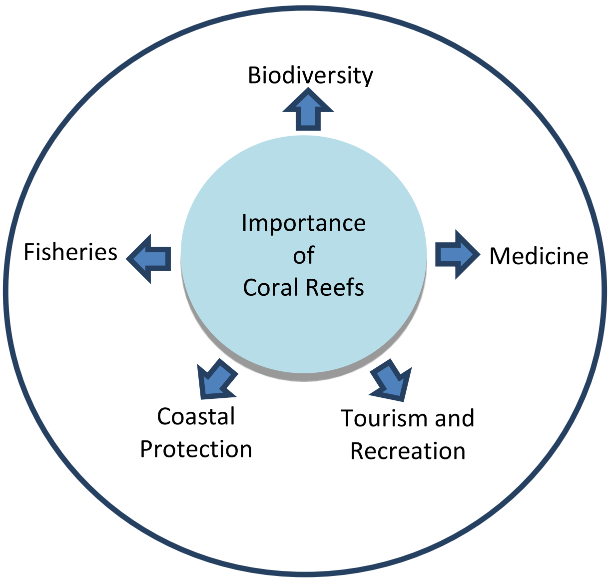


Figure 1-1. A schematic diagram representing the importance of coral reefs to human

In terms of biodiversity values, Cesar et al. (2003) estimated coral reefs (only high tourism potential) to have annual benefits of USD 5,700.00 per km^2. Coral reefs generate approximately

USD 5.5 billion per year. For dense and diverse coral reefs like the Coral Triangle, the total value is estimated at USD 2.3 billion per year (Wilkinson, 2008). Providing a nursery or breeding ground for fishes and other marine animals, the contribution of coral reefs to fisheries is significant. Coral reef fisheries not only provide food to the locals, but also to the world community. Kool et al. (2011) stated that the Coral Triangle (CT) is key to preserving fish stock and marine resources in the Asia-Pacific region. These factors make it a high priority area for conservation (Allen, 2008; Burke et al. 2002).

The existence of coral reefs in coastal waters offers natural barriers for strong waves, currents and storms, helping to reduce their impact on coastal communities. UNEP-WCMC (2006) stated that coral reefs, together with mangroves, absorb at least 70-90% of the wave energy during hurricanes and tropical storms. The contribution of coral reefs to the global tourism and recreation industry is significant. With a value of USD 9.6 billion per year (USD 330 for coral reefs with low potential and USD 56, 000.00 for good tourism potential), their contribution is highly significant (Cesar et al., 2003). Brander et al. (2007) estimated that the individual cost from a tourist for snorkelling, scuba diving, viewing coral reefs are USD 184.00 per visit (based on year 2000 prices).

In the medical field, drugs originating from coral reef ecosystems have been used in various treatments. The first drug synthesized from coral reefs was approved by the United States in 2004 for the treatment of chronic pain (Molinski et al., 2009). It was extracted from a tropical cone snail. In Europe, anti-tumour compounds from sea-squirts were approved by the European Union in 2007 for soft-tissue sarcoma treatment. Other species in coral reefs, such as marine sponges (phylum Porifera), have been recognized as the richest source of pharmacologically active compounds (Sagar et al. 2010) and are used for the treatment of Human Immunodeficiency Virus (HIV) and Herpes Simplex Virus (HSV). The high diversity of coral reefs ecosystems provides a bright future for the exploration of new compounds in the medical field. Although there are concerns about harvesting coral reefs ecosystem for medical usage, recent developments are promising. Compounds found from coral reefs presently can be reproduced in laboratories as shown by Just-Baringo et al. (2013).

Although it has been demonstrated that coral reefs have contributed significantly to humankind, recent evidence suggests that there are serious threats that could harm this fragile ecosystem. Coral bleaching, which is the expelling of coral algae from their tissue due to stressors (changes in water temperature, salinity levels, ultraviolet light etc.) have become more frequent due to climate change (Burke et al., 2012). During a bleaching event, coral reefs might lose 60% to 90% of their algae (Glynn, 1996), leaving a white reef skeleton rather than the normal colourful reef.

While coral bleaching could be caused by many factors such as 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); the major variable that contributes to the degradation of coral reefs ecosystem is in response to the increased of sea surface temperature (SST). Under normal conditions, the optimal sea temperature that supports the life of coral reefs is between 22^{o}C and 28^{o}C (Hubbard, 1997).

Several researchers have reported the significance of warming ocean temperatures towards bleaching events (Hoegh-Guldberg, 1999; Sheppard, 2003; Donner et al. 2005; Donner, 2009). Manzello et al. (2007) identified maximum monthly Sea Surface Temperature (SST) as the major variable contributing to the degradation of coral reefs ecosystems. Halpern et al. (2008), who studied the effect of 17 contributing factors towards 20 marine ecosystems, also reported that SST is the most significant factor that affects marine ecosystems such as coral reefs. These findings were supported by Tittensor et al. (2010), who highlighted using spatial regression analysis, that SST was found to be the only variable that was highly significant to diversity across all 13 major species that were tested. The author further added that the warming oceans might be changing the distribution of marine life. Hoeke et al. (2011) predicted that without the ability to adapt towards warm waters, a decline in coral cover is likely to take place in the 21st century.

Linking climate change to marine ecosystems, Brander (2010) stated that there is now a wealth of evidence supporting the idea that there exists a significant impact of climate change on the distribution, species composition, seasonality, and production of marine ecosystems. Doney et al. (2012), in a recent study reported that climate change alters vulnerable marine ecosystems by changing their species interaction, dispersal patterns, and physiological tolerance to new environments.

Looking back into history, increasing ocean temperatures is not new in itself. Ocean temperatures began to gain public attention after a report by the IPCC (2001) in their Third Assessment Report (TAR). The report projected that global average SST would increase by about 0.2^{0} C per decade for the next two decades, which would cause major changes in the world's ocean and fresh water environments. In their recent report, the IPCC (2007) confirmed without a doubt this warning about ocean surface temperatures.

With the advancement of satellite observation technologies in past decades, marine scientists now have the ability to better understand the ocean from space. Synoptic views using satellite remote sensing can be used to monitor coral reefs and the factors affecting them at various spatial resolutions, even at inaccessible sites. Previous efforts would have required extensive *in situ* measurements.

1.2 Research Problem

The Indo-Pacific Ocean that lies between 30^o North to 30^o South and 30^o East to 90^o West hosts the richest marine ecosystem on Earth. The ecosystem in this region, however, is now critically threatened as a result of the mass coral bleaching event which that has an effect to the warming of the ocean. The Indo-Pacific coral cover has been continuously declining over the years, with the rate of loss that is greater than expected. The association between ocean warming and coral bleaching is not new. It has been discussed and researched intensively, since the mass coral bleaching that occurred as a result of the 1997/1998 El Nino phenomenon. However, extensive studies related to the changes in the sea surface temperature (SST) across specific regions especially in the Indo-Pacific region are less common, yet it is very much important. Considering the size of the region, it is almost impossible to adequately measure SST directly using ships. This is due to it having a sparse distribution at any one time and, such in-situ measurement is labour-intensive and expensive. Plus, the sea condition is dynamic. Satellite sensor imagery in particular of SST, has been used as a major input for modelling and monitoring coral bleaching events.

Until now, the only operational global coral health monitoring is the U.S National Oceanic and Atmospheric Administrations (NOAA) Coral Reef Watch (CRW) programme. Nevertheless, the use of a static threshold for CRW is limited and might not be applicable to be used for refining the bleaching prediction method for the Indo-Pacific region. This is because the mean of the warmest month of each year better characterizes thermal extremes in the equatorial Pacific. In order to overcome the limitations of static thresholding, this study advances the concept of using a logistic regression approach regressing coral bleaching events against Maximum Monthly Mean (MMMmax) (referred to in this thesis as MaxSST). While well distributed bleaching and non-bleaching records from the Reefbase database allowed for logistic regression to be performed, the NOAA Coral Reef Watch (CRW) Degree Heating Week (DHW) were used to calibrate the prediction approach. In addition, a 4 kilometre SST dataset from the latest NOAA programme, CoRTAD; was used and multiscale resolutions were produced and tested to get finer spatial resolution predictions for coral bleaching.

1.3 Aims of the study

The primary aim of this research is to use satellite sensor imagery for the observation of trends in Sea Surface Temperature (SST) and coral bleaching in the Indo-Pacific region. Therefore, the objectives of this work are as follows:

i. To characterise and forecast the spatio-temporal trends in three variables of SST (MaxSST, MinSST and MeanSST) in the Indo-Pacific region.

ii. To examine the relationship of the three SST variables with coral bleaching events in the South China Sea (SCS) and the Coral Triangle (CT).

iii. To model the Coral Bleaching events in the Indo-Pacific region based on satellite sea surface temperature (SST) and available coral bleaching record.

iv. To identify the optimum spatial resolution of SST datasets for coral bleaching modelling in the Indo-Pacific region.

Chapter 2: Thesis structure

This section outlines the thesis, which is structured into eight Chapters. Chapter 1, covers the background of this research, which includes research context, research problem and research aims. Chapter 2 outlines the thesis structure. Chapter 3 describe the study area in terms of its boundary and importance. Chapter 4 describes the theory and literature of Sea Surface Temperature (SST), coral bleaching and logistic regression model. Chapter 5, 6 and 7 are research papers with their own objectives and conclusions that together have been designed to achieve the thesis aims.

Chapter 5 is a research paper entitled Looking back and looking forwards: historical and future trends in sea surface temperature (SST) in the Indo-Pacific region from 1982 to 2100 (Khalil, I., Atkinson, P.M. & Challenor, P., 2016. Looking back and looking forwards: Historical and future trends in sea surface temperature (SST) in the Indo-Pacific region from 1982 to 2100. *International Journal of Applied Earth Observation and Geoinformation*, 45(August), pp.14–26.). Temporal trends in three variables of SST (MaxSST, MinSST and MeanSST) in the Indo-Pacific region were investigated and reported. A key finding was a set of warming trends with various magnitudes observed in the South China Sea and the CT.

After characterising the SST trends in the region, this focus changes to understanding the relationship of the three SST variables with coral bleaching events. This was reported in Chapter 6 by a research paper ‘Region-Specific Modelling and Forecasting of the Effect of Sea Surface Temperature on Coral Bleaching in the Indo-Pacific region’. Coral bleaching records from online Geographical Information System (GIS), SST datasets from NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2 dataset (OISSTv2) and a suitable statistic was used to model the SST-coral bleaching relationship. Logistic regression model revealed a significant relationship between coral bleaching and MaxSST in the region. The coral bleaching probability maps produced based on the logistic model were in close agreement with NOAA Coral Reef Watch (CRW) Bleaching Alert Area maps, although there are some differences that potentially justify the additional local modelling effort.

Chapter 7 attempts to identify the optimum spatial resolution of SST datasets for coral bleaching modelling. 4 km SST weekly data from Coral Reef Temperature Anomaly Database (CoRTAD) were used. 4 km monthly mean MaxSST data were then generated and tested in a logistic model together with the coral bleaching dataset. Multiscale MaxSST with a spatial resolution of 16 km, 32 km, 64 km and 100 km were generated and also tested in the logistic regression model. Results suggest that the optimum spatial resolution for modelling coral bleaching using logistic regression was 4 km MaxSST. Chapter 8, provides a discussion about the importance of this thesis findings, their limitations and future work. Chapter 9 draws the key conclusions of this thesis.

Chapter 3: Literature Review

3.1 Sea Surface Temperature (SST)

Ocean temperature is among the most important physical properties of the marine environment as it influences many of the physical, biological, geological, and chemical aspects of the ocean (Lalli and Parsons, 1997). When coupled with salinity, for example, temperature determines the density of sea water. Temperature controls the rates of many chemical reactions and biological processes within the ocean. Ocean temperature also influences the movement and habitat of many marine organisms (Clarke, 1990; Harvell et al. 2002).

SST is the ocean temperature that approaches the sea surface and is one of the earliest measurements in oceanography, as highlighted by Emery (2003). The author further described that the usage of SST in oceanography studies can be traced back as early as 1786 when Benjamin Franklin used SST to map out the position of the Gulf Stream. Sea water samples were collected at various locations. Their temperatures were measured, and Benjamin Franklin found that there was a flow of warm water in the Gulf Stream that actually flowed north from the West Indies, along the East Coast of North America and east across the Atlantic Ocean to Europe.

Coupled with other factors, SST plays an important role not only in oceanography studies but in environmental modelling as a whole. In the fisheries field, for example, satellite sensor SST and chlorophyll concentration were used to study the pattern of jumbo squid landing in the Gulf of California (Robinson et al. 2013). In biological oceanographic studies, Schwarz et al. (2010) used SST, sea-ice concentration and wind stress to identify the connections between the physical environment and phytoplankton growth. Studying the ocean circulation, Donlon et al. (2009) highlighted SST as an important input for forecasting the upper ocean current.

In a climatological study, O'Carroll et al. (2006) used SST as a robust indicator of climatologic change. Linking the ocean to climate, Alien et al. (1994), using satellite SST, found that 15 years is a sufficient period to start tracking climatic trends in the ocean. In another climatological study, Galbraith et al. (2012) highlighted the used of satellite SST in characterising the air temperature in the Gulf of St. Lawrence from 1982 to 2011.

Traditionally, SST measurements were undertaken using a bucket that was lowered down to collect sea water while a ship was moving. The bucket was dragged through the water until it was full and hoisted back to the ship deck. Temperature was then measured using mercury. With the advancement of technology, faster ships were invented and this method was no longer practical. Sea water is collected using the ship's pipe inlet and temperature is measured using a thermistor. With this method, measurements can be made much faster and can cover a large area in a shorter amount of time. The temperature accuracy of bucket temperature and ship injection temperature is 0.1°C and 0.5°C to 1.0°C, respectively (Emery and Thomson, 2001).

Considering the size of the ocean (70% of the Earth surface), it is impossible to measure SST using ships at each location in the sea at one time, not only because of dynamic sea conditions, but also because *in situ* measurements are labour-intensive and expensive. Due to its capability in offering a wide synoptic view and regular sampling, ocean-viewing sensors offer an alternative approach (Robinson, 2010). McClain et al. (1989) stated that the retrieval of SST from satellite sensor measurements offers the advantage of global coverage and has been performed routinely since 1981 to an accuracy of ~ 0.5 K.

From time to time, satellite SST needs to be validated with *in situ* SST measurements. The accuracy of satellite SST against *in situ* measurement is often reported in terms of the mean error (bias) and scatter (standard deviation). Several *in situ* validation methods are from infrared radiometers mounted on ships (Noyes et al. 2006), fixed platforms, and aircraft (Smith et al. 1994). The absolute accuracy of the infrared radiometers mounted on ships, or Marine-Atmospheric Emitted Radiance Interferometer (M-AERI) are 0.03 K (Minnett et al. 2001). Due to the limitations of ships equipped with infrared radiometer, SST validation from buoys measurement is another alternative method. In one study by O'Carroll et al. (2008), the accuracy of SST when compared to satellite radiometers was a standard deviation error of 0.23 K.

Table 3-1. Uncertainties of in situ SST measurements and SST from several satellite sensors.

Sensors	Mean	St dev	Reference
AVHRR vs. buoys	0.02 K	0.53 K	Kilpatrick et al. (2001)
AVHRR vs. M-AERI	0.14 K	0.36 K	Kearns et al. (2000)
MODIS Terra vs buoys	-0.15 K	0.61 K	Esaias et al. (1998)
MODIS Terra vs M-AERI	0.04 K	0.53 K	Esaias et al. (1998)
MODIS Aqua vs buoys	-0.17 K	0.49 K	Esaias et al. (1998)
MODIS Aqua vs M-AERI	0.00 K	0.56 K	Esaias et al. (1998)
AATSR vs buoys	0.02 K	0.39 K	Corlett et al. (2006)
AATSR vs M-AERI	0.16 K	0.36 K	Noyes et al. (2006)

Notes: AVHRR: Advanced Very High Resolution Radiometer, MODIS: Moderate Resolution Imaging Spectrometer, AATSR: Advanced Along-Track Scanning Radiometer

3.2 SST measurement from satellite sensors

SST from satellite sensors can be obtained from two types of sensors: infrared and microwave as illustrated in Figure 3-1.

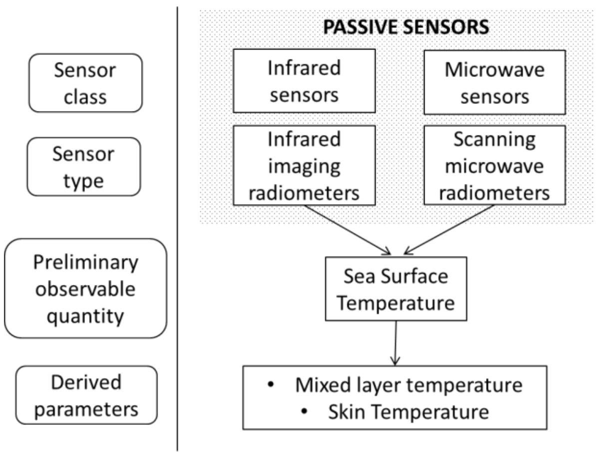


Figure 3-1. A schematic diagram of the prediction of SST from space (after Robinson, 2004)

Both sensors fall under the passive remote sensing category, which means the radiation detected at the sensor is naturally emitted or reflected by an object. Thermal infrared sensors operate between 3.5 µm to 4.1 µm and between 10 µm to 12.5 µm. Passive microwave sensors however, normally operate at a 1 mm to 75 cm wavelength (Schowengerdt, 2006).

SST measurement from satellites is not a straightforward process. The temperature values detected by infrared sensors do not represent true temperature, but the 'brightness temperature'. In order to estimate true temperature from infrared sensors, for example, the radiance measured by radiometers is first converted into brightness temperature using the inverse Plank's radiation equation (Goodrum et al. 2009):

$$T = \frac{c_2\eta}{\ln(1+\frac{C_1\eta^3}{L})} \qquad \text{Equation 3-1}$$

where T = brightness temperature (degrees Kelvin); L = radiance; η = wavenumber for the AVHRR channel (cm^{-1}); c_1 = 1.1910659 x 10^{-5} ($mWm^{-2} sr^{-1} cm^{-4}$) and c_2 = 1.438833 (cm Kelvin).

The brightness temperature can then be converted into actual ocean temperature based on the multi-channel methods developed by McClain et al. (1985):

$$T_s = a_o T_i + a_1 (T_i - T_j) + a_2 \qquad \text{Equation 3-2}$$

where Ts = true temperature, T_i and T_j are brightness temperatures determined from the radiance values in two different infrared window channels i and j; a_0, a_1 and a_2 are obtained by linear regression between pairs of simultaneously measured *in situ* temperatures and satellite sensor radiance.

Recent high-quality satellite infrared radiometers that measure SST are the National Aeronautics and Space Administration's (NASA) Advanced Very High Resolution Radiometer 3 (AVHRR/3) and AVHRR/2; European Space Agency's (ESA) Along-Track Scanning Radiometer (ATSR-1, ATSR-2); ESA Advanced Along-Track Scanning Radiometer (AATSR); NASA Moderate Resolution Imaging Spectrometer (MODIS) and the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Spinning Enhanced Visible and Infrared Imager (SEVIRI). Among all the sensors, AVHRR/2 provides the longest temperature records. The AVHRR/2 was launched in 1981 on the NOAAA-7 satellite. The latest AVHRR sensor is known as AVHRR/3 and was launched in 1998.

The measurement of SST from microwave sensors shares the same basic principle; the measurement of the ocean surface radiance. The microwave brightness temperature of an object is not related directly to its temperature, but to other properties such as surface roughness, the dielectric constant of seawater, and local surface slope. Robinson (2010) simplified the Plank equation to show the relationship between microwave radiance and brightness temperature as follows:

$$B_f = \frac{2kT}{c^2} \qquad \text{Equation 3-3}$$

where B_f = spectral radiance; c = speed of light = 2.9979 x 10^8 ms^{-1}; k = Boltzmann's constant = 1.38 x 10^{-23} J K^{-1}; T = the temperature of the emitter in degrees K.

Although microwave radiometers provide coarser SST spatial resolution compared to infrared radiometers, they have their advantages. Their capability to penetrate clouds offers an alternative method in obtaining SST, especially in cloudy regions like Tropical waters. There is now an increasing trend towards merging infrared SST and microwave SST to provide data with better temporal and spatial resolution (Blackmore et al. 2012; O'Carroll et al. 2012).

The current series of satellite microwave radiometers that measure SST are: NASA/ Japan Aerospace Exploration Agency (JAXA), Tropical Rainfall Measuring Mission (TRMM) Microwave Image (TMI), JAXA/NASA Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E), and United States Department of Defence (U.S. DoD) WindSat. Apart from SST, TMI and AMSR-E also measure wind speed, atmospheric water vapour, cloud liquid water, rain rate and sea ice. WindSat measures only SST, wind speed and direction. The mean and standard deviation of SST from TMI, AMSR-E and Windsat are 0.07 K and 1.11 K (Qiu et al., 2009); -0.06 K and 0.42 K (Peng and Yanchen, 2008); and 0.17 K and 1.12 K, respectively (Meissner and Wentz, 2006).

The standard definition of satellite SST has long been debated. Corlett (2013), from The Group for High Resolution Sea Surface Temperature (GHRSST) highlighted the difficulty of defining SST. This is due to the fact that the upper ocean is very dynamic. The air-sea interaction at a very thin layer of surface water, turbulence, and mixing of sea water at certain depths, and diurnal warming are processes that limit attempts to produce a single definition of SST. At the moment, GHRSST defines SST into several categories as shown in Figure 3-2.

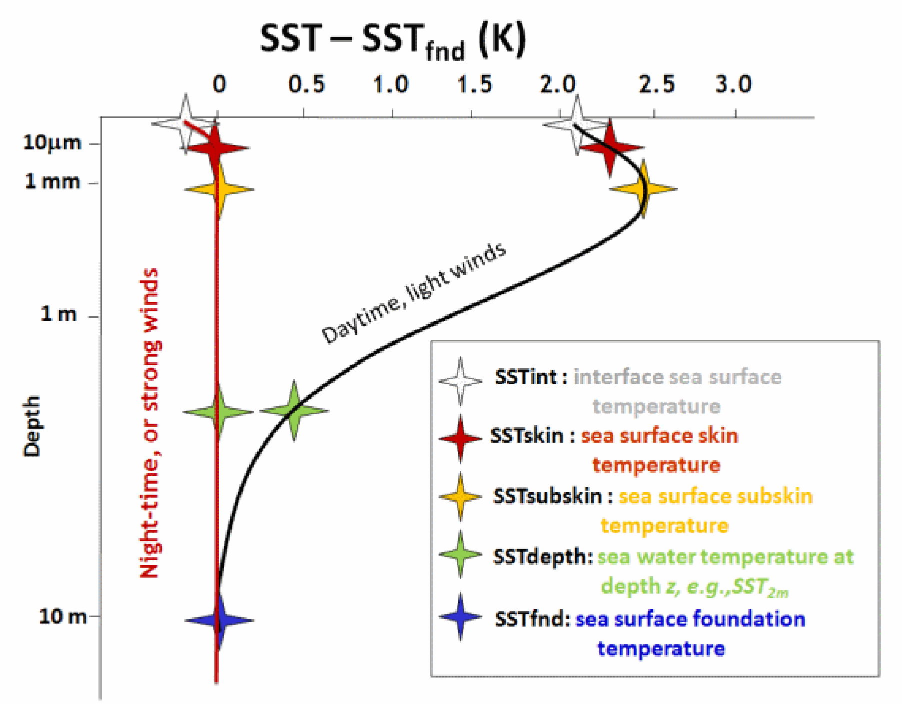


Figure 3-2. SST definition based on depth profile (Corlett, 2013)

Interface Temperature (SSTint) is the temperature at the exact air-sea interface and has no practical use because it cannot be measured. The Skin Sea Surface Temperature (SSTskin) is defined as the temperature measured by satellite sensors (infrared radiometer). The Subskin Sea Surface Temperature (SSTsub-skin) is the temperature at approximately a depth of 1 mm and is detected by microwave radiometers that operate in the 6-11 GHz frequency range. All SSTs below the SSTsub-skin can be called SSTdepth. This includes SST measured from drifting buoys, vertical profiling floats etc. Donlon et al. (2007) attempted to report the depth at which SST was obtained (*Tz*). The last category is the Foundation Temperature (SSTfnd), which is the temperature that is free from diurnal warming. In the absence of diurnal warming, SSTfnd is considered equivalent to SSTsub-skin.

The SST definition by GHRSST is quite similar to that of Donlon et al. (2002), except no definition of SSTfnd was included. The SST definition by Donlon et al. (2002) appears in Figure 3-3.

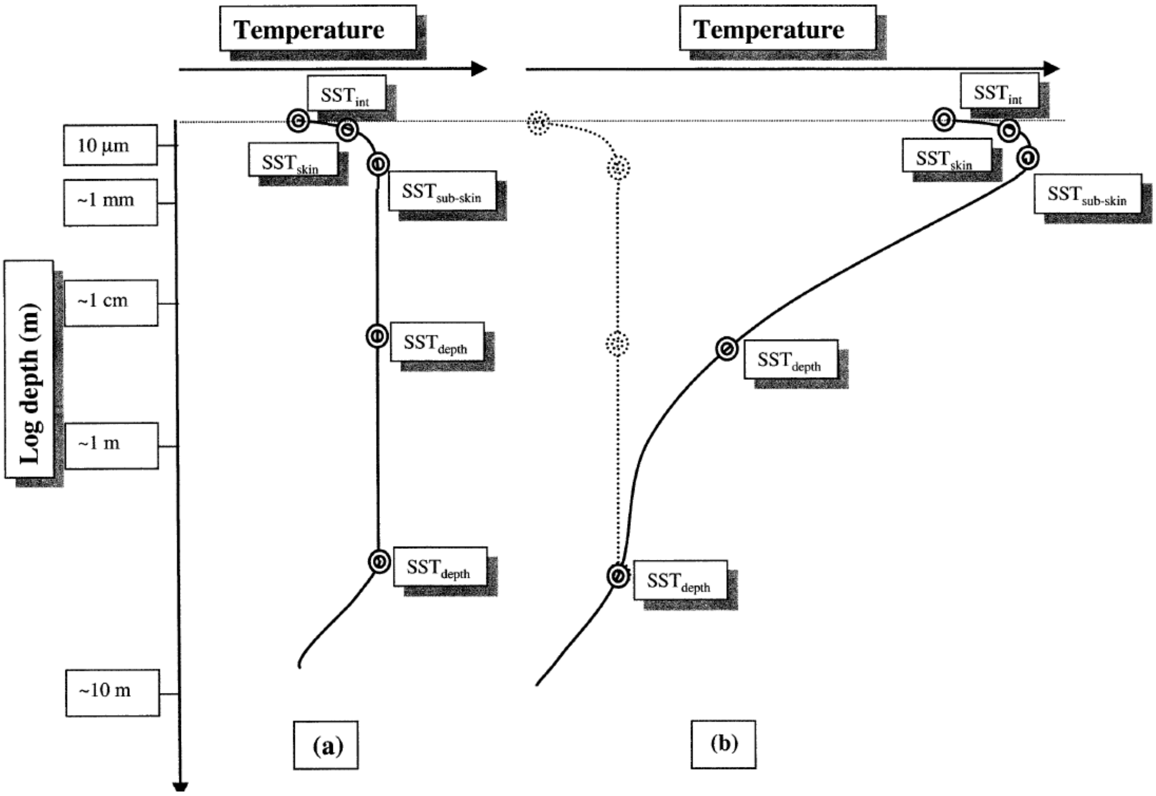


Figure 3-3. Temperature profiles for an ocean water column. (a) during night-time and daytime during strong wind conditions and (b) daytime low–wind speed conditions and high insolation resulting in thermal stratification of the surface layers (Donlon et al. 2002).

Donlon et al. (2002) defined Interface SST (SSTint) as the temperature at the very top of the ocean, sometimes also referred to as the air-sea thin layer temperature. SSTskin was defined as water temperature up to 500 µm from the ocean surface. Just below the SSTskin, there is a water body that plays an important role in heat transfer process, which is known as Subskin SST (SSTsubskin). The last category of SST is the subsurface SST (SSTdepth), also known as 'bulk' SST.

3.3 Coral reefs and coral bleaching

Hatcher (1997) defines a coral reef as "…a marine limestone structure built by calcium-carbonate secreting organisms, which, with its associated water volumes supports a diverse community of predominantly tropical affinities, at a higher density of biomass than the surrounding ocean…". In a more modern definition, Done (in Hopley, 2011) defines coral reefs as “[a] tract of corals growing on a massive, wave resistant structure and associated sediments, substantially built by skeletons of successive generations of corals and other calcareous reef-biota.” Geologists usually refer to reefs as rock formations while biologists define coral reefs as a complex ecosystem that consists of living organisms (Veron in (Hopley, 2011).

Coral reefs constitute the most diverse and the oldest ecosystem on Earth (Porter and Tougas (2001). Falling under Cnidaria phylum, these marine invertebrates create a unique symbiotic relationship with microscopic algae, zooxanthellae, which live within their tissues (Muscatine, 1990). In return for a ‘home’ to live, the algae provide food in terms of organic matter to their host.

Under extreme conditions such as changes in light intensity and exposure time (Fitt et al. 2001), decreased salinity (Coles and Jokiel, 1992), increased sedimentation, and decreased water quality (Dollar and Grigg, 1981) corals eject some or all of their algae, leading to a scenario called coral bleaching. Figure 5 illustrates the coral bleaching framework by Douglas (2003).

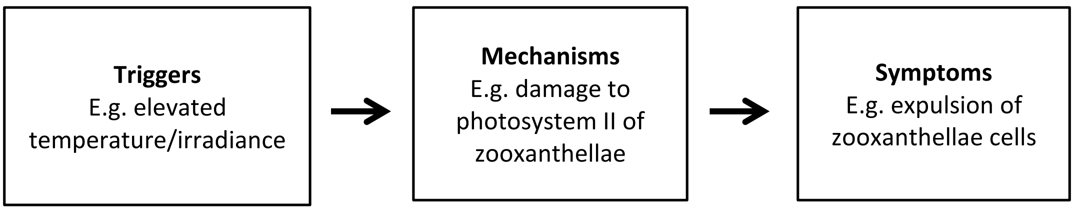


Figure 3-4. Coral bleaching framework (after Douglas, 2003)

According to Burkepile and Hay (2008), although the symbiotic relationship can be recovered after weeks or months, the efficiency of calcification will not be the same as before. Not only that, their efficiency in reproduction, growth, and disease resistance decreases (Hoegh-Guldberg, 1999; Douglas, 2003).

For the last decade, although other stressors for coral bleaching exist, mass bleaching caused by increases in temperature has been of significant interest to researchers (Sheppard, 2003; Donner et al. 2005; Hoegh-Guldberg et al. 2007; Donner, 2009). Many earlier studies (Glynn, 1993; Brown, 1997; Winter et al. 1998) relate bleaching to the warming of the ocean. Coral bleaching in this study refers to a situation where coral loses its colour due to the degradation of algal pigments in response to increased ocean temperature. In day to day operations, coral bleaching is initiated by thermal conditions as little as 1^0C higher than the climatological maximum for a month (Donner, 2011).

3.4 Coral bleaching prediction using SST

Several methods are used in forecasting coral bleaching from SST. In an early work by Strong et al. (1997), the author produced a satellite SST climatology to predict bleaching events. A SST dataset was obtained from NOAA AVHRR. Bleaching events were predicted when the SST was greater than 1^0C above the highest monthly mean value. Applying a similar fixed threshold temperature technique, Hoegh-Guldberg (1999) was able to model bleaching events for seven different sites. Different thermal threshold values from 28.3 ^0C to 30.2 ^0C were applied based on historical records. The author developed coral bleaching predictions using a modelled SST from Global Circulation Models (GCM).

Berkelmans (2002) provided an in-depth analysis of the most important environmental variables for bleaching predictions: temperature, wind speed, solar radiation, and barometric pressure. Using 10 to 12 years of data, temperature was found to be the most significant variable. A time-temperature curve was created for bleaching predictions. Time was represented by cumulative days from December to March each year. Bleaching was predicted when the warmest average temperature coincided with the cumulative curve.

Using an index called Degree Heating Weeks (DHW), Gleeson and Strong (1995) found that, apart from the temperature intensity, the duration that the coral was exposed to warm water was an additional variable that can also be used to predict bleaching. This study was among the early studies that led to the development of the U.S. National Oceanic and Atmospheric Administration (NOAA)'s Coral Reef Watch (CRW) Programme. It was experimental in 1997, and a monitoring tool known as Hotspots (SST anomaly) was used to monitor coral bleaching around the globe. In 2000, a thermal stress index called DHW was introduced in CRW. Together with Hotspots, it was tested and became operational in 2003. DHW for a single pixel is a cumulative thermal stress value over 12 weeks (Liu et al., 2003). One week of Hotspot with a value staying at 1^0C is considered as a DHW. Significant coral bleaching is likely when DHW reaches 4°C-weeks and mass bleaching when DHW reaches 8°C-weeks. The bleaching information was disseminated to coral reef managers, scientists and the public (Liu et al. 2006; Strong et al. 2011). This coral bleaching monitoring system is the only operational global-scale monitoring system used successfully for the monitoring and reporting of bleaching events (Skirving et al. 2006).

As stated earlier in this section, Hoegh-Guldberg (1999) was among the early researchers that used General Circulation Models (GCM) to predict coral bleaching. As older generations of GCMs were used in the study, the spatial resolution of the models varied from $2.8\,^{0}$ x 2.8^{0} latitude-longitude to 5.6^{0} to 5.6^{0} latitude-longitudes. To improve bleaching predictions, Sheppard (2003) combined the historical SST data from the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST1) dataset (Sheppard and Rayner, 2002) with SST from 1950-2099 from the Hadley Centre Coupled Model, version 3 (HadCM3). This time the GCM's spatial resolution was improved from the HadISST1 pixels spatial resolution of 2.5^{0} x 3.75^{0} to 1^{0} for HadCM3. In the study, it was reported that coral reefs located $10\text{-}15^{0}$ south of the Indian Ocean would be affected by coral bleaching every 5 years from 2010-2025.

Using a modified thermal stress index from DHW, Donner et al. (2005) reported that coral bleaching could become an annual or biannual event for the majority of the world's coral reefs in the next 30-50 years. The SST datasets were obtained from the Parallel Climate Model (PCM) of the National Centre for Atmospheric Research (NCAR) and HadCM3. The new index, which is the Degree Heating Month (DHM), was found to be a reasonable proxy for DHW. It agreed with the 68% of bleaching events predicted by DHW from 1985 to 2002. In overall performance, it predicted 8% greater total bleaching events.

Testing several greenhouse scenarios in the Eastern Caribbean, Donner et al. (2007) used GCM to simulate SST from 1870 to 2100. Geophysical Fluid Dynamics Laboratory (GFDL) climate models CM2.0 and CM2.1 were used in the study. The Hadley Centre (U.K. Met. Office) global Sea-ice and Sea-surface Temperature dataset (HadISST) was used for comparison. A long-term SST trend was detected; HadISST data (0.34°C per century); CM2.0 (0.42°C per century) and CM2.1 (0.54°C per century). Under the business-as-usual future emission scenario, the work predicted that the mass bleaching of the Eastern Caribbean in 2005 could occur biannually in 20-30 years.

Looking at the recent literature (Hooidonk et al., 2013), there is a tendency for climate models with satellite SST to become a major source of SST in the future for predicting coral bleaching. It is hoped that the latest initiative in climate modelling, namely the Coupled Model Intercomparison Project Phase 5 (CMIP5), could provide an improved SST model.

One major issue in coral bleaching predictions is accuracy assessment. Despite increased trends of coral bleaching forecasting using various sources of SST (e.g. when different climate models arise), little effort has been done to quantify prediction quality. Quality assessment is either qualitative or subjective. Hooidonk and Huber (2009) highlighted that only 10 out of 57 articles that predicted coral bleaching reported their prediction quality. Furthermore, only 3 out of those 10 articles reported quality in quantitative terms. The author then used the Peirce Skill Score (PSS) technique created by Peirce (1884) to quantify coral bleaching predictions. PSS is a skill score that ranges from -1 to 1 and can be written as:

$$PSS = H - F \qquad \text{Equation 3-4}$$

where H = Hit rate, F = false alarm rate.

Hit rate, H and false alarm rate, F can further be written as $H = a/(a+c)$ and $F = b/(b+d)$, where, a = correct forecast, b = false forecast, c = bleaching events not forecast and d= correctly predicted non bleaching events.

3.5 Logistic regression for predicting coral bleaching

Logistic regression is a common method used to fit the relationship of a binary dependent variable to one or more covariates (Quinn and Keough, 2002). This type of regression analysis, which is a sigmoidal shape model, has been used widely over the last two decades (Oommen et al., 2011). Proposed in the late 1960s (Cabrera, 1994), logistic regression has been used in various applications including, but not limited to, assessment of landslide susceptibility (Atkinson and Massari, 1998; Yilmaz, 2009; Park et al. 2013; Wang et al. 2013), wildfire risk prediction (Hoyo et al. 2011; Cao et al. 2013) and medical science (Staskiewicz et al. 2013; Zhang et al. 2013).

The usage of logistic regression in coral bleaching predictions is limited. A search of the ISI Web of Knowledge reveals that only 2 papers have been published in which "coral bleaching logistic regression" was a the key word. Further searching revealed that logistic regression was used in certain aspects of their research (Berkelmans et al. 2004; Manzello et al. 2007; Pandolfi et al. 2011; De'ath et al., 2012).

3.5.1 Logistic model and parameters

In logistic regression, the log odds of the outcome are modelled as a linear combination of the predictor variables.

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

where x are independent variables, p is the probability of presence of the characteristic of interest. $\beta_0, \beta_1, \ldots, b_k$ are model parameters.

The logit transformation is defined as the log odds:

$$odds = \frac{p}{1-p} = \frac{probability\ of\ presence\ of\ characteristics}{probability\ of\ absence\ of\ characteristics}$$

and $$logit(p) = ln(\frac{p}{1-p})$$

The logit (p) can be back-transformed to probability, p by the following formula:

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

The null hypotheses for logistic regression, H_0 is that $\beta_1 = 0$ which means that, there is no relationship between the binary variable and the predictor variable. The usual method of testing H_0 is by the use of a Wald or likelihood ratio statistic as stated by Quinn and Keough (2002).

To assess the overall model fit, several available tests are the Hosmer–Lemeshow test (Hosmer and Lemesbow, 1980), McFadden pseudo r-squared (McFadden, 1974), Cox and Snell pseudo r-squared (Cox and Snell, 1989), Nagelkerke pseudo r-squared (Nagelkerke, 1991) and Akaike's Information

Criterion (AIC) (Akaike, 1973).

Logistic regression is bound by certain assumptions that limit its usage as described by (Burns and Burns, 2008) and (Reed and Wu, 2013). Some assumptions are, rather than a linear relationship between the dependent and independent variables, logistic regression represents the logit mapping of the outcome on the predictor variables. Another assumption is that the independent variables are not necessary normally distributed.

The characterisation of seasonal and inter-annual variability in SST is important in coral bleaching prediction (Hooidonk and Huber, 2012). In the study, the authors highlighted the influence of the SST annual cycle towards increasing predictive skill. There is a need to understand such variability in line with coral bleaching modelling.

Literature on spatio-temporal SST variability in the study area is limited. Most of the literature is focused on the global scale, and this represents potentially an important gap. Peñaflor et al.(2009) used a 0.5^0 resolution, biweekly SST data from the National Oceanic and Atmospheric Administration’s (NOAA)-Coral Reef Watch (CRW). SST trends were obtained from fitting a linear regression to the 22-year data using geospatial clustering techniques. An overall warming trend of 0.2^0C was detected during this period. However, a detailed investigation revealed that the northern and eastern parts of the CT were facing significant temperature increases compared to other areas.

Further research conducted with much finer spatial resolution SST data was done by Selig et al. (2010). The SST anomalies for 21 years were produced from 4 km SST Pathfinder Version 5.0 data from the Advanced Very High Resolution Radiometer (AVHRR) sensor. The new dataset was called the National Oceanic and Atmospheric Administration's (NOAA) National Oceanographic Data Center (NODC) Coral Reef Temperature Anomaly Database (CoRTAD) Version 1.0. At the moment, this dataset has the finest spatial resolution of any available dataset, and covers the longest time period. The median spatial filter and Piecewise Cubic Hermite Interpolation were used to fill in the SST data gaps. Further climatology pattern was created using a harmonic analysis procedure as follows:

$$SST(t)_{clim} = A\cos(2\pi t + B) + C\cos(4\pi t + D) + E$$

where *t* is time, *A* and *B* are coefficients representing the annual phase and amplitude, *C* and *D* are the semi-annual phase and amplitude and *E* is the long-term temperature mean.

A few other studies in this region focused on a much smaller area. Iskandar (2010) studied SST patterns of the Banda Sea, a sub-area of the CT using monthly SST AVHRR data from January 1985 to December 2007. The Self-Organizing Map (SOM), a type of unsupervised Artificial Neural Network (ANN), was used to study seasonal and inter-annual SST patterns. One interesting finding was that a low SST was observed during El-Nino and a high SST was observed during La Nina. The movement of ocean currents is believed to contribute to this phenomenon.

Chapter 4: The Study Area

The study area lies approximately between Latitudes 16.5^0 South to 26.5^0 North and Longitudes 96.5^0 East to 165.5^0 East as shown in Figure 4-1. Two main water bodies, the South China Sea (SCS) and the CT (CT), were selected for study based on their importance to marine ecosystems. Saha (2010) classified this region as a Maritime Continent.

Being at the centre of monsoon circulations between the Indian and the Pacific oceans, it experiences mostly warm and humid water throughout the year. Two main monsoon systems are the North East (NE) monsoon (October to February) and the South West (SW) monsoon (June and September). The main ocean current systems that flow to and from this region are the Indonesian, South Equatorial, North Equatorial, Equatorial Counter, and Kuroshio. The Intertropical Convergence Zone (ITCZ) which lies between 10^0 North and 10^0 South of the equator moves northward and southward depending on the Sun's location.

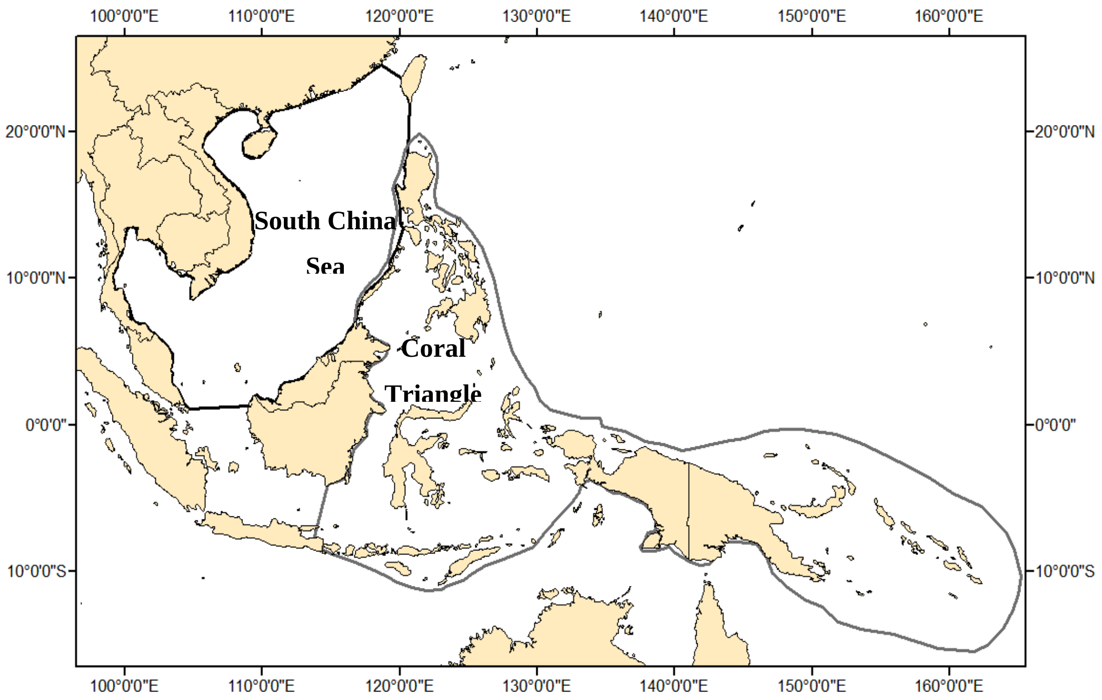


Figure 4-1: Study area

4.1 The South China Sea

The South China Sea (SCS) is the largest marginal sea of the world with an area of approximately 3.5×106 km^2 (Jilan, 2004). It is connected to the Western Philippine Sea (WPS) through the Luzon Strait. The exchange of cool water from the Pacific ocean into SCS through the Luzon Strait was discovered by Wyrtki (1961). The cool water travels across the SCS and leaves as a warm current through the Karimata Strait to enter the CT region (Qu et al., 2006). There is also a warm current that flows out from SCS into the Sulu Sea through the Mindoro Strait. A detailed ocean current diagram appears in Figure 4-2.

While the behaviour of deep water currents in this region is complex, the surface current is normally influenced by monsoonal winds as shown in Figure 4-3 (Hu et al., 2000). During the winter, the wind blows in a southwestern direction. Due to Ekman transport, the top layer (0-5 m) will shift westward. The situation reverses in the summer.

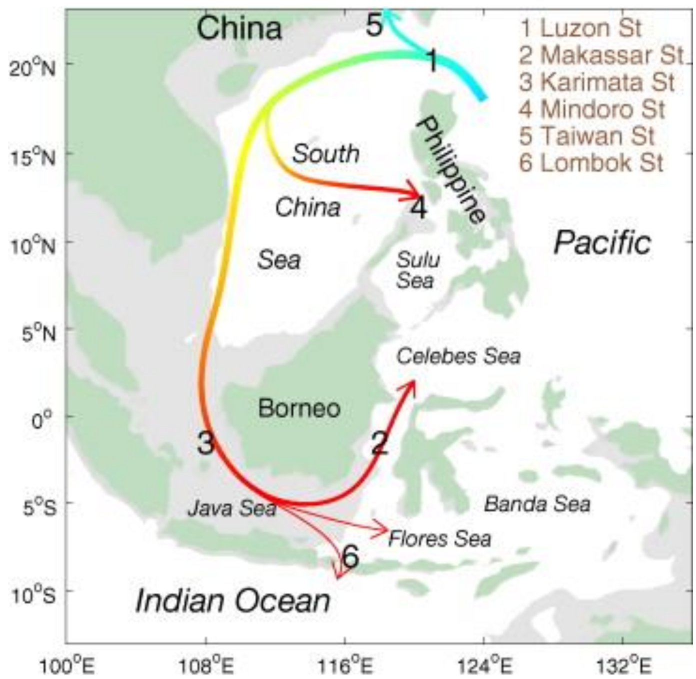


Figure 4-2. A schematic diagram of the South China Sea through flow (Qu et al., 2009)

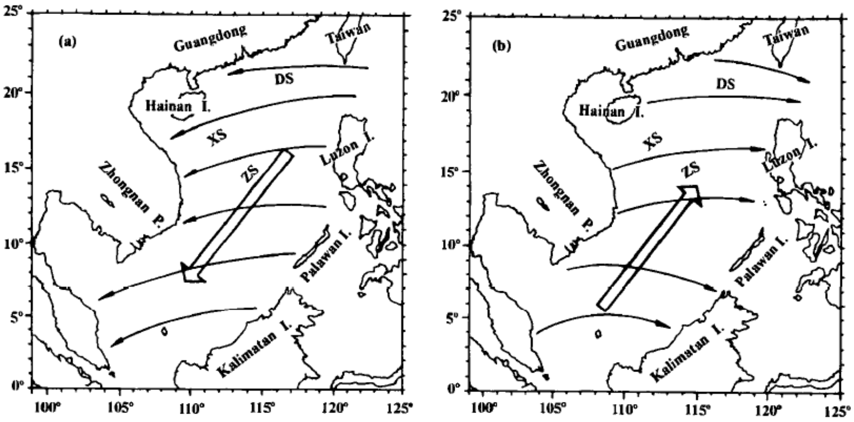


Figure 4-3. The overall seasonal ocean current pattern in SCS. White arrow shows the wind direction and black arrows, the top layer ocean current (Hu et al., 2000)

4.2 The Coral Triangle

The unique ecosystem of the Coral Triangle encompasses six countries: Indonesia, the Philippines, Malaysia, Papua New Guinea, Solomon Islands and Timor Leste. It is considered to be the richest ecosystem on Earth (Allen and Werner, 2002). This region supports the livelihood of 100 million people (Hoegh-Guldberg et al., 2009). McLeod et al. (2010) estimated the economic value of coral reef fisheries for the six countries in this region to be US$2.3 billion per annum. Veron et al. (2009) used the Coral Geographic spatial database to delineate sixteen ecoregions in the Coral Triangle based on the species richness of zooxanthellate corals as shown in Figure 4-4. Each ecoregion has more than 500 coral species and represents 76% of the world's total species.

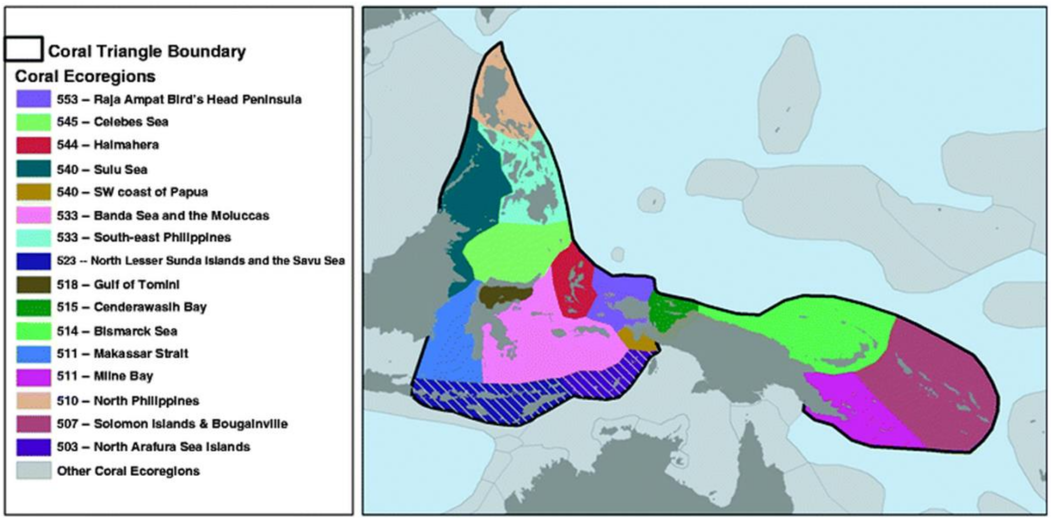


Figure 4-4. Ecoregions and species richness of zooxanthellate corals (Veron et al., 2009)

Chapter 5: Looking back and looking forwards: historical and future trends in sea surface temperature (SST) in the Indo-Pacific region from 1982 to 2100

Khalil, I., Atkinson, P.M. & Challenor, P., 2016. Looking back and looking forwards: Historical and future trends in sea surface temperature (SST) in the Indo-Pacific region from 1982 to 2100. *International Journal of Applied Earth Observation and Geoinformation*, 45(August), pp.14–26.).

5.1 Abstract

The ocean warming trend is a well-known global phenomenon. As early as 2001, and then reiterated in 2007, the Intergovernmental Panel on Climate Change (IPCC) reported that the global average sea surface temperature (SST) will increase by about 0.2˚C per decade. To date, however, only a limited number of studies have been published reporting the spatio-temporal trends in SST in the Indo-Pacific region, one the richest marine ecosystems on Earth. In this research, the monthly 1˚ spatial resolution NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2 dataset (OISSTv2) derived from measurements made by the Advanced Very High Resolution Radiometer (AVHRR) and *in situ* measurements, were used to examine the spatio-temporal trends in SST in the region. The multi-model mean SST from the Representative Concentration Pathways (RCP2.6) mitigation scenario of the Coupled Model Intercomparison Project Phase 5 (CMIP5) was also used to forecast *future* SST from 2020 to 2100, decadally. Three variables from the OISSTv2, namely maximum (MaxSST), mean (MeanSST) and minimum (MinSST) monthly mean SST, were regressed against time measured in months from 1982 to 2010 using linear regression. Results revealed warming trends detected for all three SST variables. In the Coral Triangle (CT) a warming trend with a rate of 0.013 ˚C yr^{-1}, 0.017 ˚C yr^{-1}, and 0.019 ˚C yr^{-1} was detected over 29 years for MaxSST, MeanSST and MinSST, respectively. In the South China Sea (SCS), the warming rate was 0.011 °C yr^{-1}, (MaxSST), 0.012 °C yr^{-1} (MeanSST) and 0.015 °C yr^{-1} (MinSST) over 29 years. The CMIP5 RCP2.6 forecast suggested a future warming rate to 2100 of 0.004˚C yr^{-1} for both areas, and for all three SST variables. The warming trends reported in this study provide useful insights for improved marine-related management.

Key words — SST, space-time, Coral Triangle, South China Sea

5.2 Introduction

Ocean temperature is among the most important physical properties of the marine environment as it influences many physical, biological, geological and chemical aspects of the ocean (Lalli and Parsons, 1997). Temperature plays an important role in changing sea water properties and controls the rates of many chemical reactions and biological processes within the ocean. Coupled with salinity, for example, an increase in ocean temperature increases the space between water molecules and reduces the density of water which can affect many bio-chemical processes. Ocean temperature also influences the movement and habitat of many marine organisms (Clarke, 1990; Harvell et al. 2002).

Sea surface temperature (SST), the temperature of the ocean close to the sea surface, is one of the earliest measured properties in oceanography, as highlighted by Emery (2003). Today, coupled with other factors, SST plays an important role in environmental and oceanographic modelling. In the fisheries field, for example, satellite-based SST and chlorophyll concentration were used to study the pattern of jumbo squid landing in the Gulf of California (Robinson et al. 2013). In biological oceanographic studies, Schwarz et al. (2010) used SST, sea-ice concentration and wind stress to identify the connections between the physical environment and phytoplankton growth. Studying ocean circulation, Donlon et al. (2009) highlighted SST as an important input for forecasting the upper ocean current. In a climatological studies, O'Carroll et al. (2006) used SST as a robust indicator of climatological change, while Alien et al. (1994), in an early study, used 15 years of satellite-based SST to identify climatic trends in the ocean.

Research into changes in SST are crucial in the Indo-Pacific region which hosts the richest marine ecosystem on Earth. The Coral Triangle (CT), which is at the heart of the region, is reported as the main habitat for 76% of the world's reef-building coral species, and 37% of the world's coral reef fish species (Eakin, 2015; Hoegh-Guldberg et al. 2009; Veron et al., 2009). This region, however, is now threatened by ocean warming (GCRMN, 2010; Yeemin et al. 2010, Yeemin et al. 2012). Bruno and Selig (2007) reported that the Indo-Pacific coral cover is declining at a rate of 1% per year and the rate of loss is greater than previously expected. The impact of increasing temperature on coral reefs in the study area was also highlighted by Carpenter et al. (2008) who revealed that amongst the world's coral reefs, the coral zooxanthellate in the Coral Triangle has the top ranking of extinction risk due to climate change. This statement was also supported by McLeod et al. (2010) who suggested that changes in SST are threatening the corals in the Indo-Pacific. Burke et al. (2012)

highlighted that the combination of warming SST together with other local threats (overfishing, pollution etc.) may increase the percentage of reefs threatened to more than 90%, which is greater that the global average of 75%.

Thus, there is a need to understand the spatio-temporal pattern of SST in the Indo-Pacific region as it has an important potential impact on coral reef health. Considering the size of the region, it is almost impossible to measure adequately SST directly using ships, which inevitably have a sparse distribution at any one time and such in situ measurement is labour-intensive and expensive. In addition, the sea condition is dynamic. Due to their wide synoptic view and regular sampling capability, ocean-viewing sensors offer an alternative approach (Robinson, 2010). McClain et al. (1989) stated that the retrieval of SST from satellite sensor measurements offers the advantage of global coverage and has been performed routinely since 1981 to an accuracy of ~ 0.5 K. In the past, satellite sensors were used to measure radiance and SST was calculated by investigators (McClain et al. 1985; Reynolds, 1988; Donlon et al. 2009; Reynolds and Chelton, 2010). Now, sensors such as the National Aeronautics and Space Administration's (NASA) Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS), and the European Space Agency's (ESA) Along Track Scanning Radiometer (ATSR) provide daily-to-monthly SST data available for download.

Past SST studies have demonstrated that warming trends occur on a global scale (IPCC, 2007; IPCC 2001; Levitus et al. 2005; Casey and Cornillon, 2001). It is, however, well known that ocean warming is not uniform (Rayner et al. 2003; Levitus et al. 2000; Lin et al. 2013). Quantifying the warming (or potentially cooling) rate for a particular area in the Indo-Pacific would be potentially valuable for decision-makers. To date, however, little attention has been devoted to characterising the space-time patterns in SST from satellite sensor data in the area. The only comprehensive study done was by Penaflor (2009) who reported SST trends in the CT from 1985 to 2006.

Using similar methods to Penaflor (2009), this study used linear regression techniques to capture the trends and expand the time period from 1982 to 2010. Specifically, this paper's first goal was to look for possible trends in SST and quantify the magnitude of changes in the Indo-Pacific Ocean over the last 29 years. The second goal of this paper was to forecast possible trends until the year 2100. Both goals should provide valuable information for future marine management.

5.3 Methods

5.3.1 Study site and data

The study area covers the South China Sea (SCS) and the Coral Triangle (CT) (Figure 5-1), a section of the Indo-Pacific region between Latitudes 16.5^0 South to 26.5^0 North and Longitudes 96.5^0 East to 165.5^0 East. This region is subject to a monsoon-type climate, and is mostly warm and humid, throughout the whole year (Saha, 2010). The North East monsoon and South West monsoon typically occur between October to February and June to September, respectively. The cool current from the Pacific Ocean travels across the SCS and leaves as a warm current through the Karimata Strait to enter the CT (Qu et al., 2009). While the region exhibits complex deep water current behaviour, the surface current is normally influenced by monsoonal winds (Hu et al. 2000).

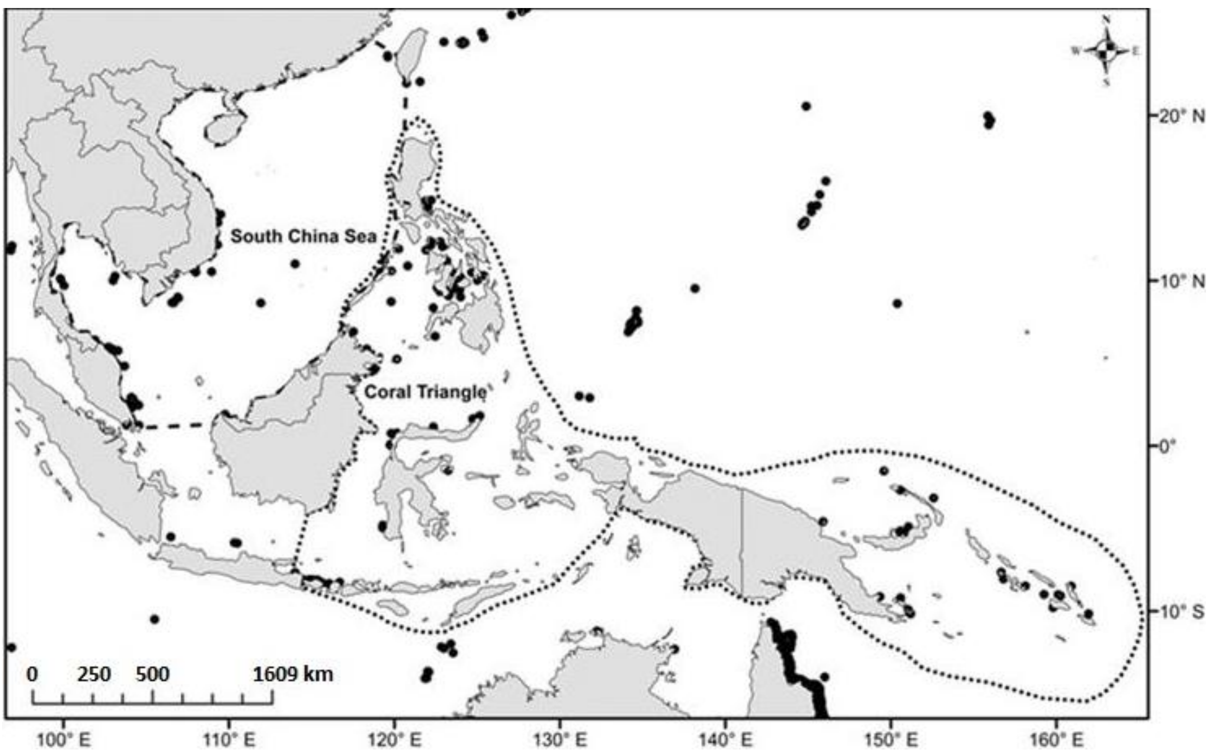


Figure 5-1. Map showing the spatial boundary of the South China Sea and Coral Triangle.

5.3.1.1 SST data

SST data, specifically the Optimum Interpolation SST V2 (OISSTv2), was obtained from the NOAA Earth System Research Laboratory (www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.html). The OISSTv2 is based on merging satellite sensor (AVHRR) SST data with in situ measurements from ships and buoys which form parts of the International Comprehensive Ocean–Atmosphere Data Set (ICOADS). The monthly datasets that wereused, with a bias of -0.03^{0}C, were produced by NOAA using a linear interpolation of their weekly and optimum interpolation data (Reynolds et al., 2002). 29-years of OISSTv2 datasets were acquired and provided as 360 columns by 180 rows in the World Geodetic System (WGS) projection. A total of 348 time-series images from January 1982 to December 2010 were then converted into a manageable format for processing.

5.3.1.2 Climate model datasets

Forecasts of historic and future SST were obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) under the Representative Concentration Pathway RCP2.6, which itself is built from 22 climate models (Table 5-1). The data were made available by the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer (http://climexp.knmi.nl/CMIP5/monthly/tos/index.cgi). Using the study area as the model boundary, the multi-model mean SST was simulated from 1861 to 2100. A total of 2880 global monthly CMIP5 mean SST forecasts were downloaded and analysed.

Table 5-1. List of the 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

5.3.2 Data pre-processing

348 global monthly OISSTv2 images (360 columns x 180 rows) were sub-setted to Latitudes 16.5^0 South to 26.5^0 North and Longitudes 96.5^0 East to 165.5^0 East, defining the spatial boundary. The annual maximum, minimum, and mean monthly mean SST values were then calculated for each pixel of the sub-setted data. A masking procedure was applied to the SCS and CT for further analysis. The SCS and CT images were represented by 271 pixels and 535 pixels, respectively. Based on these pixels, SST trend analysis was conducted.

The same sub-setting procedure was applied to the CMIP5 dataset to produce SST data with 52 columns and 37 rows, with a spatial resolution of 1°. The masking procedure was again applied to limit the analysis to the SCS (220 pixels) and CT (477 pixels). Before further analysis was conducted, the data were converted from Kelvin to Celsius.

5.3.3 Methods

To characterise any long-term trends in SST and to estimate their significance, linear regression was applied. The structural ordinary least squares linear regression can be written as :

$$E(Y \mid x) = \beta_0 + \beta_1 x$$

Where x is time and Y is SST. The slope coefficient, β_1 , is the rate of change per time step. For the OISSTv2 dataset, the time step is 29 years (1982 until 2010) and for CMIP5, the time step is 9 decades (2010 until 2100). The *p*-value represents the probability of obtaining the results observed given that the null hypothesis, H_0, is true, which in this study is defined as $H_0: \beta_1 = 0$. In simple terms, H_0 means that there is no change of temperature over the time period.

Pixel-by-pixel linear regression was conducted for each site (SCS and CT) using the OISSTv2 data from 1982 to 2010. Spatial maps were then plotted to show the exact location of the warming (and any cooling) trends during the 29-year time period. The significance maps (the *p*-value) were also plotted and reported. The same procedure was repeated for the MaxSST CMIP5 dataset. However, instead of using an annual time-step a decadal timestep was chosen. A flowchart illustrating the methodology used is shown in Figure 5-2.

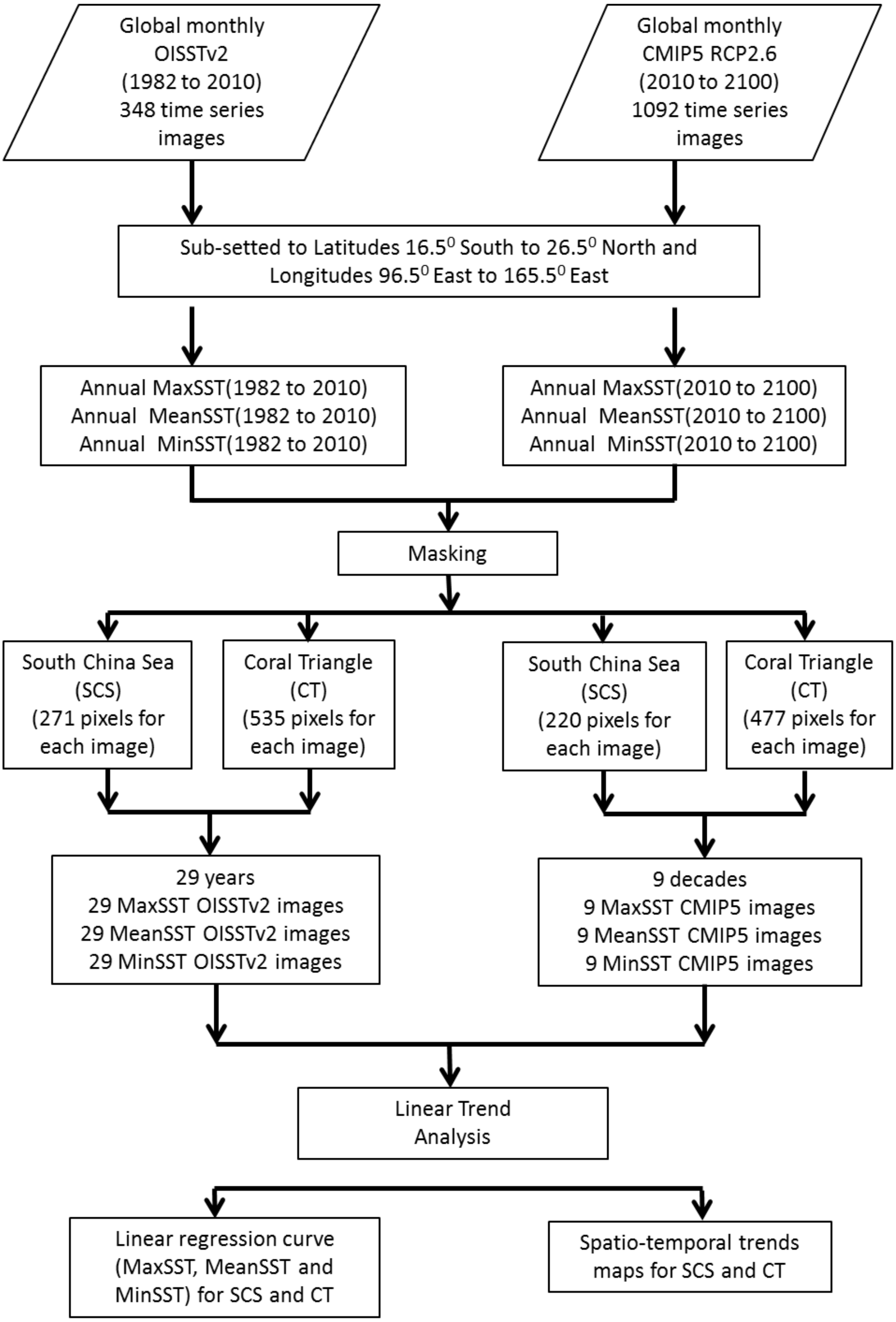


Figure 5-2. Flowchart illustrating the applied methodology.

5.4 Results

The long-term trends (i.e., regression slopes) in the averages for the maximum, mean and minimum SST from 1982 to 2010 are shown for the SCS (Figure 5-3) and CT (Figure 5-4). In general, an upward trend was detected for all three SST variables (maximum, minimum, mean) in both areas from 1982 to 2010. The SCS, however, exhibited a lower warming rate than the CT. During the 29-years, the CT experienced a warming trend of 0.013 °C yr^{-1}, 0.017 °C yr^{-1}, and 0.019 °C yr^{-1} over 29 years for MaxSST, MeanSST and MinSST, respectively. In the SCS, the warming rate was 0.011 °C yr^{-1}, (MaxSST), 0.012 °C yr^{-1} (MeanSST) and 0.015 °C yr^{-1} (MinSST) over 29 years. The CMIP5 RCP2.6 forecast suggested a warming rate to 2100 of 0.004°C yr^{-1} to 0.006°C yr^{-1} for both areas, and for all three SST variables.

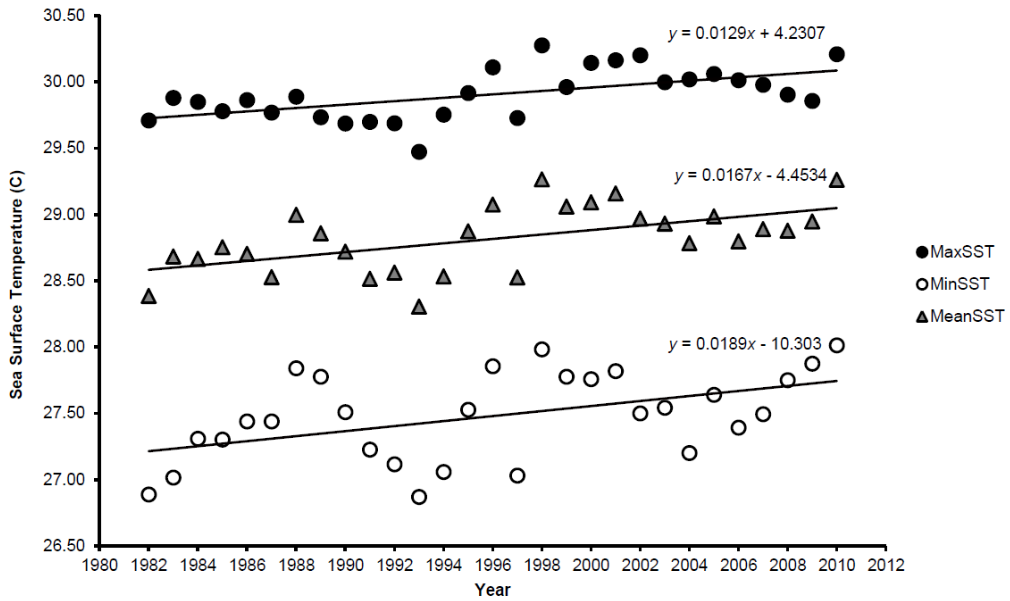


Figure 5-3. Linear regression of maximum, mean and minimum monthly mean SST (OISSTv2) in the Coral Triangle extracted from 535 pixels for the period 1982 to 2010.

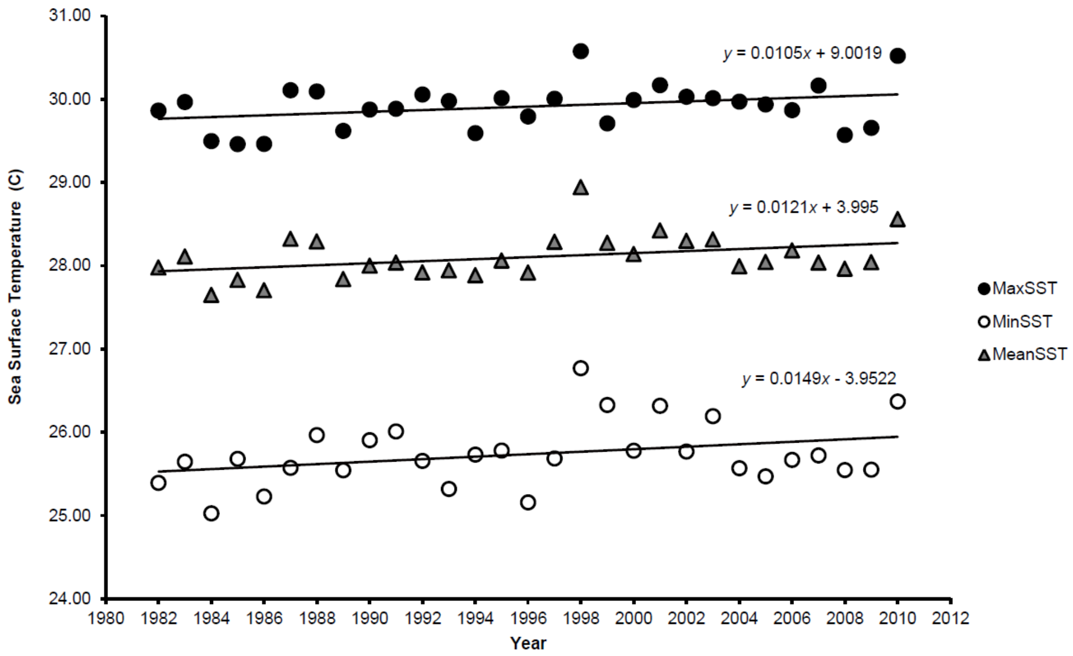


Figure 5-4. Linear regression of maximum, mean and minimum monthly mean SST (OISSTv2) in the South China Sea extracted from 271 pixels for the period 1982 to 2010.

The forecasted trends in the averages for the maximum, mean and minimum SST from 2010 to 2100 are shown for the CT (Figure 5-5) and SCS (Figure 5-6), respectively. Similar to OICCTv2 datasets, the warming trend was also clearly detected for all three SST variables (maximum, mean, minimum) in both areas.

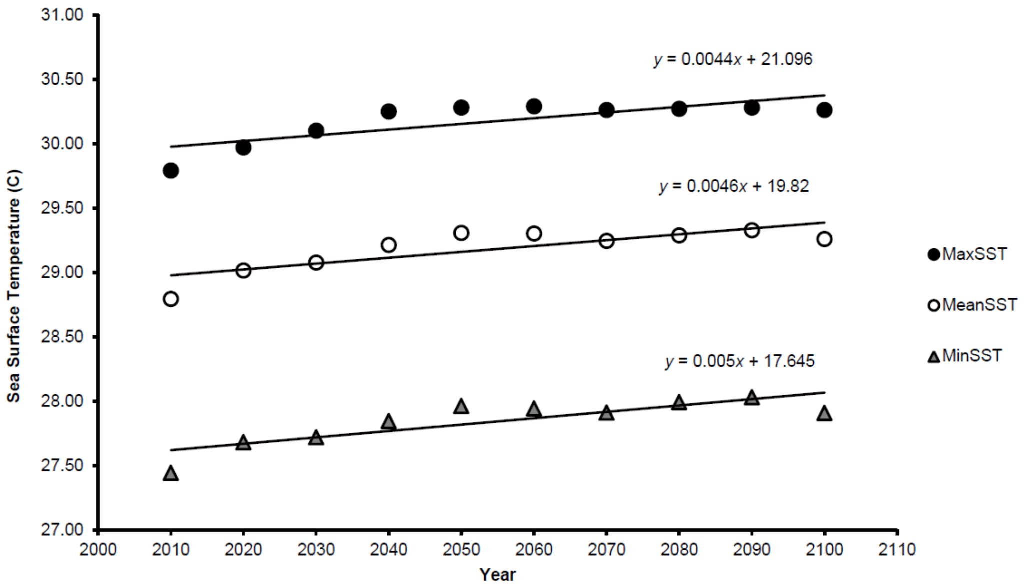


Figure 5-5. Linear regression of maximum, mean and minimum monthly mean SST (CMIP5) in the Coral Triangle extracted from 477 pixels for the period 2010 to 2100.

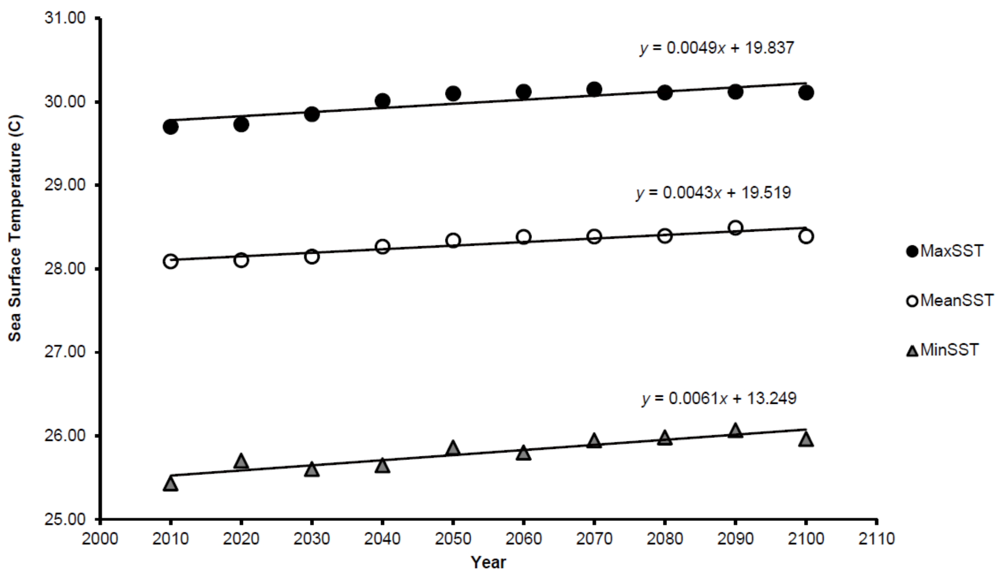


Figure 5-6. Linear regression of maximum, mean and minimum monthly mean SST (CMIP5) in the South China Sea extracted from 220 pixels for the period 2010 to 2100.

Starting from 2010 until 2100 (9 decades), SST in the CT is forecasted to experience a warming trend with a rate of 0.004˚C yr^{-1} (MaxSST), 0.005˚C yr^{-1} (MeanSST and MinSST). The warming rate in the SCS however, is expected to be at 0.005˚C yr^{-1} (MaxSST), 0.004˚C yr^{-1} (MeanSST) and 0.06˚C yr^{-1} (MinSST).

To better understand the location of the warming/cooling trends in both sites, maps showing the spatial distribution of these trends were produced. Figure 5-7 and Figure 5-8 map the linear regression trends for the South China Sea and the Coral Triangle together with their *p*-values.

The long-term trends in SST in both the SCS and CT from 2010 until 2100 were then investigated using the CMIP5 forecast and these are shown in Figure 5-9 and Figure 5-10, respectively.

The future forecast based on MaxSST CMIP5 suggests a warming rate of 0.004 ˚C yr^{-1} over 90 years in the CT and a slightly higher rate of 0.005 ˚C yr^{-1} over 90 years in the SCS from 2010 until 2100.

The relatively low warming rate in the SCS (Figure 5-4) is reversed in the future forecast based on the CMIP5 dataset (Figure 5-6). However, note that the majority of this change is forecast to occur between the present and 2040 (i.e., over the next 30 years) as clearly shown in Figure 5-6. This represents a continuation of the historical warming trends described above.

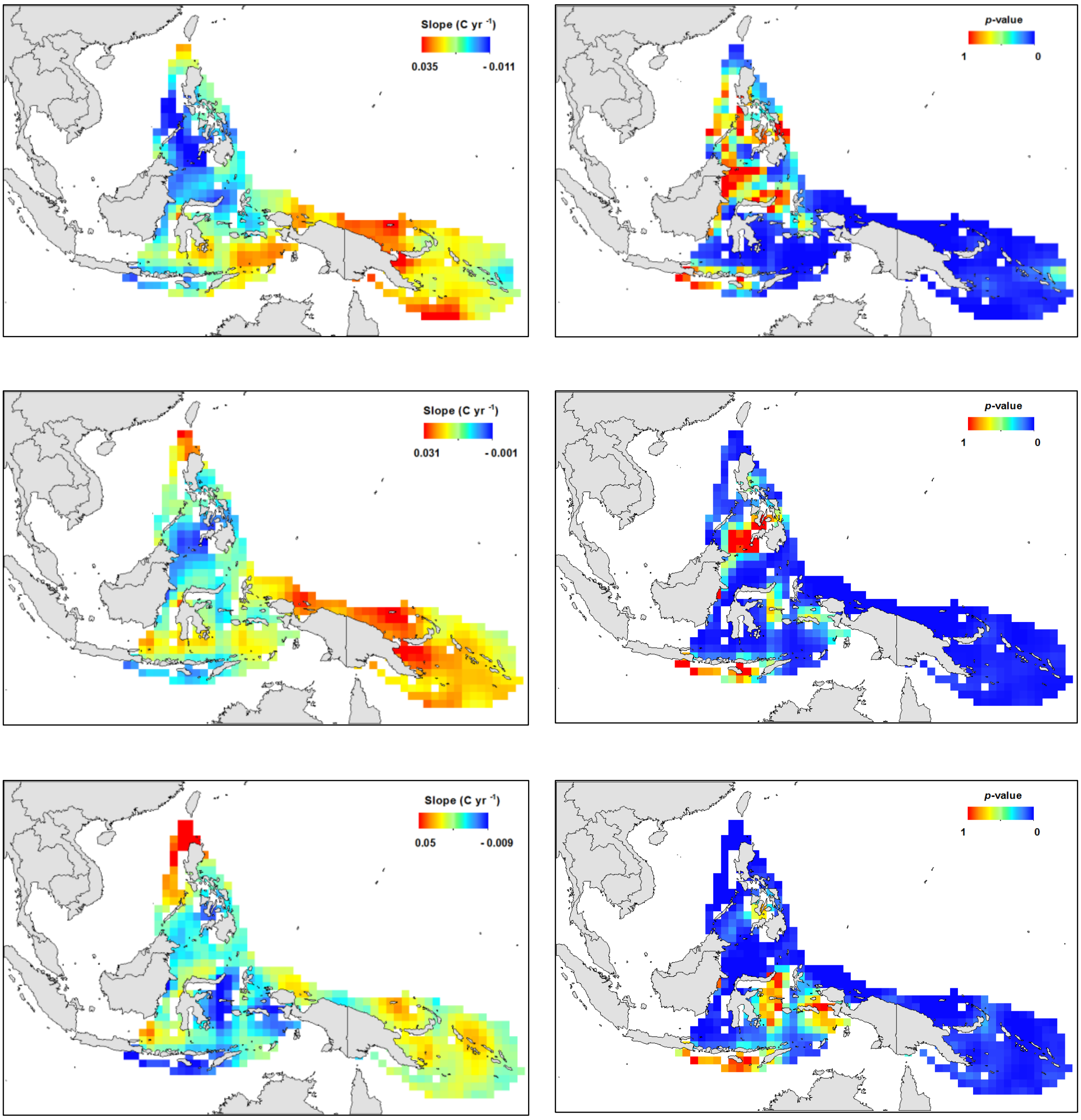


Figure 5-7. (Left) Spatio-temporal trends estimated through linear regression and (right) *p*-value of the (top) maximum, (middle) mean and (bottom) minimum SST in the Coral Triangle generated from OISSTv2 dataset for the period 1982 to 2010.

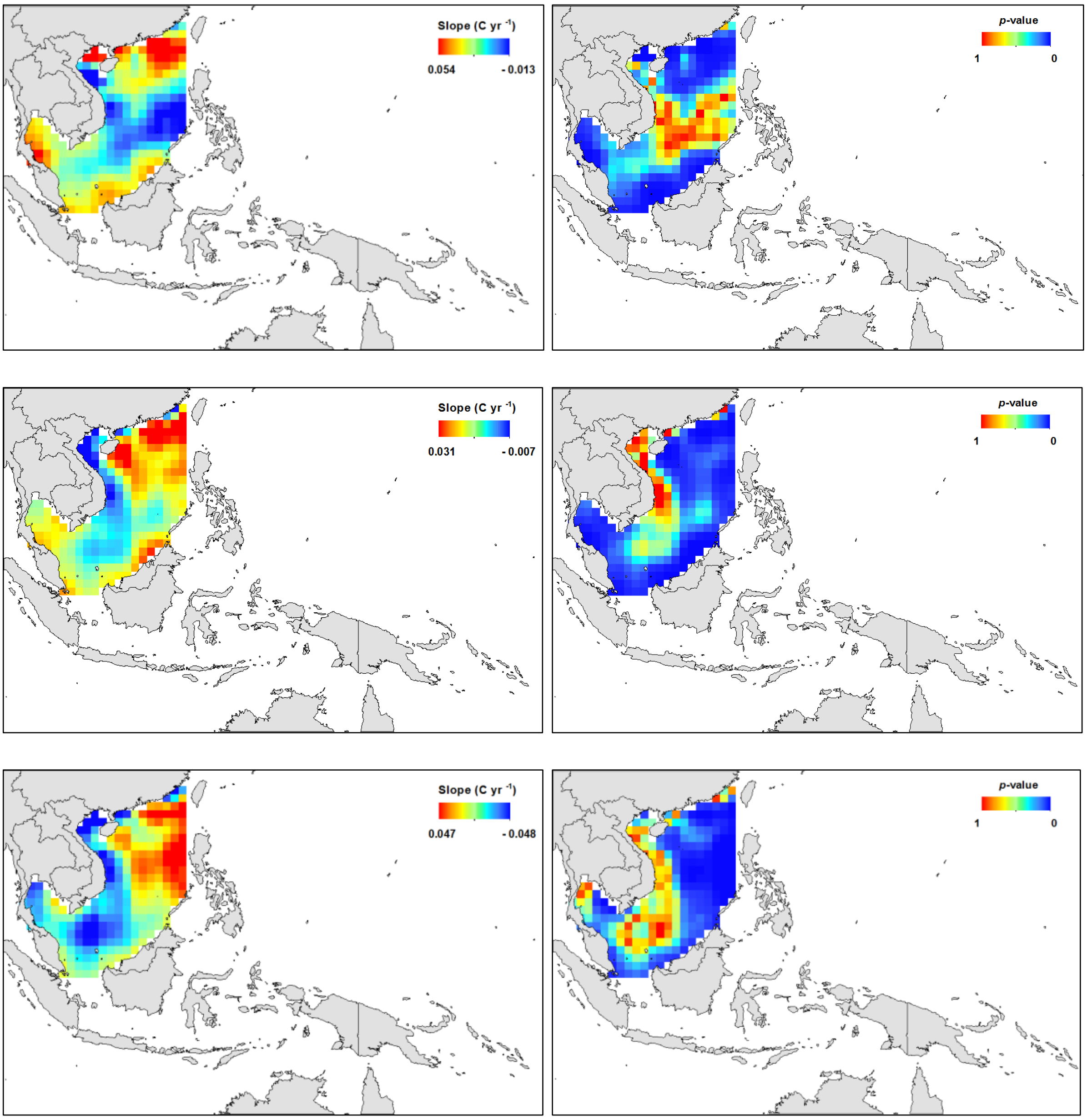


Figure 5-8. (Left) Spatio-temporal trend estimated through linear regression and (right) *p*-value of the (top) maximum, (middle) mean and (bottom) minimum SST in the South China Sea generated from OISSTv2 for the period 1982 to 2010.

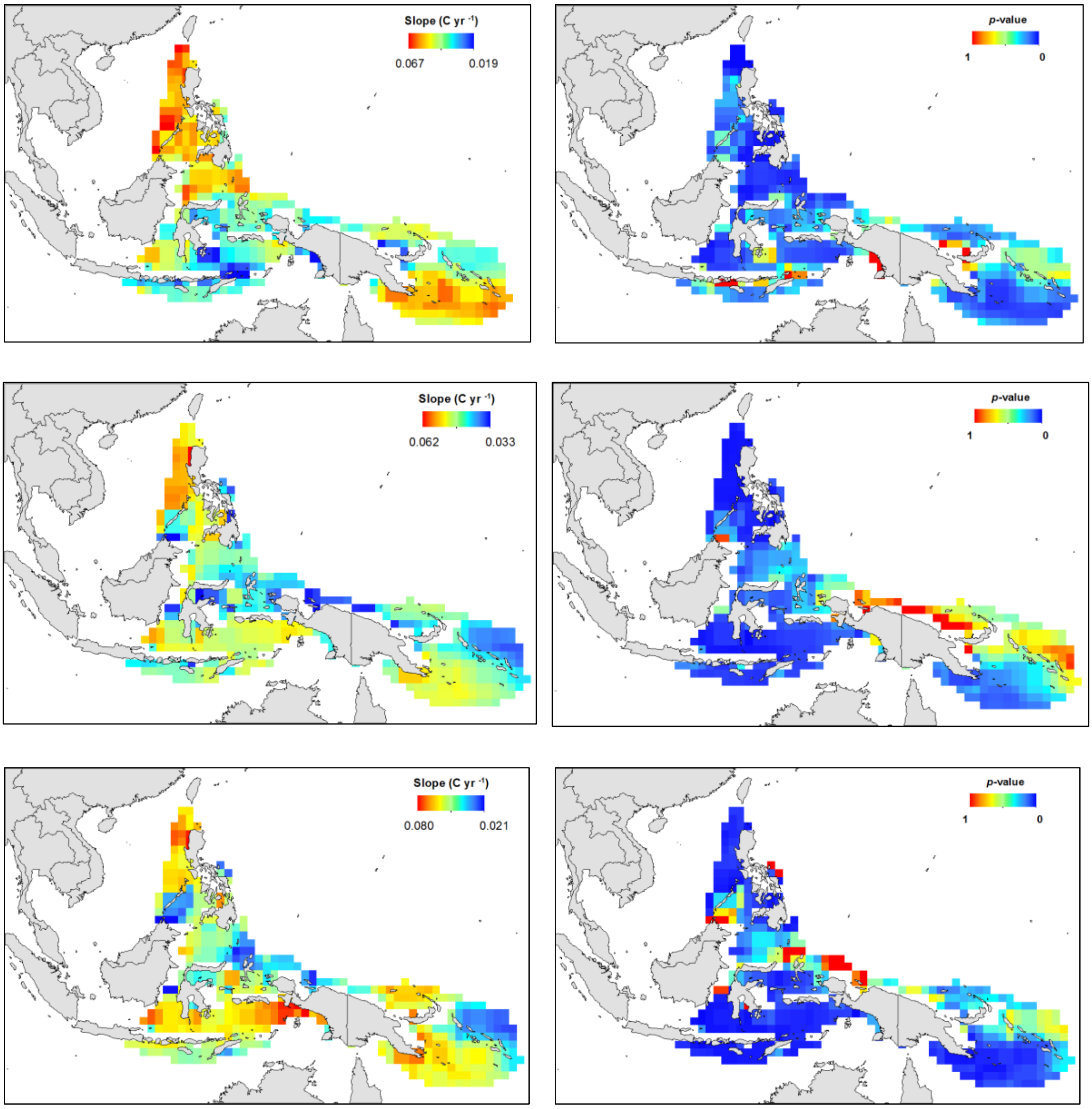


Figure 5-9. (Left) Spatio-temporal trend estimated through linear regression and (right) *p*-value of the (top) maximum, (middle) mean and (bottom) minimum SST in the Coral Triangle generated from CMIP5 for the period 2010 to 2100.

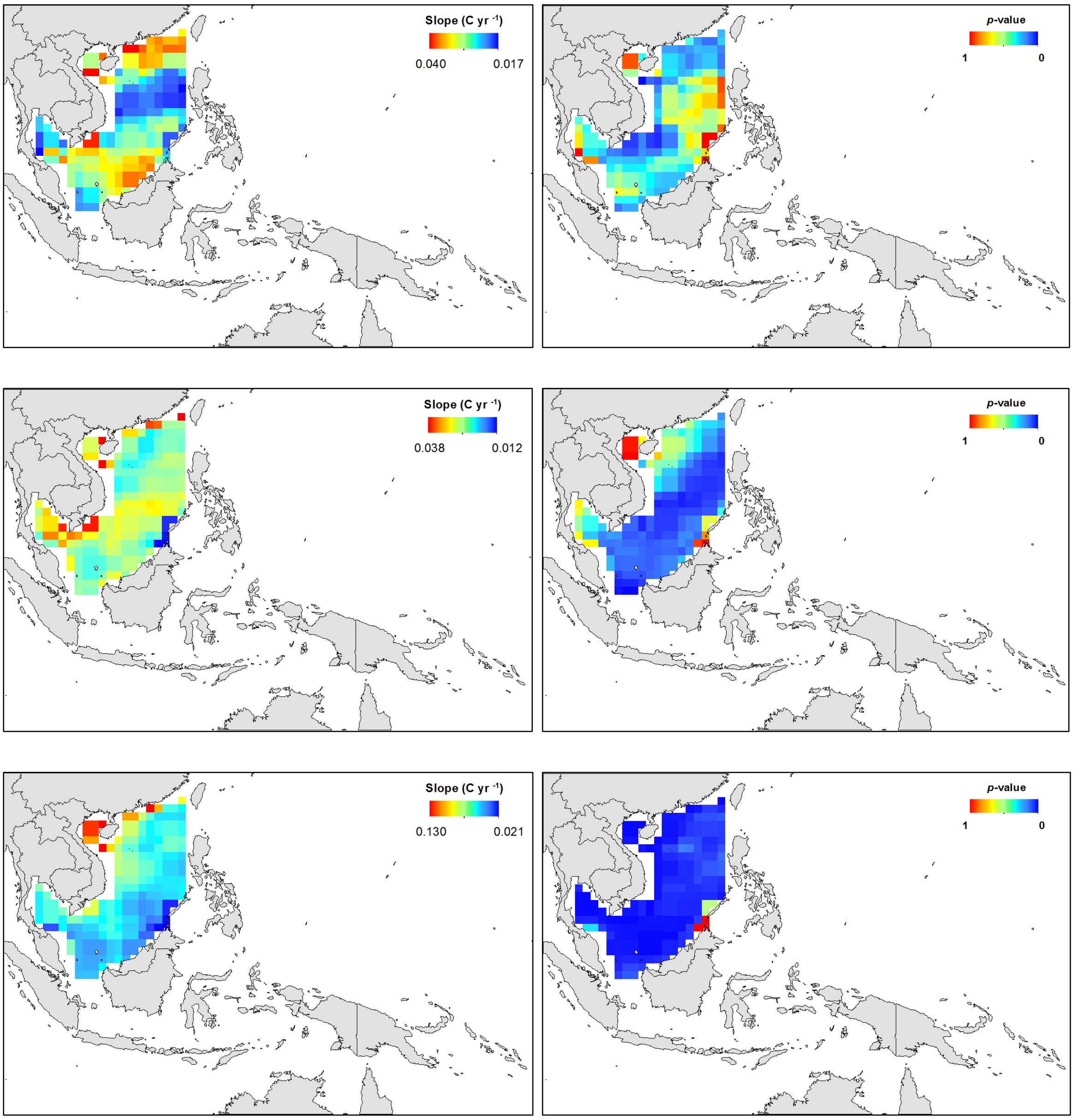


Figure 5-10. (Left) Spatio-temporal trend estimated through linear regression and (right) *p*-value of the (top) maximum, (middle) mean and (bottom) minimum SST in the South China Sea generated from CMIP5 for the period 2010 to 2100.

5.5 Discussion

Ocean warming due to global climate change has been highlighted and demonstrated by The Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007). It was reported that the first decade of the 21st century was the warmest detected. Globally, average sea surface temperature is expected to rise between 0.3 to 0.7°C between 2016 and 2035 (IPCC, 2014). Such forecasts are alarming and underline the requirement for local monitoring. While global SST monitoring can provide a macro-level view, localised monitoring of empirical trends in SST should also be undertaken especially in important regions such as the Indo-Pacific.

This research was undertaken to characterise in detail the trends in SST in the Indo-Pacific region, particularly in the South China Sea and the Coral Triangle. The gap-free SST datasets from OISSTv2 were used to characterise the trends in SST from 1982 to 2010. Future SST trends from 2020 to 2100 were then predicted based on the CMIP5 RCP2.6 dataset. The RCP2.6 includes an aggressive mitigation scenario which involves an approximately 50% reduction in global emissions by 2050 and near-zero emissions when approaching 2100 (van Vuuren et al, 2011). The use of the latest climate model under the CMIP5 framework provides a fine spatial resolution and considers major events that could affect the SST (e.g. the 1999 Mount Pinatubo eruption). For example, the models used by Donner et al. (2005) (e.g., the Hadley Centre Coupled Model version 3 (HadCM3) and Parallel Climate Model (PCM)) had spatial resolutions of 2.5°× 3.75° and 2.8125°× 2.8125°, respectively, whereas the CMIP5 framework provides a resolution of 1.25° x 1.25°.

Linear trend analysis revealed that from 1982 to 2010, the South China Sea experienced a lower warming rate compare to the Coral Triangle for all three SST variables (MinSST, MeanSST and MaxSST). During the 29-years, the Coral Triangle experienced a warming trend with a rate of 0.013 ˚C yr^{-1} (MaxSST), , 0.017 ˚C yr^{-1} (MeanSST) and 0.019 ˚C yr^{-1} (MinSST) (Figure 5-3). Figure 5-4 shows that in the SCS, the warming rates were 0.011 °C yr^{-1} (MaxSST), 0.012 °C yr^{-1} (MeanSST) and 0.015 °C yr^{-1} (MinSST) over the 29 years. Analysis of the space-time trends in SST revealed that the region's warming trend was not spatially uniform (Figure 5-7 and Figure 5-8). The space-time SST trends in the Coral Triangle shown in Figure 5-7 are interesting. While the western part of the CT exhibited either a cooling trend or lower warming as revealed by the linear regression and *p*-value, the eastern part of the area exhibited a warming trend. The *p*-value in Figure 5-7 and Figure 5-9 lead to rejection of the null hypothesis (that no significant trend occurred) for the vast majority of pixels. Thus, the eastern part of the CT which is already warm due to the Western Pacific Warm Pool (WPWP) (Figure 5-11), has experienced a consistent and statistically significant increase in temperature over the period 1982 to 2010. Worryingly, the WPWP is already the warmest water in the region (>29^{0}C) as described by Linsley et al. (2010).

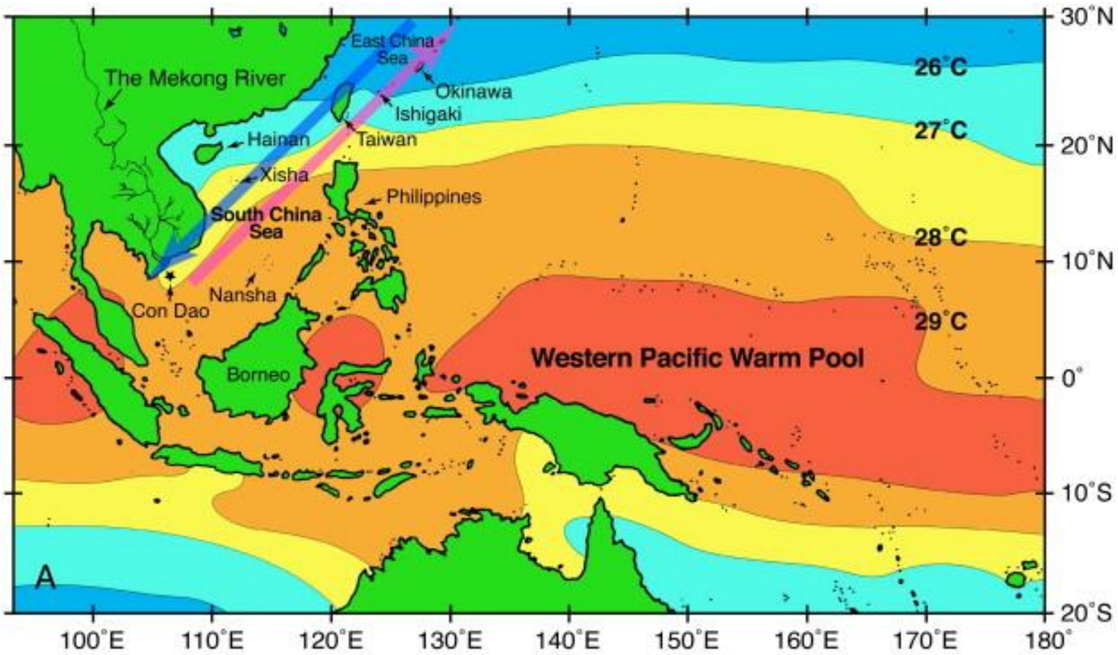


Figure 5-11. Location of the Western Pacific Warm Pool (WPWP) (after Mitsuguchi et al., 2008).

In Figure 5-7, the yellow-to-red zone represents an increase of approximately 0.02°C-to-0.03°C yr^{-1}, or 0.58℃-to-0.87℃ over 29 years, which is significant at the 95% confidence level. This finding corroborates the warming rate of +0.2℃ per decade suggested by Peñaflor et al. (2009), captured using finer spatial resolution data (0.5° biweekly SST). While the overall magnitude of the trends was similar, Peñaflor et al. (2009) reported that the greatest warming during 1985 to 2006 occurred in the north and east of the CT.

Considering now the SCS region, this study observed a blue zone in the SCS (off the coast of Vietnam) that clearly suggested a lower warming rate compared to other areas (Figure 5-8). The slower warming in the SCS might be explained by the existence of the 'cold tongue' described by Liu et al. (2004). The *p*-value (Figure 5-8) agreed well with the linear regression with *p*-values less than 0.05 in the SCS. The only area that has higher *p*-value is in the middle section (Figure 5-8), the area where the cold current (cold tounge) originated from the Vietnam coast.

Further analysis was conducted to find the exact timing of cold tongue occurrence. SST anomalies were mapped by specific month as shown in Figure 5-12.

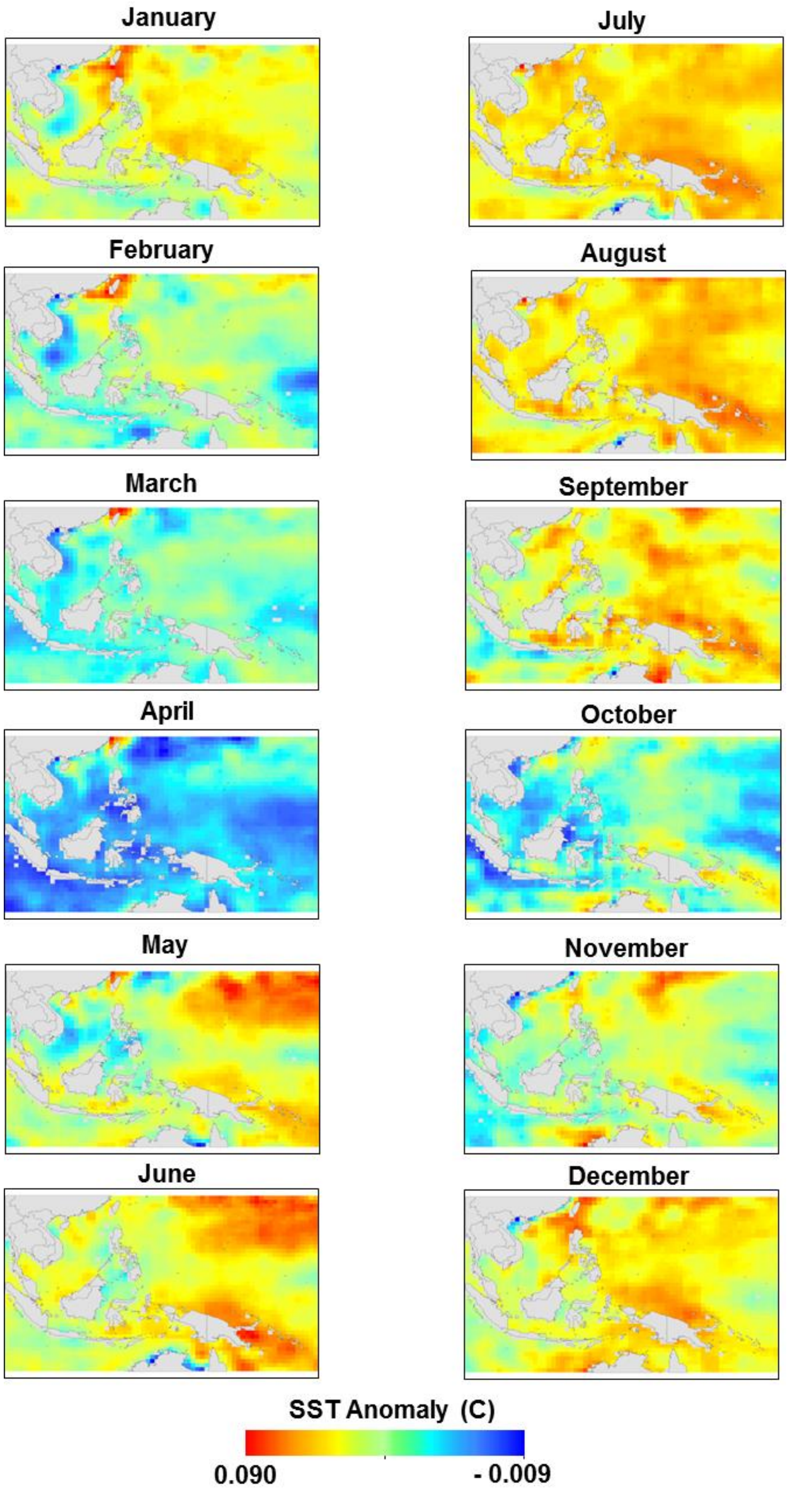


Figure 5-12. Monthly SST anomalies from OISSTv2 from 1982 to 2010.

Contradicting studies by Liu et al. (2004) and Xie et al. (2003), which found that surface warm water appeared off the coast of Vietnam in June, spread in July and became intense in August, we found that it started to form as early as January and was sustained in February and March before disappearing in April. A large cooling event was then detected in May. No explanation can be provided given present understanding, except that there might exist a seasonal shift in events. Liu et al. (2004) and Xie et al. (2003) used SST for 15 years (1985 to 1999) while this study used data for a much longer time period (1982 to 2010). This phenomenon, thus, requires further investigation.

The slopes of the trends fitted to monthly SST anomalies were plotted to (i) check that all months had a warming trend and (ii) determine if any months were warming at a greater rate than others (Figure 5-13). It was found that over the past 29 years, December produced the trend with the largest slope (i.e., the fastest rate of warming). While warm water in December is normal due to wind and ocean current movements from the Eastern Pacific Ocean to the Western Pacific Ocean, the warming trend is worrying in relation to coral survival. Further investigation into the relationship of SST and the El Nino-Southern Oscillation (ENSO) events should be undertaken.

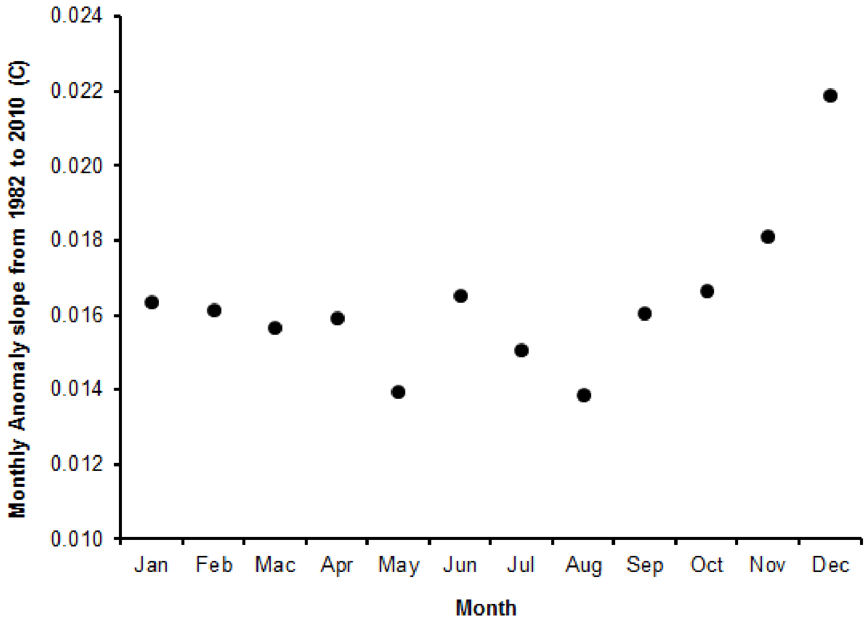


Figure 5-13. Anomalies in monthly SST from 1982 to 2010 using OISSTv2 plotted against month.

Moving forward into the future, on average, warming was forecast in the CT and SCS at a rate of 0.04°C yr^{-1} over 90 years. However, the majority of this warming is expected in the next 30 years, in line with the RCP2.6 scenario. All three SST variables suggested that the northern and eastern parts of the CT will be much warmer. In the SCS, the northern area is predicted to have a higher warming rate.

5.6 Conclusion

Analysis of trends in SST in complex seas such as found in the Indo-Pacific region is challenging, but necessary given the rate of change expected in ocean warming in the area. The magnitude of ocean warming in the study area was investigated both historically between 1982 and 2010 using archive NOAA AVHRR OISSTv2 data and forecasted between 2020 and 2100 using CMIP5 RCP2.6 data. A historical warming trend was detected in the SCS and CT, with increases of approximately 0.30°C to 0.43°C in the SCS and approximately 0.37°C to 0.55°C in the CT. Spatial variation existed in the historical SST trends over the 29-year period. Using the latest climate models in the CMIP5 framework, future maximum SST was simulated under the RCP2.6 scenario. The analysis showed that the historical trends in SST are expected to continue up to around 2045. These changes are likely to have important consequences for biochemical processes in the region, particularly those that affect coral survival.

5.7 Acknowledgements

The authors would like to acknowledge NOAA/OAR/ESRL PSD, Boulder, Colorado, USA for the NOAA_OI_SST_V2 data from their web site at http://www.esrl.noaa.gov/psd/. The authors would also like to thank Royal Netherlands Meteorological Institute (KNMI) Climate Explorer for the CMIP5 datasets and Belle van Zuylen Chair from the Faculty of Geosciences at Utrecht University, the Netherlands.

5.8 References

Alien, M.R. et al., 1994. Global change detection. *Nature*, 370(6484), p.24. Available at: http://dx.doi.org/10.1038/370024b0.

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), p.e711. Available at: http://dx.plos.org/10.1371/journal.pone.0000711.

Burke, L. et al., 2012. *Reefs at Risk Revisited in the Coral Triangle*, Washington D.C, USA: World Resource Institute.

Carpenter, K.E. et al., 2008. One-third of reef-building corals face elevated extinction risk from climate change and local impacts. *Science*, 321(5888), pp.560–563. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18653892.

Casey, K.S. & Cornillon, P., 2001. Global and Regional Sea Surface Temperature Trends. *Journal of Climate*, 14(18), pp.3801–3818. Available at: http://dx.doi.org/10.1175/1520-0442(2001)014<3801:GARSST>2.0.CO;2.

Clarke, A., 1990. Temperature and evolution: Southern Ocean cooling and the Antarctic marine fauna. In *Antarctic ecosystems*. Springer, pp. 9–22.

Donlon, C. et al., 2009. The GODAE high resolution sea surface temperature pilot project. *Oceanography*, 2(3), pp.34–45.

Donner, S.D. et al., 2005. Global assessment of coral bleaching and required rates of adaptation under climate change. *Global Change Biology*, 11(12), pp.2251–2265. Available at: http://dx.doi.org/10.1111/j.1365-2486.2005.01073.x.

Emery, W.J., 2003. AIR-SEA INTERACTION | Sea Surface Temperature. In R. H. James, ed. *Encyclopedia of Atmospheric Sciences*. Oxford: Academic Press, pp. 100–109. Available at: http://www.sciencedirect.com/science/article/B77C7-4B0C797-1B/2/f3eb223e65ba49df6b4924ae825870b0.

Emery, W.J. & Thomson, R.E., 2001. *Data Analysis Methods in Physical Oceanography*, Available at: http://www.sciencedirect.com/science/article/pii/B978044450756350006X.

Galbraith, P.S. et al., 2012. Sea-surface temperature in relation to air temperature in the Gulf of St. Lawrence: Interdecadal variability and long term trends. *Deep Sea Research Part II: Topical Studies in Oceanography*, 77–80(0), pp.10–20. Available at: http://www.sciencedirect.com/science/article/pii/S0967064512000495.

GCRMN, 2010. *Status of Coral Reefs in East Asian Seas Region: 2010* G. C. R. M. Network, ed., Ministry of the Environment, Japan.

Harvell, C.D. et al., 2002. Climate warming and disease risks for terrestrial and marine biota. *Science*, 296(5576), pp.2158–2162.

Hoegh-Guldberg et al., 2009. *The Coral Triangle and Climate Change: Ecosystems, People and Societies at Risk*, Brisbane, Australia: WWF Australia.

Hu, J. et al., 2000. A Review on the Currents in the South China Sea: Seasonal Circulation, South China Sea Warm Current and Kuroshio Intrusion. *Journal of Oceanography*, 56, pp.607–624. Available at: http://www.ingentaconnect.com/content/klu/joce/2000/00000056/00000006/00351943.

IPCC, 2001. Climate Change 2001: Synthesis Report. A Contribution of Working Groups I, II, and III to the Third Assessment Report of theIntegovernmental Panel on Climate Change R. T. Watson & C. W. Team, eds. , p.398.

IPCC, 2007. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change IPCC Core Writing Team, Pachauri, & A. R.K and Reisinger, eds. , p.104.

IPCC, 2014. *Summary for Policymakers*,

Lalli, C.M. & Parsons, T.R., 1997. *Biological Oceanography: An Introduction*, Elsevier, Butterworth Heinemann. Available at: http://books.google.co.uk/books?id=qjcUAQAAIAAJ.

Levitus, S. et al., 2000. Warming of the World Ocean. *Science*, 287(5461), pp.2225–2229. Available at: http://www.sciencemag.org/content/287/5461/2225.abstract.

Levitus, S., Antonov, J. & Boyer, T., 2005. Warming of the world ocean, 1955–2003. *Geophysical Research Letters*, 32(2), p.n/a–n/a. Available at: http://dx.doi.org/10.1029/2004GL021592.

Lin, C.-Y. et al., 2013. Thermal variability of the Indo-Pacific warm pool. *Global and Planetary Change*, 100(0), pp.234–244. Available at: http://www.sciencedirect.com/science/article/pii/S0921818112002123.

Linsley, B.K., Rosenthal, Y. & Oppo, D.W., 2010. Holocene evolution of the Indonesian throughflow and the western Pacific warm pool. *Nature Geosci*, 3(8), pp.578–583. Available at: http://dx.doi.org/10.1038/ngeo920.

Liu, Q. et al., 2004. A gap in the Indo-Pacific warm pool over the South China Sea in boreal winter: Seasonal development and interannual variability. *J. Geophys. Res.*, 109(C7), p.C07012. Available at: http://dx.doi.org/10.1029/2003JC002179.

McCLAIN, E.P., 1989. Global sea surface temperatures and cloud clearing for aerosol optical depth estimates. *International Journal of Remote Sensing*, 10(4), pp.763–769. Available at: http://www.informaworld.com/10.1080/01431168908903917.

McClain, E.P., Pichel, W.G. & Walton, C.C., 1985. Comparative performance of avhrr-based multichannel sea surface temperatures. *J. Geophys. Res.*, 90(C6), pp.11587–11601. Available at: http://dx.doi.org/10.1029/JC090iC06p11587.

McLeod, E. et al., 2010. Warming Seas in the Coral Triangle: Coral Reef Vulnerability and Management Implications. *Coastal Management*, 38(5), pp.518–539.

Minnett, P.J. et al., 2001. The Marine-Atmospheric Emitted Radiance Interferometer: A High-Accuracy, Seagoing Infrared Spectroradiometer. *Journal of Atmospheric and Oceanic Technology*, 18(6), pp.994–1013. Available at: http://dx.doi.org/10.1175/1520-0426(2001)018<0994:TMAERI>2.0.CO;2.

Mitsuguchi, T. et al., 2008. Coral Sr/Ca and Mg/Ca records in Con Dao Island off the Mekong Delta: Assessment of their potential for monitoring ENSO and East Asian monsoon. *Global and Planetary Change*, 63(4), pp.341–352. Available at: http://www.sciencedirect.com/science/article/pii/S092181810800088X.

Noyes, E.J. et al., 2006. The accuracy of the AATSR sea surface temperatures in the Caribbean. *Remote Sensing of Environment*, 101(1), pp.38–51. Available at: http://www.sciencedirect.com/science/article/pii/S0034425705004062.

O'Carroll, A.G., Saunders, R.W. & Watts, J.G., 2006. The Measurement of the Sea Surface

Temperature by Satellites from 1991 to 2005. *J. Atmos. Oceanic Technol.* , 23(11), pp.1573–1582.

Peñaflor, E. et al., 2009. Sea-surface temperature and thermal stress in the Coral Triangle over the past two decades. *Coral Reefs*, 28(4), pp.841–850. Available at: http://dx.doi.org/10.1007/s00338-009-0522-8.

Rayner, N.A. et al., 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research: Atmospheres*, 108(D14), p.n/a–n/a. Available at: http://dx.doi.org/10.1029/2002JD002670.

Reynolds, R.W., 1988. A real-time global sea surface temperature analysis. *J. Climate*, 1, pp.75–86.

Reynolds, R.W. & Chelton, D.B., 2010. Comparisons of Daily Sea Surface Temperature Analyses for 2007 - 08. *Journal of Climate (Formerly : Journal of Climate and Applied Meteorology)*, 23(13), pp.3545–3562.

Robinson, C.J., Gómez-Gutiérrez, J. & de León, D.A.S., 2013. Jumbo squid (Dosidicus gigas) landings in the Gulf of California related to remotely sensed SST and concentrations of chlorophyll a (1998–2012). *Fisheries Research*, 137(0), pp.97–103. Available at: http://www.sciencedirect.com/science/article/pii/S0165783612002755.

Robinson, I.S., 2010. *Discovering the Ocean from Space: The Unique Applications of Satellite Oceanography*, Springer. Available at: http://books.google.co.uk/books?id=u-CwzWN3Zg8C.

Saha, K., 2010. *Tropical Circulation Systems and Monsoons*, Berlin, German: Springer.

Schwarz, J.N. et al., 2010. Biophysical coupling in remotely-sensed wind stress, sea surface temperature, sea ice and chlorophyll concentrations in the South Indian Ocean. *Deep Sea Research Part II: Topical Studies in Oceanography*, 57(9–10), pp.701–722. Available at: http://www.sciencedirect.com/science/article/pii/S0967064509003853.

Veron, J.E.N. et al., 2009. Delineating the Coral Triangle. *Galaxea, Journal of Coral Reef Studies*, 11(2), pp.91–100.

van Vuuren, D.P. et al., 2011. The representative concentration pathways: An overview. *Climatic Change*, 109(1), pp.5–31.

Xie, S.-P. et al., 2003. Summer upwelling in the South China Sea and its role in regional climate variations. *J. Geophys. Res.*, 108(C8), p.3261. Available at: http://dx.doi.org/10.1029/2003JC001867.

Yeemin, T. et al., 2012. Impacts of coral bleaching, recovery and management in Thailand. In *Proceedings of the 12th International Coral Reef Symposium*. Cairns, Australia.

Yeemin, T. et al., 2010. Status of coral reefs in Thailand following the 2010 coral bleaching event. In Kimura T & K. Tun, eds. *Status of Coral Reefs in East Asian Seas Region*. Ministry of the Environment, Japan, pp. 29–49.

Chapter 6: Region-Specific Modelling and Forecasting of the Effect of Sea Surface Temperature on Coral Bleaching in the Indo-Pacific Region

6.1 Abstract

The Coral Triangle (CT) is one of the tropical sea in the world located in the Indo-Pacific region. Moreover it is known to have 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 amount of studies covering larger areas have recommended that the warming trends should be adopted at both the South China Sea and the Coral Triangle. Hence, with the help of locally-specified data and suitable statistical models, it is very important to explore the possible consequences of Sea Surface Temperature warming on the rich ecosystems, especially on the coral reefs found in the region. In this study, the monthly NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2 dataset (OISSTv2) was utilised by deriving it from the measurements developed by the Advanced Very High-Resolution Radiometer (AVHRR) and *in situ* measurements with the purpose of examining their relationship with coral bleaching in the Indo-Pacific region. On top of that, three different categories of monthly mean SST are tested in this study, namely minimum SST, mean SST, and maximum SST from a 25km spatial resolution OISSTv2 (1982 to 2012). The logistic regression model revealed a significant relationship between coral bleaching and annual maximum monthly mean SST in the study area using extensive and spatially well-distributed bleaching data from an online database and a time-series of AVHRR images. The results are very consistent with the NOAA Coral Reef Watch (CRW) Degree heating Weeks (DHW) maps. However, there were also some important discrepancies resulted by the more specific local fitting used in this study. The maximum SST was forecasted from 2020 to 2100 on the Coupled Model Intercomparison Project Phase 5 (CMIP5) dataset under the Representative Concentration Pathways (RCP2.6) scenario. In the case of this study, the fitted logistic regression model was employed to transform the estimated maximum SST values into the forecasts of coral bleaching from 2020 to 2100. The results provide the general cause for concern, including the high possibility for the widespread of coral bleaching forecast to many places over the next 30 years.

Key words — SST, space-time, coral bleaching, Coral Triangle, South China Sea

6.2 Introduction

The Indo-Pacific Ocean lies between the latitude of 30° North to 30° South and the longitude of 30° East to 90° West. This region receives the required amount of sunlight for coral reef growth which further allows the calcification process or also known as coral reef formation to occur at a higher rate than the physical and biological erosion. As a result, the region has become renowned for its vast expanse of coral reefs. Fugure 6-1 shows the general distribution of world coral reefs and their species richness based on the data provided by Veron et al. (2009). In relation to this, Hoegh-Guldberg et al. (2009) and Veron et al. (2009) state that the Coral Triangle located in the centre of the Indo-Pacific Ocean possess the richest marine ecosystem on earth with a total of 76% reef-building coral species and 37% world's coral reef fish species. Kool et al. (2011) went further by pointing out that the Coral Triangle is the main key in preserving fish stocks and marine resources in the Asia-Pacific region. Hence, these factors have turned the Coral Triangle into a high priority conservation area (Burke et al., 2002; Allen, 2008).

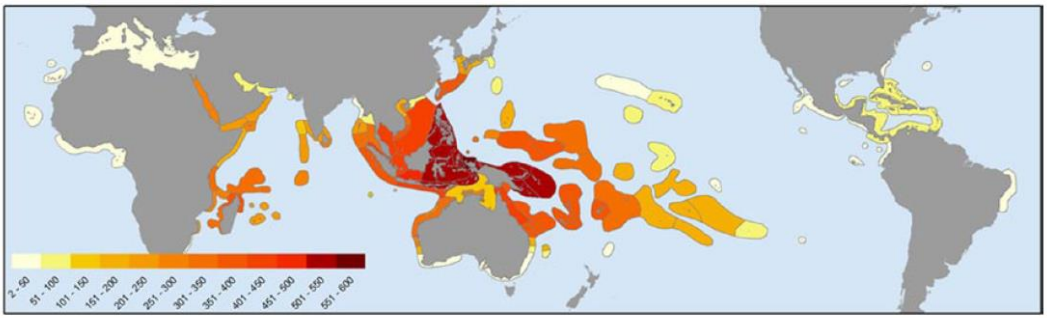


Figure 6-1. Map showing the global biodiversity of zooxanthellate corals. The colours indicate the total species richness of the corals (Veron et al., 2009).

Coral reefs are beneficial in a number of ways to the people worldwide, specifically in terms of biodiversity, fisheries, coastal protection, tourism and recreation as well as medicine. In the aspect of biodiversity, Cesar et al. (2003) estimated that the annual benefits of coral reefs is US$5,700.00 per km^2, which consequently increase their global contribution to an approximate total of US$5.5 billion per year. Meanwhile, the total value is estimated at US$2.3 billion per year for Coral Triangle that produces denser and more diverse coral reefs (Wilkinson, 2008). Coral reefs act as a nursery or breeding ground for fish and other marine animals; hence, they are very significant to fisheries because they provide food to both local communities and the world. On top of that, it is important to note that coral reefs in coastal waters are natural barriers against strong waves, currents and storms, which help to reduce the impact on coastal communities. UNEP-WCMC (2006) states that coral reefs alongside mangroves absorb at least 70% to 90% of the wave energy during hurricanes and tropical storms.

Nevertheless, recent evidence suggests that this fragile ecosystem is threatened despite its benefits mentioned above. Coral bleaching that is expelled from coral algae has become more frequent due to climate change, which is particularly caused by stress as a result of the change in water temperature, salinity levels, or ultraviolet light (Burke et al. 2012). Moreover, coral reefs might lose 60% to 90% of their algae during a bleaching event (Glynn, 1996), which then leaves a white reef skeleton in place of a colourful reef. On another note, almost all algae and coral pigment may be lost in extreme bleaching.

Carpenter et al. (2008) describe that the zooxanthellate corals in the Coral Triangle are at the highest risk of extinction due to climate change. This statement reflects those of McLeod et al. (2010) who suggested that the change in sea surface temperature (SST) is threatening the coral. A considerable amount of studies (e.g. GCRMN, 2010; Yeemin et al., 2010, 2012; Vinoth et al., 2012) have revealed a large-scale deterioration in the coral conditions. In relation to this, Bruno and Selig (2007) revealed that the coral cover loss rate in the Indo-Pacific was 3,168 km^2 per year between 1997 and 2003, which is faster than the expected rate. In the same case, Donner (2009) further highlights that the anticipated increase in sea surface temperature over the following decades will continue to cause coral bleaching. Furthermore, Burke et al. (2012) rated 95% of the Coral Triangle reefs as threatened, especially when thermal stresses are combined with other local threats such as overfishing and destructive fishing. Hence, this clearly reflects the impact of local ocean warming that is commonly linked to the mass coral bleaching.

The optimal sea temperature to support coral reefs is between 22°C and 28°C (Hubbard, 1997); however, the accepted range is between 18°C to 36°C. Goreau and Hayes (1994) and Liu et al. (2003) stress that bleaching is initiated when the sea temperature stays above the climatological maximum for a month or longer. It has been noted that bleaching may be caused by many factors which include the change in light intensity and exposure time (Fitt et al., 2001), reduced salinity (Coles & Jokiel, 1992), sedimentation, and reduced water quality (Dollar & Grigg, 1981); however, the primary interest of this study is to investigate coral bleaching in response to the increased sea temperature.

In the case of the Coral Triangle, satellite remote-sensing is a crucial tool for ocean monitoring and management due to the large area covered by it. On top of that, satellite sensor images have been used to measure SST which acts as an indicator for coral bleaching (McClain et al., 1985; Reynolds, 1988; Donlon et al., 2009; Reynolds & Chelton, 2010). The daily-to-monthly SST predictions are provided by sensors such as the National Oceanic and Atmospheric Administration’s (NOAA) Advanced Very High-Resolution Radiometer (AVHRR), the National

Aeronautics and Space Administration's (NASA), Moderate Resolution Imaging Spectroradiometer (MODIS), and the European Space Agency's (ESA), and Along Track Scanning Radiometer (ATSR).

The vast majority of researchers have used various methods in predicting coral bleaching based on sea surface temperature. A study conducted by Strong et al. (1997) utilised the exceedance of fixed temperature thresholds by determining it based on the historical climatology data. The findings reported that temperature above 1°C of the monthly mean maximum is necessary to estimate bleaching. Meanwhile, Berkelmans (2002) introduced a time–temperature curve where the cumulative exposure time that is measured in days was plotted against sea surface temperature. Hence, this allows the bleaching events to be detected when the cumulative exposure time and temperature curve coincide. On the other hand, Liu et al. (2003) introduced a concept known as Degree Heating Weeks (DHW) in predicting bleaching, which was subsequently adopted by NOAA's Coral Reef Watch (CRW). The DHW approach managed to show that the heat stress was accumulated over a 3-month period (12 weeks). Nevertheless, it is important to note that significant bleaching is likely to occur when the DHW reaches 4°C-weeks, while mass bleaching is bound to happen when the DHW reaches 8°C-weeks. Hence, this system is regarded as the only operational global scale system that can be used in monitoring and reporting bleaching events (Skirving et al., 2006).

On another note, McClanahan et al. (2007) demonstrated that DHW tends to over-predict and under-predict coral bleaching in some areas. Moreover, there has been some concern over the use of a static threshold by CRW, especially in the regions with high thermal variability over time (McClanahan et al., 2007; Oliver & Palumbi, 2011). One of the examples can be described based on the possibility that corals in thermally variable waters might be more resilient to bleaching events (Goreau & Hayes, 1994; Brown et al., 2002; Donner, 2011; Carilli et al., 2012). On the other hand, Logan et al. (2012) found that the mean of the warmest month of each year was the best predictor of coral bleaching in the equatorial Pacific, particularly because the timing of the seasonal peak in sea surface temperature differs from year to year. However, it is very important to fit models that are specific to the Indo-Pacific region instead of relying on globally fitted models which can be poorly fitted to the local regions.

The first objective of this paper was to examine the empirical relations between coral bleaching and sea surface temperature in the South China Sea (SCS) and the Coral Triangle by only focusing on data for this region. Moreover, Berkelmans (2009) reported that mean and minimum sea surface temperature are the important variables among other 17 potential variables related to coral bleaching based on the annual maximum. In another case, Manzello et al. (2007) highlight the monthly maximum sea surface temperature as the most significant variable. Hence, the annual maximum monthly mean SST (MaxSST) (Logan, 2012), together with the minimum monthly mean SST (MinSST) as well as the mean monthly mean SST (MeanSST) are employed for comparison purposes, which also acts as inputs to models in characterising the relationship between coral bleaching and SST. The probability of coral bleaching measured based on the region-specific fitted model was then mapped in order to provide a valuable resource for coral reef management in the area. The second objective was to forecast the maximum monthly mean SST from the year 2020 to 2100 using the latest Coupled Model Intercomparison Project Phase 5 (CMIP5) dataset under the Representative Concentration Pathways (RCP2.6) scenario. The region-specific fitted model above was employed to transform the forecasts of maximum sea surface temperature into a spatially distributed forecast probabilities of coral bleaching.

6.3 Materials and Methods

6.3.1 Study site and data

The research area selected for this study covers the South China Sea and the Coral Triangle. Figure 6.2 presents a section of the Indo-Pacific region between the latitude of 16.5° South to 26.5° North and the longitude of 96.5° East to 165.5° East.

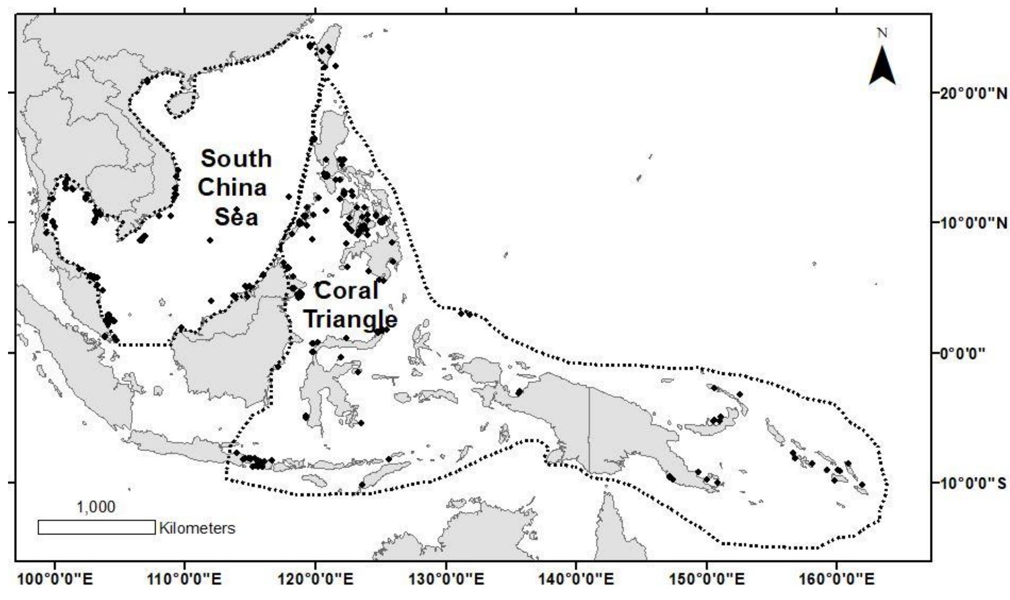


Figure 6-2. Map showing the spatial boundary of the South China Sea and the Coral Triangle. The dots shown in the map represents coral bleaching events from the year 1982 to 2012 (ReefBase 2012; Donner, 2017)

This region is subject to a monsoon-type climate; hence, it is expected to be mostly warm and humid throughout the year (Saha, 2010). On top of that, the North-East monsoon and South West monsoon typically occur around October to February and June to September, respectively. On another note, the hottest sea surface temperature is expected in May with the average temperature of 30.8 ^{0}C, while the coldest is scheduled in August as illustrated in Figure 6-3.

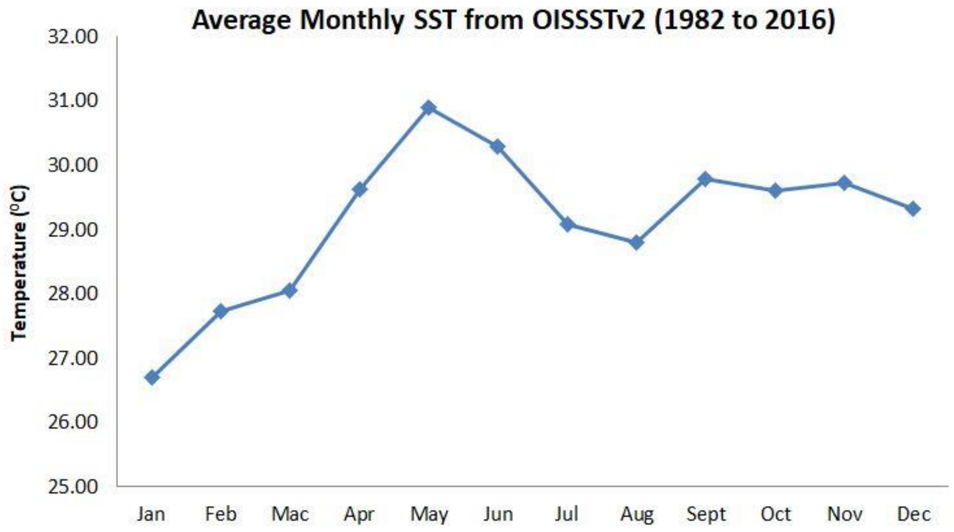


Figure 6-3. The average monthly sea surface temperature (SST) extracted from OISSTv2 from the year 1982 to 2016.

6.3.1.1 Sea Surface Temperature data

The sea surface temperature data which specifically refers to the 25 km resolution Optimum Interpolation SST (OISSTv2) data (Banzon, 2015) were obtained from the NOAA Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html). The latest OISSTv2 dataset is gathered based on the merging satellite sensor (AVHRR) SST data with *in situ* measurements from ships and buoys, which tend to form part of the International Comprehensive Ocean–Atmosphere Data Set (ICOADS). The monthly datasets used with a bias of -0.03°C were produced by NOAA using a linear interpolation generated by their weekly and optimum interpolation data (Reynolds et al., 2002). On another note, 35-years of OISSTv2 datasets were acquired and produced as 276 columns and by 172 rows in the World Geodetic System (WGS) projection. Following it, a total of 1260 time-series images from January 1982 to December 2016 were then converted into a manageable format for processing purposes. The time series are comprised of 420 monthly max SST (the maximum daily value among all the daily values in a month), 420 monthly min SST (the minimum daily value among all the daily values in a month), and 420 monthly mean SST (the mean daily value of all the daily values in a month).

6.3.1.2 Coral bleaching data

The coral bleaching records from 1982 to 2016 were obtained from the ReefBase Online Geographic Information System (ReefGIS), which was developed and managed by the WorldFish Center. In relation to this, a query to ReefGIS produced 390 bleaching or no bleaching records for the South China Sea and Coral Triangle area. Hence, an additional 312 records were obtained from Donner (2017) at http://simondonner.com/bleachingdatabase/. The records were then merged, while the redundant records were omitted. As a result, only a total of 460 records can be used for further analysis. The new bleaching database developed by Donner (2017) is the combination of ReefBase records together with additional reports collected from researchers and reef managers. The present study has managed to contribute to an additional amount of 15% of the ReefBase records, especially in Papua New Guinea waters and the South China Sea. Meanwhile, the information regarding the severity of coral bleaching was extracted with the results presented as follows: (1) No Bleaching: 147, (2) Low: 55, (3) Medium: 96, (4) High: 104, and (5) Unknown Severity. The spatial distribution of coral bleaching records can be referred in **Error! eference source not found.**.

6.3.1.3 Climate model datasets

The forecasts of historic and future sea surface temperature (SST) were obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) that was developed from 22 constituent climate models as presented in Table 6-1. The data were produced by the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer (http://climexp.knmi.nl/CMIP5/monthly/tos/index.cgi).

Table 6-1. List of climate models used in 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

The multi-model mean SST was simulated from 1861 to 2100 using the study area as the model boundary. In the case of this study, a total of 2,880 global monthly CMIP5 mean SST forecasts were downloaded and analysed. As presented in Figure 6.4, early inspection of the CMIP5 models revealed that the temperature forecasted is below the OISSTv2 temperature.

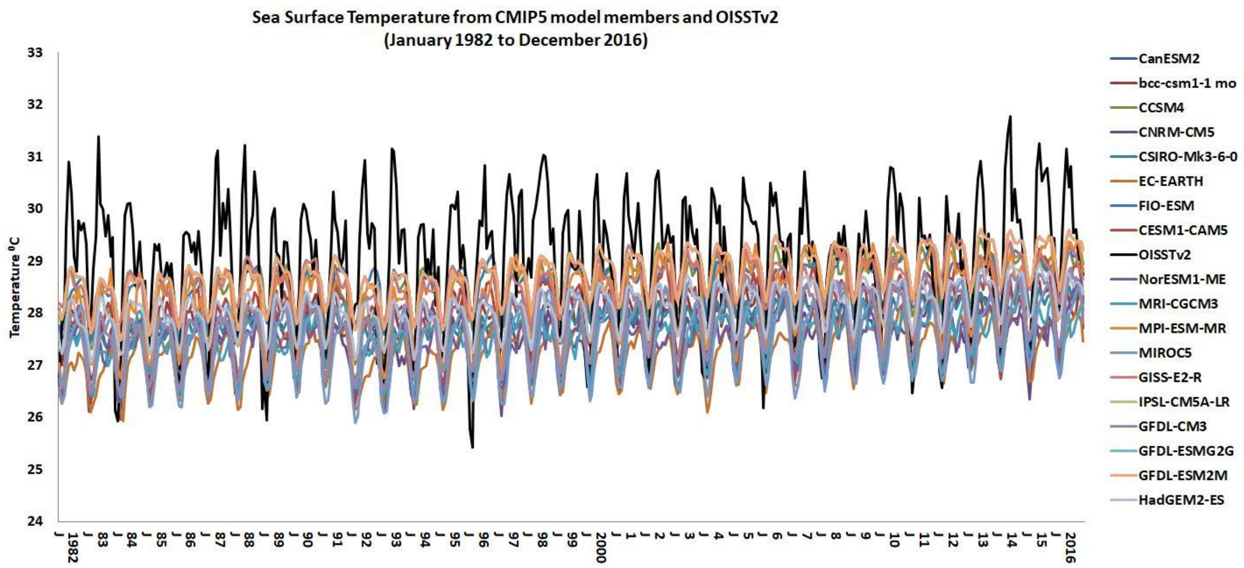


Figure 6-4. The SST forecasted by all models in CMIP5 is below the OISSTv2 (black line).

6.3.1.4 NOAA’s Coral Reef Watch (CRW), Degree Heating Week(DHW) data

NOAA has utilised their 50-km satellite coral bleaching Degree Heating Week (DHW) product to monitor coral bleaching events all over the world since 1990’s. DHWs refer to the thermal stress accumulated over 12-week period. The scale is 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. Currently, the 50 km resolution DHW dataset is only available from 2001 to present which can be downloaded from https://data.nodc.noaa.gov/crw/tsps50km/dhw/.

The new DHW dataset from 25 km resolution OISSTv2 were generated and obtained from NOAA in order to match the availability of ReefBase coral bleaching records from 1982. Kayanne (2016) evaluated the new 25 km DHW against 50 km DHW and managed to find a good positive correlation (r = 0.81), with the root mean square error (RMSE) = 0.008. The 25 km DHW (1982 to 2016) was then adopted to provide a benchmark comparison and reference for the predicted maps produced in this study.

6.3.2 Data pre-processing

A total of 1260 global monthly OISSTv2 images were sub-setted to cover the coral bleaching data spatially, which then produces 276 columns with 172 rows by also maintaining the original spatial resolution of 25 km by 25 km. A window covering the latitude 16.5° South to 26.5° North and longitude 96.5° East to 165.5° East was defined as the spatial boundary. The next step involved the entering of SST dataset into a geographic information system (GIS) environment together with the coral bleaching records. All the coral data were plotted according to location (Longitude and Latitude) and overlaid with the SST data. Moreover, obvious errors in the coral data caused by the records with unknown severity and land mask pixels in the SST images were removed. Finally, only a total of 460 coral bleaching records were considered to be adequately clean and useable for further analysis. Specifically, there were 313 occurrences of bleaching and 147 occurrences of no bleaching out of the total of 460 coral bleaching records in the Coral Triangle and the South China Sea.

Majority of the coral records were reported by year instead of by month of occurrence which allows the comparison of the bleaching events with the annual minimum (MinSST), mean(MeanSST), and maximum (MaxSST) monthly mean SST selected from the corresponding 12 months of sea surface temperature (SST). For example, the maximum monthly mean SST in the relevant year was extracted for all sites producing 460 records containing the bleaching condition (bleaching=1 or no bleaching=0) and the maximum SST. A logistic regression model was fitted to overcome the binary predicted variable in order to characterise the relation between the probability of bleaching towards minimum, mean, and maximum SST separately. This method is further described in the following section.

6.3.3 Methods

6.3.3.1 Logistic Regression (LR)

6.3.3.2 Model development

A logistic regression (LR) model was fitted to model the relationship between coral bleaching and annual maximum (mean, minimum) SST. LR characterises the relationship between a binary outcome variable and a group of predictor variables (or covariates), with the main purpose of modelling the logit-transformed probability to have a linear relationship with the predictor variables. Apart from that, LR also estimates the logistic model parameters, standard errors, and significance levels. The LR of coral bleaching on some SST variable, x_1, ..., x_k estimates parameter values for β_0, β_1, . . . , β_k using Equation 6.1:

$$\text{Logit}(p) = log(\frac{p}{1-p}) = b_0 + b_1 X_1 + b_2X_2 + \ldots + b_kX_k \qquad \text{Equation 6.1}$$

or, in the present case:

$$\text{logit}(p) = \beta_0 + \beta_1 * \text{SST} \qquad \text{Equation 6.2}$$

where p is the probability of the presence of the characteristic of interest, specifically refers to the presence of coral bleaching. The logit(p) can be back-transformed to probability, p by the following formula:

$$p = \frac{1}{1+ e^{-logit(p)}} \qquad \text{Equation 6.3}$$

The fitted model can be applied to new data such as the annual maximum SST in order to predict the probability of coral bleaching. The fitting method employed standard generalized linear modelling (GLM) approaches which involves a maximum likelihood (McCullagh & Nelder., 1989).

6.3.3.3 Model Accuracy Assessment

The Akaike information criterion (AIC) (Akaike, 1973) was adopted to select the best fitting LR model. In general terms, the AIC can be considered as a mean for ranking models instead of the measure of significance (Cannarozzi & Schneide, 2012).The smallest AIC decides the best fitting model using the Kullback-Leibler distance between a model probability distribution and the truth. It was found that the smaller the distance; hence, the smaller the number of information losses between the models. However, the model with the smallest AIC values is preferable.

$$\text{AIC} = 2K - 2\text{Log}(L) \qquad \text{Equation 6.4}$$

where *K* presents the number of predictor variables and *L* refers to the likelihood. The area under the curve (AUC) of the receiver operating characteristic (ROC) curve from a single cross-validation and bootstrapping exercise were also reported.

6.3.3.4 Coral Bleaching Probability Map

The probability of bleaching was predicted for each pixel in the image using the best fitting SST variable as the input such as the MaxSST based on Equation 6.2 and 6.3 which was reported as a set of bleaching probability maps. Each pixel represents the probability of bleaching from 0 to 1. The yearly probability maps for 1998 and 2010 were selected due to mass coral bleaching in those years with a spatial resolution of 25 km, which were then compared with the 25 km NOAA DHW. It is important to note that the representation is neither error-free nor does the purpose of making such a comparison was exploratory and not to validate either map. The CMIP5 models monthly mean SST data was utilised to predict future bleaching, which was first processed to obtain the annual maximum SST (MaxSST) as well as to produce decadal coral bleaching prediction maps from 2020 to 2100.

6.4 Results

6.4.1 Logistic model

The logistic model characterises the relationship between coral bleaching events and sea surface temperature (SST) variables in the area of study. As can be observed, the relative goodness-of-fit for the three logistic models is reported in Table 6-2

Model	AIC
MaxSST	443.17
MinSST	504.50
MeanSST	492.60

Table 6-2. The AIC of the models fitted to MaxSST, MeanSST, and MinSST

As shown in Figure 6.5, the best fitting model was successfully produced with MaxSST.

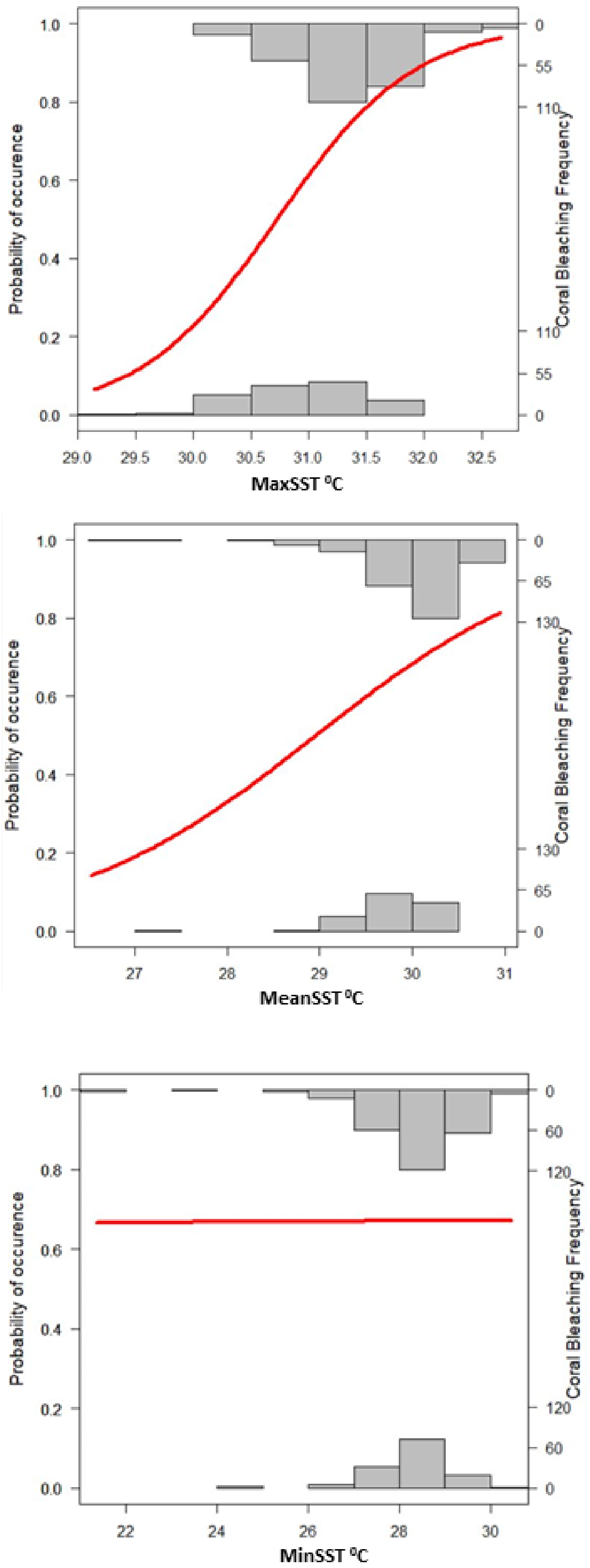


Figure 6-5. Logistic regression of coral bleaching occurrence against (a) maximum SST (Intercept = -51.736, slope=1.684), (b) mean SST (Intercept=-21.473, slope=0.741, and (c) minimum SST (Intercept = 0.631, slope = 0.002)

A random sample of 280 (70%) data pairs was drawn from the 400-coral bleaching-MaxSST data pairs, while the remaining 120 (30%) data points were held back for model validation. The area under the ROC curve (AUC) is 0.75, which indicates good predictive ability. For further clarification, the full ROC curve is illustrated in Figure 6.6.

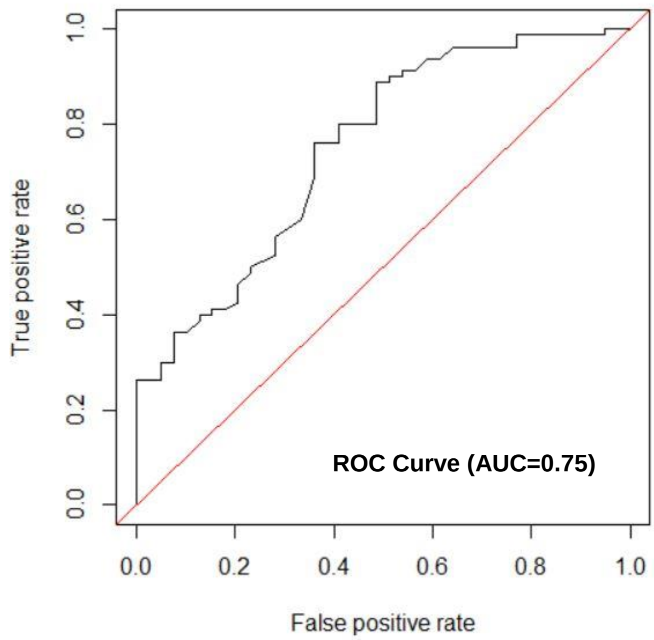


Figure 6-6. The area under the ROC curve (AUC) for the LR model based on MaxSST.

6.4.2 Coral bleaching probability map comparison

Figure 6-8 to Figure 6-10 show a comparison of the LR-based predicted maps with the NOAA Coral Bleaching Alert Area data for 2001. While overall agreement was found between the predicted probability maps and bleaching alert area, especially during May to December 2001, some important discrepancies are apparent. Using the bleaching probability value for each pixel, it is possible to obtain a clearer picture of the possible bleaching area in the region. The month of July 2001, as it appears in Figure 6-9, is a good example. While the NOAA Bleaching Alert map shows the majority of the region as at 'Watch' status, the new map predicts a bleaching probability ranging from 0.1 to 0.3. Some small areas are highlighted as 0.4 bleaching probability. Further comparison was then made between 2010 bleaching probability map and NOAA Coral Reef Watch (CRW) Degree Heating Week (DHW) product for comparison. Both dataset were first normalised and a total of 396 pairwise pixels were selected for correlation analysis as shown in Figure 6-7. Year 2010 was selected for comparison due to latest El Nino event occurred in that year.

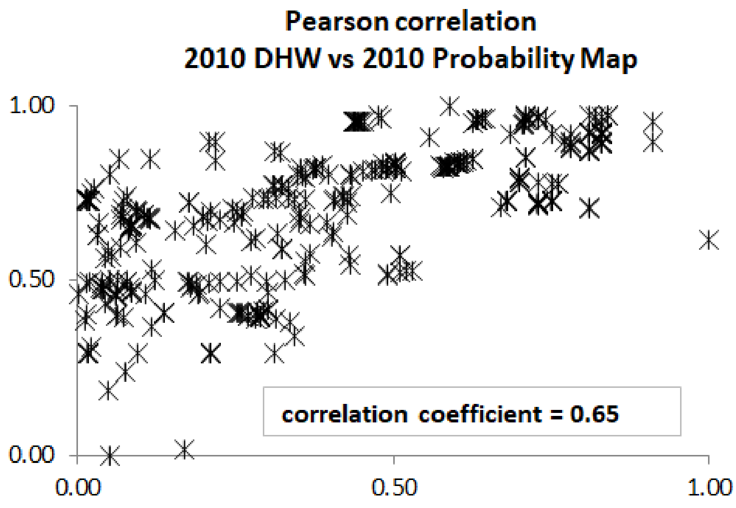
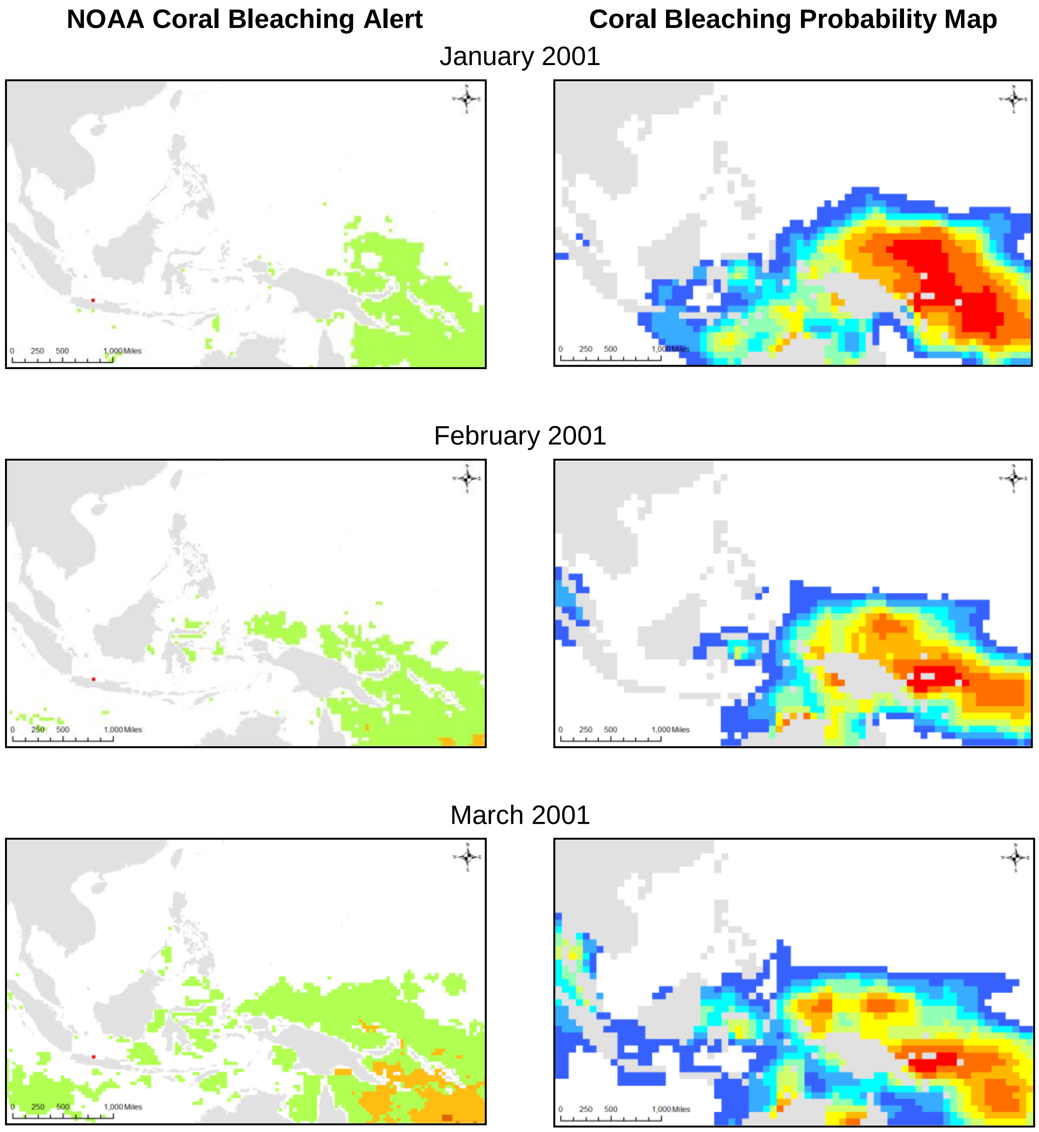


Figure 6-7. Pearson correlation showing the comparison between 2010 DHW and probability map



April 2001

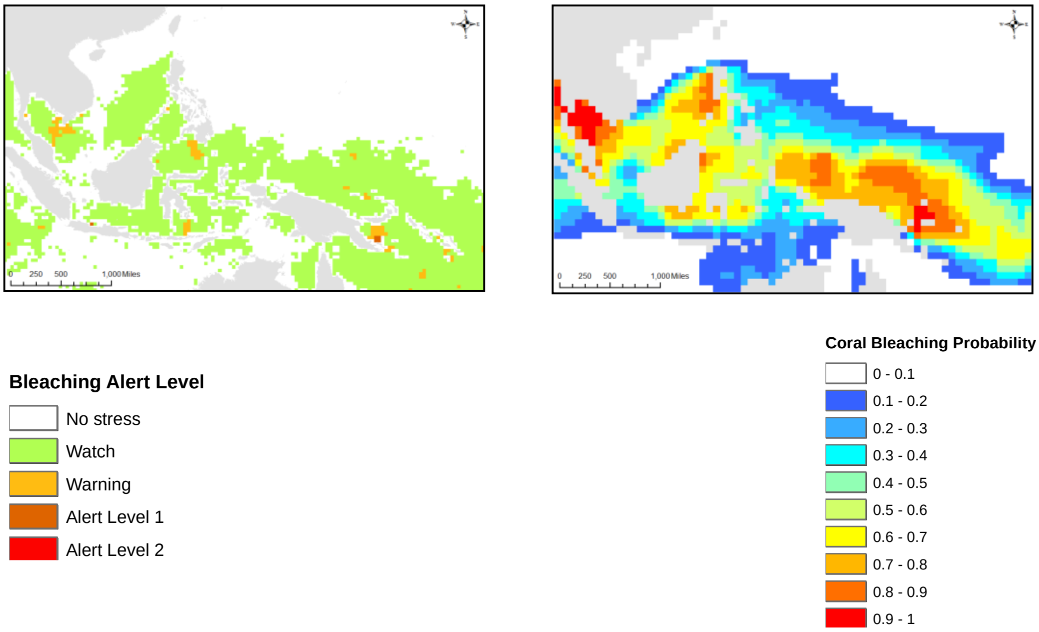
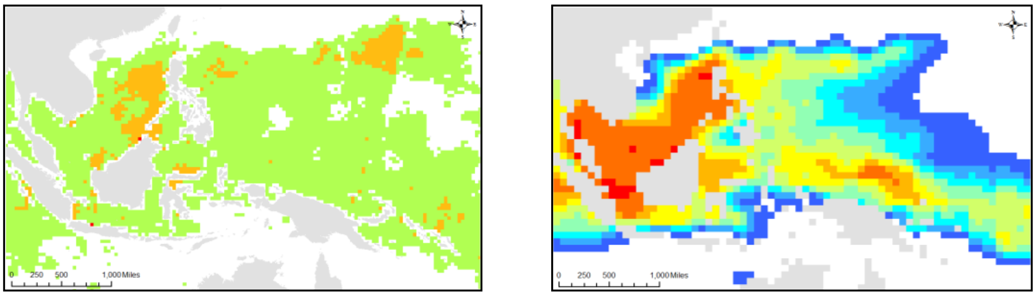


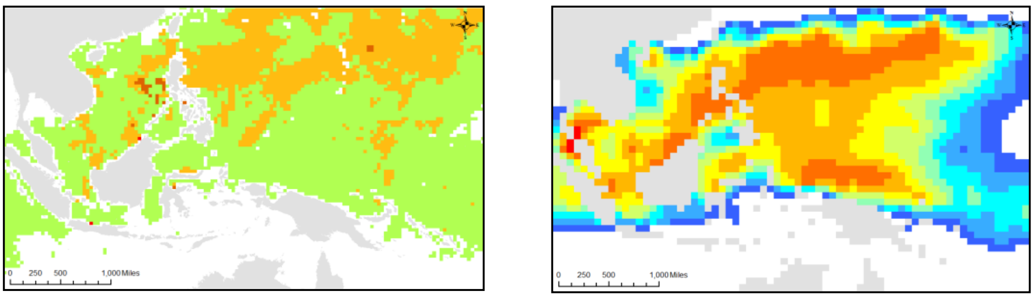
Figure 6-8. Coral Bleaching probability map and CRW bleaching alert for Jan to April 2001.

NOAA Coral Bleaching Alert **Coral Bleaching Probability Map**

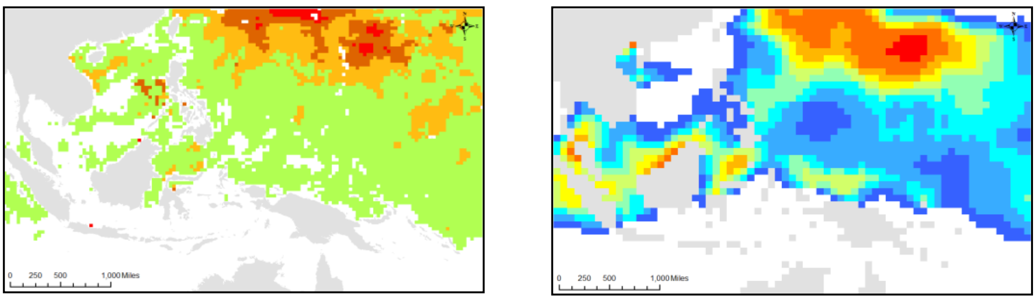
May 2001



June 2001



July 2001



August 2001

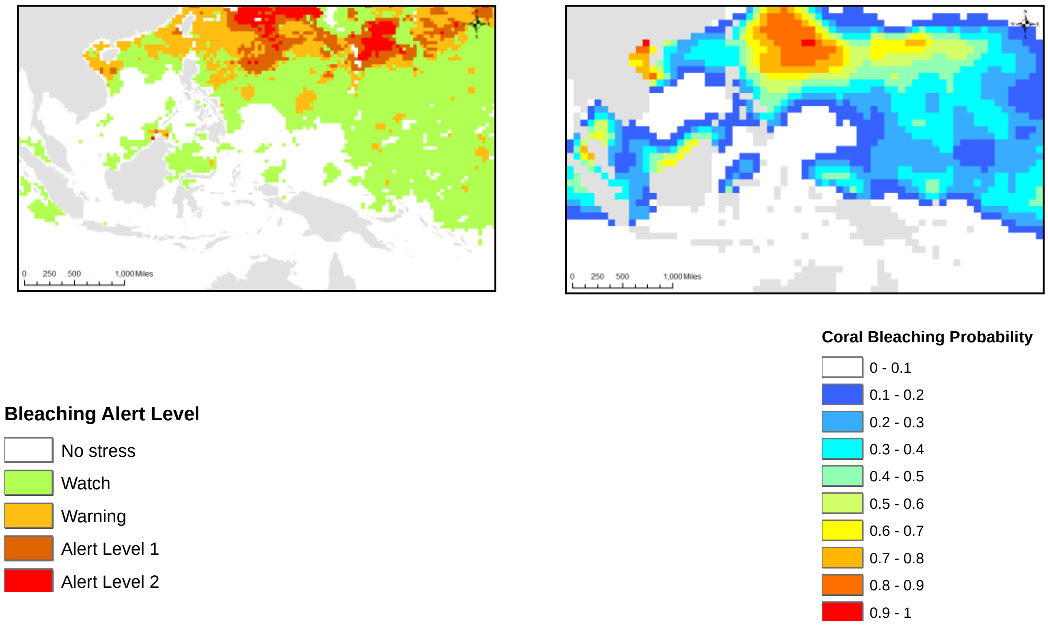
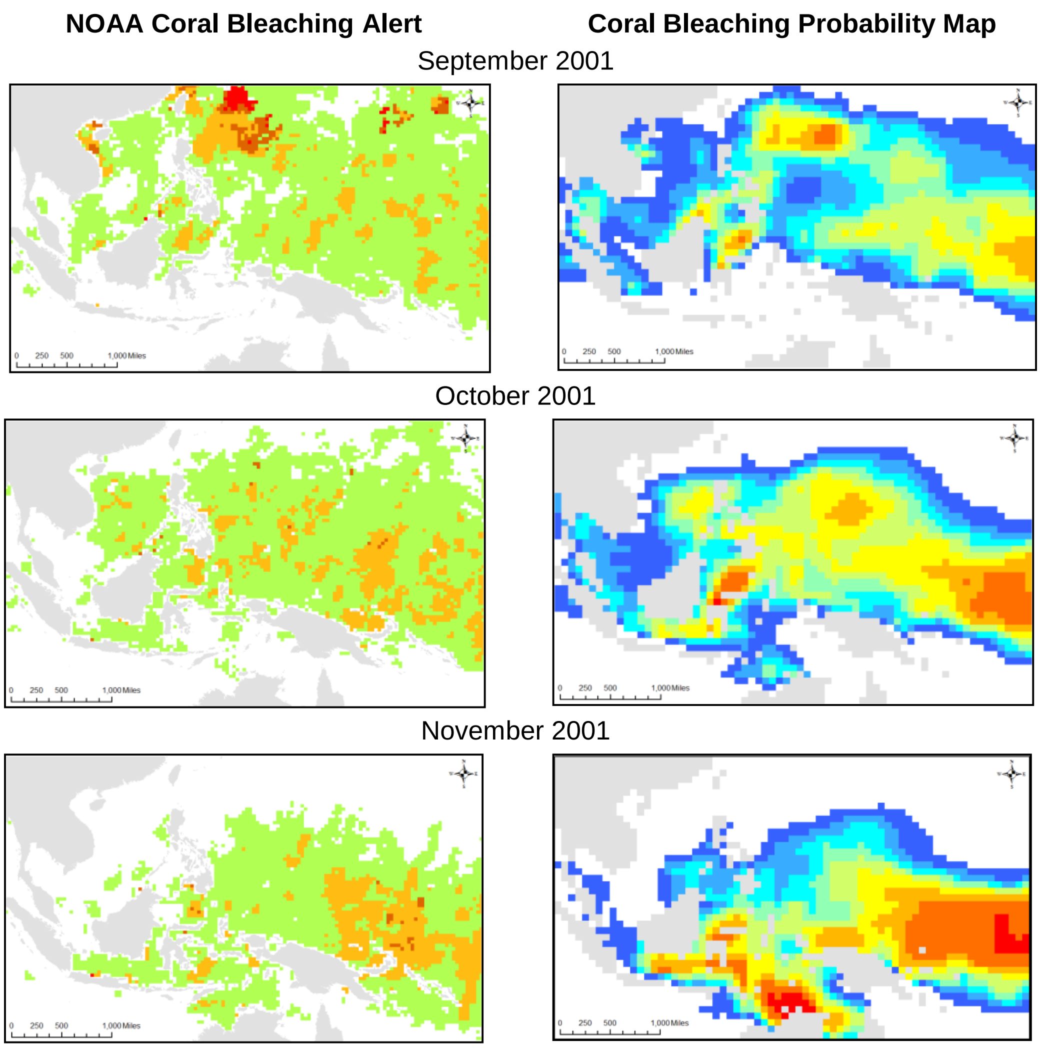


Figure 6-9. Coral Bleaching probability map and CRW bleaching alert for May to August 2001.



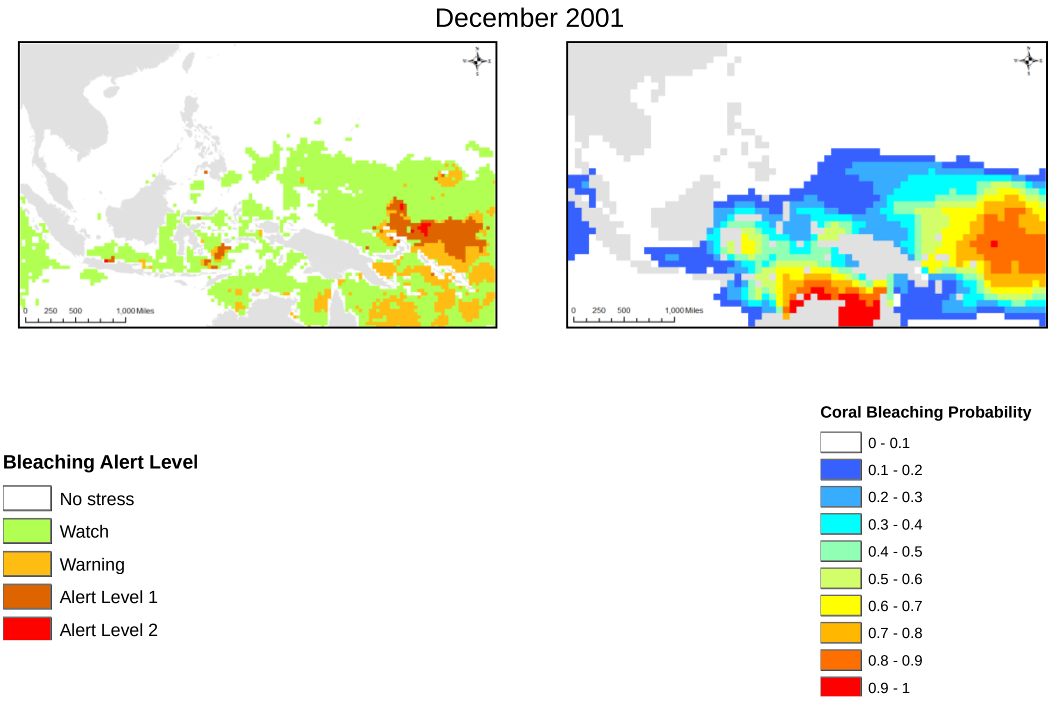


Figure 6-10. Coral Bleaching probability map and CRW bleaching alert for September to December 2001.

6.4.3 Forecasted coral bleaching probability maps

Nine decadal coral bleaching probability maps generated using models run from CMIP5 for 2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090 and 2100 are presented in Figure 6-11. In the same figure, a gradual increase in the probability can be observed in the maps from the present day to around the year 2050. In the same case, the probability plateaus after 2050. This can be seen clearly in Table 6-3 , which shows the percentage area of bleaching based on probability thresholds. As an example, focus on bleaching probability greater than 0.5. 33.7% of the region will be exposed to bleaching probability greater than 0.5 in 2020; 41.5% in 2030; 51.4% in 2040; 57.8% in 2050; 57.1% in 2060; 55.8% in 2070, 56.3% in 2080, 54.9% in 2090 and finally 55.5% in 2100.

This result is consistent with the increasing trend in sea surface temperature that was forecasted by CMIP5. Moreover, a careful examination on the decadal coral bleaching probability maps presented in Figure 6.9 shows that the Coral Triangle area is forecasted to be in a critical situation by as early as 2040. This is shown in the map by the yellow colour (0.6-0.7 probability) which gradually dominates the region, and will remain in the heart of the Coral Triangle for at least a few decades more.

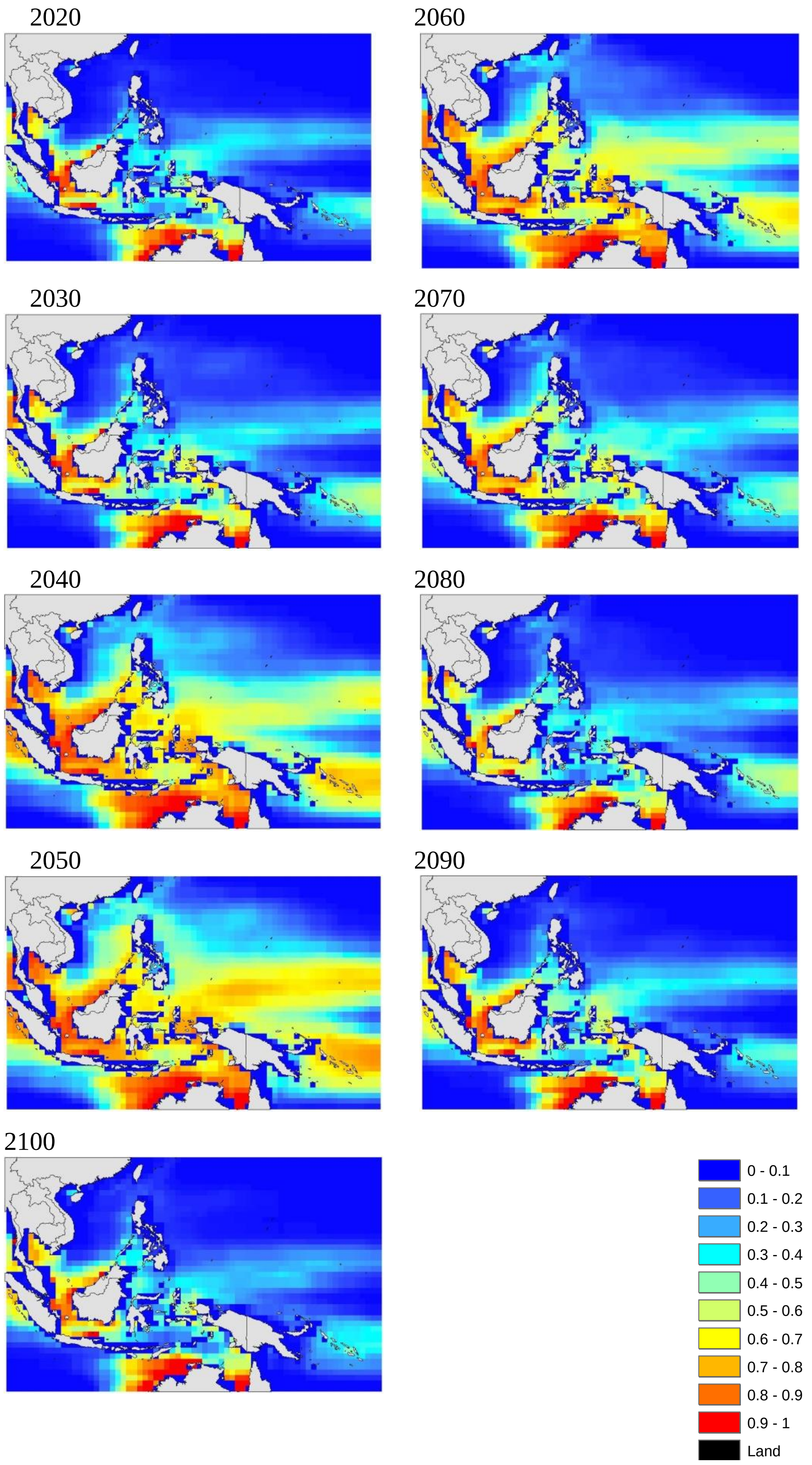

2020
2060
2030
2070
2040
2080
2050
2090
2100
0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1
Land

Figure 6-11. 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.

Table 6-3. Bleaching probability percentage in the Indo-Pacific region from 2020 to 2100

	Number of pixels (%) for CMIP5 decadal maps								
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

6.5 Discussion

6.5.1 The relation between coral bleaching and maximum SST

The prediction and forecasting of coral bleaching do not only require the handling of large datasets and statistical modelling, but it is also prohibitively labour and cost intensive using *in situ* data collection due to the size of the ocean. Hence, it cannot be denied that the satellite remote sensing plays a vital role in providing a spatially extensive prediction. Meanwhile, it is also worth to note the existence of a variety of remotely sensed ocean temperature datasets that are important in predicting coral bleaching. NOAA AVHRR data have been widely used in many studies; hence, it was also employed in this study to determine the heat stress in the ocean as an input to predict coral bleaching using DHW maps.

The effects of MaxSST, MinSST, and MeanSST derived from NOAA AVHRR OISSTv2 on the binary occurrence of coral bleaching were modelled using LR, and then evaluated using the AIC and AUC. According to the result, MaxSST was found to be the most significant covariate, which further explains the event of coral bleaching in the Indo-Pacific region. This finding is in agreement with Logan (2012) who proposed the use of the mean of the warmest month of each year instead of the mean of the average warmest month shown in the climatological period. Apart from that, the spatial pattern in the coral bleaching probability maps produced using the LR model at the spatial resolution of 25 km were found to be generally consistent with the NOAA DHW maps at 25 km spatial resolution, which also managed to predict different variables (probabilities v. degree heating variables, respectively).

Interestingly, the empirical methods applied in this research managed to reveal greater attribute details which include the variation in the probability of coral bleaching throughout the region without taking into account the coarser spatial resolution. Moreover. this can also be attributed primarily to different variables predicted by emphasizing more on the local model fitting employed in the probability maps particularly the Coral Triangle and the South China Sea instead of utilising the global fitting employed in the DHW developed for the entire globe.

The adoption of LR allows the calculation for a change of 1°C in corresponds to a change of e^{b} in the odds of bleaching occurring, where *b* represents the slope of LR. The slope is 1.69 which caused the odds of bleaching to increase by a factor of 5.36 for each 1°C increase in MaxSST. On another note, 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 odd of 2.13 x 5.36 = 11.42. As a result, this corresponds to a probability of 11.42/1+11.42 = 0.91 overall, which emphasise more on the vulnerability of the region to coral bleaching due to the continuously increasing temperature.

A finer spatial resolution such as a 4 km SST data may be utilised in the future to assess the variability in the sea surface temperature properties in this region. Therefore, it is hoped that bleaching events can be captured with greater geometric precision using a much finer spatial resolution satellite sensor data , as stated by Weeks et al. (2008).

The LR model may be limited based on the assumption that there are no abrupt changes in the temperature from the surface to the approximated 20 m depth in the region which has become very common in the region. Akhir and Chuen (2011) conducted a localized study in Malaysian waters which reported that the change in the temperature profile from the ocean surface to 40 m depth were less than 1°C. On another note, Castillo and Lima (2010) concluded that the differences between satellite sensor-derived SST and *in situ* measurements at different depths were small and not important from a biological point-of-view. Apart from that, McClanahan et al. (2007) found that water depth was insignificant when modelled together with heat stress from satellite sensor data in predicting coral bleaching.

6.5.2 Coral bleaching in future based on CMIP5 forecasts

A considerable amount of studies has forecasted coral bleaching based on projected SST that was generated from an ocean-atmosphere general circulation model (Hoegh-Guldberg, 1999; Sheppard, 2003; Donner et al., 2005). These temperatures are utilised as the indicator for bleaching events. However, the latest integrated climate model initiative known as the CMIP5 was adopted in the present study for the purpose of forecasting decadal coral bleaching from the year 2020 to 2100. The use of the latest climate model provides finer spatial resolution, which automatically considers major events that could affect the SST such as the 1999 Mount Pinatubo eruption. For example, the models used by Donner et al. (2005) known as 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, whereas the CMIP5 framework provides a resolution of 1.25° x 1.25°.

The first Representative Concentration Pathways (RCPs) scenario was simulated to forecast future maximum SST as well as the future probability of coral bleaching, which is RCP2.6 in CMIP5 (Moss et al., 2010). The CMIP5 model simulated a rate of ocean warming in the study area from 1982 to 2012 which was less rapid than the one predicted by satellite sensor data. Meanwhile, Forster et al. (2013) report that the constituent models in CMIP5 tend to overestimate the observed temperature which is in agreement with the present study. On the other hand, Kim et al. (2012) presented a decadal SST prediction by reporting that most models tested in CMIP5 tend to produce cooler SST. Overall, the present research supports the finding that when dealing with short time-series, the data produced by CMIP5 tend to underestimate the observed SST.

Furthermore, a gradual increase towards a high probability of bleaching was predicted to dominate the study area from the year 2020 to 2050 before reaching a plateau. The decadal maps of coral bleaching Presented in Figure 6.9 shows that the early trend of bleaching is consistent with Hooidonk et al. (2013), who found that majority of corals in tropical waters will face bleaching in 2040 to 2050. The situation of widespread bleaching in 2050 was also reported by Burke et al. (2012). Moreover, the lower probability of bleaching from 2070 to 2100 is interesting given the general understanding that the Earth is warming. However, this is merely an outcome of the long-term trend in maximum SST forecast from CMIP5. Reto et al. (2013) and Villarini and

Vecchi (2012) also point out that a flat trend of global mean SST was detected from approximately year 2060 until 2100 under the RCP2.6 scenario.

Looking closely at the forecasted maps of coral bleaching, the northern part of the SCS (coast of Vietnam and northwards) is forecasted to be safe for coral reefs until at least the year 2100. However, it is a important matter considering that the Coral Triangle that acts as the heart of the coral reefs is threatened by a high probability of coral bleaching at least between 2040 to 2060.

The present research also indicates that serious coral bleaching is forecasted in the near future due to ocean warming. However, this scenario is subjected to changes depending on the SST trend as well as the coral resilience to future warming (Carilli et al., 2009; 2012) by the adaptation of physiological tolerance (West & Salm, 2003). On another note, Frieler et al. (2013) state thatglobal mean temperature should be limited to 1.2°C above pre-industrial temperatures to preserve at least 50% of the global coral reef.

6.6 Conclusion

The forecasting for the coral bleaching events at the Indo-Pacific region was very challenging; however, it was very necessary considering the rate of change expected in ocean warming in that area. Most studies have established modelled predictions that are dependent on global parameters, but they were not sufficient to capture local detail as well as to forecast bleaching in the future. The LR model fitted here managed to reveal 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 sea surface temperature. Moreover, this empirical relation had allowed the prediction of coral bleaching probability across the study area. The result obtained was in overall general agreement with the NOAA Coral Reef Watch (CRW) Degree Heating Weeks (DHW) map despite the discrepancies resulted by the more local fitting conducted in the region.

The coral bleaching over the coming decades managed to be forecasted based on the rigorous and locally-specific modelling developed using historical maximum SST data that is coupled with the forecasted maximum SST obtained from the latest CMIP5 model ensemble. According to the LR model fitted in this study, an expected increase in sea temperature in the region has been forecasted by the CMIP5 model. Therefore, the increase is believed to bring devastating effects to the world's most important coral region over the next three decades, with most areas experiencing losses within the next decade.

6.7 Acknowledgements

The authors would like to acknowledge NOAA/OAR/ESRL PSD, Boulder, Colorado, USA for the NOAA_OI_SST_V2 data from their web site at http://www.esrl.noaa.gov/psd/. The authors would also like to thank Reefbase (http://www.reefbase.org) for the coral bleaching datasets and Royal Netherlands Meteorological Institute (KNMI) Climate Explorer for the CMIP5 datasets.

6.8 References

Akaike, H., 1973. Information theory & an extension of the maximum likelihood principle. B. N. Petrov & F. Csaki, eds. *2nd International Symposium on Information Theory*, pp.pp. 267–281.

Akhir, M.F.M. & Chuen, Y.J., 2011. Seasonal variation of water characteristics during inter-monsoon along the east coast of johor. *Journal of Sustainability Science and Management*, 6 (2), pp.206–214.

Allen, G.R., 2008. Conservation hotspots of biodiversity and endemism for Indo-Pacific coral reef fishes. *Aquatic Conservation: Marine and Freshwater Ecosystems*, 18(5), pp.541–556. Available at: http://dx.doi.org/10.1002/aqc.880.

Banzon V, Smith TM, Chin TM, Liu C, Hankins W (2016) A long-term record of blended satellite and in situ sea-surface temperature for climate monitoring, modeling and environmental studies. Earth Syst Sci Data 8:165–176

Berkelmans et al., 2004. *A comparison of the 1998 and 2002 coral bleaching events on the Great Barrier Reef: spatial correlation, patterns, and predictions*, Berlin, ALLEMAGNE: Springer.

Berkelmans, R., 2009. Bleaching and Mortality Thresholds: How Much is Too Much? In M. J. H. Oppen & J. M. Lough, eds. *Coral Bleaching*. Springer Berlin Heidelberg, pp. 103–119. Available at: http://dx.doi.org/10.1007/978-3-540-69775-6_7.

Brown et al., 2002. Experience shapes the susceptibility of a reef coral to bleaching. *Coral Reefs*, 21(2), pp.119–126. Available at: http://dx.doi.org/10.1007/s00338-002-0215-z.

Bruno, J.F. et al., 2007. Thermal Stress and Coral Cover as Drivers of Coral Disease Outbreaks. *PLoS Biol*, 5(6), p.e124. Available at: http://dx.doi.org/10.1371%2Fjournal.pbio.0050124.

Burke, L. et al., 2012. *Reefs at Risk Revisited in the Coral Triangle*, Washington D.C, USA: World Resource Institute.

Burke, L.M. et al., 2002. *Reefs at Risk in Southeast Asia*, World Resources Institute, Washington, DC. Available at: http://books.google.co.uk/books?id=WScVAQAAIAAJ.

Cannarozzi, G.M. & Schneide, A., 2012. *Codon Evolution: Mechanisms and Models*, United States: Oxford University Press Inc., New York.

Carilli, J., Donner, S.D. & Hartmann, A.C., 2012. Historical Temperature Variability Affects Coral Response to Heat Stress. *PLoS ONE*, 7(3), p.e34418. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0034418.

Carilli, J.E. et al., 2009. Local Stressors Reduce Coral Resilience to Bleaching. *PLoS ONE*, 4(7), p.e6324. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0006324.

Carpenter, K.E. et al., 2008. One-third of reef-building corals face elevated extinction risk from climate change and local impacts. *Science*, 321(5888), pp.560–563. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18653892.

Castillo, K.D. & Lima, F.P., 2010. Comparison of in situ and satellite-derived (MODIS-Aqua/Terra) methods for assessing temperatures on coral reefs. *Limnology and Oceanography: Methods*, 8, pp.536–554.

Cesar, H., Burke, L. & Pet-Soeda, L., 2003. *The Economics of Worldwide Coral Reef Degradation*, The Netherlands: Cesar Environmental Economics Consulting (CEEC).

Coles, S.L. & Jokiel, P.L., 1992. Effects of Salinity on coral reefs. In Connell Des W. & Hawker D.W., eds. *Pollution in Tropical Aquatic Systems*. Boca Raton: CRC Press Inc, p. pp 147–166.

Dollar, S.J. & Grigg, R.W., 1981. Impact of a Kaolin Clay Spill on a Coral-Reef in Hawaii. *Marine Biology*, 65(3), pp.269–276. Available at: <Go to ISI>://A1981MV64200008.

Donlon, C. et al., 2009. The GODAE high resolution sea surface temperature pilot project. *Oceanography*, 2(3), pp.34–45.

Donner SD, Rickbeil GJM, Heron SF (2017) A new, high-resolution global mass coral bleaching database. PLoS ONE 12(4): e0175490. https://doi.org/10.1371/journal.pone.0175490

Donner, S.D., 2011. An evaluation of the effect of recent temperature variability on the prediction of coral bleaching events. *Ecological Applications*, 21(5), pp.1718–1730. Available at: http://dx.doi.org/10.1890/10-0107.1.

Donner, S.D., 2009. Coping with Commitment: Projected Thermal Stress on Coral Reefs under Different Future Scenarios. *PLoS ONE*, 4(6), p.e5712. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0005712.

Donner, S.D. et al., 2005. Global assessment of coral bleaching and required rates of adaptation under climate change. *Global Change Biology*, 11(12), pp.2251–2265. Available at: http://dx.doi.org/10.1111/j.1365-2486.2005.01073.x.

Fitt, W. et al., 2001. Coral bleaching: interpretation of thermal tolerance limits and thermal thresholds in tropical corals. *Coral Reefs*, 20(1), pp.51–65. Available at: http://dx.doi.org/10.1007/s003380100146.

Forster, P.M. et al., 2013. Evaluating adjusted forcing and model spread for historical and future scenarios in the CMIP5 generation of climate models. *Journal of Geophysical Research: Atmospheres*, 118(3), pp.2169–8996. Available at: http://dx.doi.org/10.1002/jgrd.50174.

Frieler, K. et al., 2013. Limiting global warming to $2^{0}C$ is unlikely to save most coral reefs. *Nature Clim. Change*, 3(2), pp.165–170. Available at: http://dx.doi.org/10.1038/nclimate1674.

GCRMN, 2010. *Status of Coral Reefs in East Asian Seas Region: 2010* G. C. R. M. Network, ed., Ministry of the Environment, Japan.

Glynn, P.W., 1997. Bioerosion and coral reef growth: a dynamic balance. In C. Birkeland., ed. *Life and Death of Coral Reefs*. New York: Chapman and Hall.

Glynn, P.W., 1996. Coral reef bleaching: facts, hypotheses and implications. *Global Change Biology*, 2(6), pp.495–509. Available at: http://dx.doi.org/10.1111/j.1365-2486.1996.tb00063.x.

Goreau, T.J. & Hayes, R.L., 1994. Coral bleaching and ocean "hot spots. *Ambio*, 23(23), pp.176–180.

Hoegh-Guldberg et al., 2009. *The Coral Triangle and Climate Change: Ecosystems, People and Societies at Risk*, Brisbane, Australia: WWF Australia.

Hoegh-Guldberg, O., 1999. Climate change, coral bleaching and the future of the world's coral reefs. *Marine and Freshwater Research*, 50(8), pp.839–866. Available at: http://www.publish.csiro.au/paper/MF99078.

van Hooidonk, R. et al., 2013. Temporary refugia for coral reefs in a warming world. *Nature Clim. Change*, 3(5), pp.508–511. Available at: http://dx.doi.org/10.1038/nclimate1829.

Hu, J. et al., 2000. A Review on the Currents in the South China Sea: Seasonal Circulation, South China Sea Warm Current and Kuroshio Intrusion. *Journal of Oceanography*, 56, pp.607–624. Available at: http://www.ingentaconnect.com/content/klu/joce/2000/00000056/00000006/00351943.

Hubbard, D.K., 1997. Reefs as dynamic systems. In C. Birkeland., ed. *Life and Death of Coral Reef*. New York: Chapman and Hall.

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

Kim, H.-M.H.-M. et al., 2012. Evaluation of short-term climate change prediction in multi-model CMIP5 decadal hindcasts. *Geophysical Research Letters*, 39(10), p.L10701. Available at: http://dx.doi.org/10.1029/2012GL051644.

Kool, J.T. et al., 2011. Connectivity and the development of population genetic structure in Indo-West Pacific coral reef communities. *Global Ecology and Biogeography*, 20(5), pp.695–706. Available at: http://dx.doi.org/10.1111/j.1466-8238.2010.00637.x.

Liu, Q. et al., 2004. A gap in the Indo-Pacific warm pool over the South China Sea in boreal winter: Seasonal development and interannual variability. *J. Geophys. Res.*, 109(C7), p.C07012. Available at: http://dx.doi.org/10.1029/2003JC002179.

Logan CA, Dunne JP, Eakin CM, Donner SD (2012) A framework for comparing coral bleaching thresholds. In: Proceedings of the 12th International Coral Reef Symposium (ed. Yellowlees D, Hughes TP), pp. 10A3. Townsville.

Manzello, D.P., Berkelmans, R. & Hendee, J.C., 2007. Coral bleaching indices and thresholds for the Florida Reef Tract, Bahamas, and St. Croix, US Virgin Islands. *Marine Pollution Bulletin*, 54(12), pp.1923–1931. Available at: http://www.sciencedirect.com/science/article/pii/S0025326X07003074.

McClain, E.P., Pichel, W.G. & Walton, C.C., 1985. Comparative performance of avhrr-based multichannel sea surface temperatures. *J. Geophys. Res.*, 90(C6), pp.11587–11601. Available at: http://dx.doi.org/10.1029/JC090iC06p11587.

McClanahan, T. et al., 2007. Predictability of coral bleaching from synoptic satellite and in situ temperature observations. *Coral Reefs*, 26(3), pp.695–701. Available at: http://dx.doi.org/10.1007/s00338-006-0193-7.

McClanahan, T.R. et al., 2007. Effects of Climate and Seawater Temperature Variation on Coral Bleaching and Mortality. *Ecological Monographs*, 77(4), pp.503–525. Available at: http://dx.doi.org/10.1890/06-1182.1.

McLeod, E. et al., 2010. Warming Seas in the Coral Triangle: Coral Reef Vulnerability and Management Implications. *Coastal Management*, 38(5), pp.518–539.

Moss, R.H. et al., 2010. The next generation of scenarios for climate change research and assessment. *Nature*, 463(7282), pp.747–756. Available at: http://dx.doi.org/10.1038/nature08823.

Oliver, T.A. & Palumbi, S.R., 2011. Do fluctuating temperature environments elevate coral thermal tolerance? *Coral Reefs*, 30(2), pp.429–440. Available at: http://dx.doi.org/10.1007/s00338-011-0721-y.

Reto, K. et al., 2013. Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, 3(4), pp.369–373. Available at:

http://dx.doi.org/10.1038/nclimate1716.

Reynolds, R.W., 1988. A real-time global sea surface temperature analysis. *J. Climate*, 1, pp.75–86.

Reynolds, R.W. et al., 2002. An Improved In Situ and Satellite SST Analysis for Climate. *Journal of Climate*, 15(13), pp.1609–1625. Available at: http://dx.doi.org/10.1175/1520-0442(2002)015<1609:AIISAS>2.0.CO;2.

Reynolds, R.W. & Chelton, D.B., 2010. Comparisons of Daily Sea Surface Temperature Analyses for 2007 - 08. *Journal of Climate (Formerly : Journal of Climate and Applied Meteorology)*, 23(13), pp.3545–3562.

Saha, K., 2010. *Tropical Circulation Systems and Monsoons*, Berlin, German: Springer.

Sheppard, C.R.C., 2003. Predicted recurrences of mass coral mortality in the Indian Ocean. *Nature*, 425(6955), pp.294–297. Available at: http://dx.doi.org/10.1038/nature01987.

Skirving, W., Heron, M. & Heron, S., 2006. The Hydrodynamics of a Bleaching Event: Implications for Management and Monitoring. In *Coral Reefs and Climate Change: Science and Management*. American Geophysical Union, pp. 145–161. Available at: http://dx.doi.org/10.1029/61CE09.

Strong, A.E. et al., 1997. Improved satellite techniques for monitoring coral reef bleaching. In *Proc 8th International Coral Reef Society Symposium*. Panama, pp. 1495–1498.

UNEP-WCMC, 2006. *In the Front Line: Shoreline Protection and Other Ecosystem Services from Mangroves and Coral Reefs.* , United Kingdom : UNEP-WCMC, Cambridge.

Veron, J.E.N. et al., 2009. Delineating the Coral Triangle. *Galaxea, Journal of Coral Reef Studies*, 11(2), pp.91–100.

Villarini, G. & Vecchi, G.A., 2012. Twenty-first-century projections of North Atlantic tropical storms from CMIP5 models. *Nature Clim. Change*, 2(8), pp.604–607. Available at: http://dx.doi.org/10.1038/nclimate1530.

Vinoth, R. et al., 2012. Coral reef bleaching at Agatti Island of Lakshadweep atolls, India. *Journal of Ocean University of China*, 11(1), pp.105–110. Available at: http://dx.doi.org/10.1007/s11802-012-1822-0.

Weeks, S.J. et al., 2008. Improved predictions of coral bleaching using seasonal baselines and higher spatial resolution. *Heron*, 53(4), pp.1369–1375

West, J.M. & Salm, R. V, 2003. Resistance and Resilience to Coral Bleaching: Implications for Coral Reef Conservation and Management. *Conservation Biology*, 17(4), pp.956–967. Available at: http://dx.doi.org/10.1046/j.1523-1739.2003.02055.x.

Wilkinson, C., 2008. *Status of coral reefs of the world: 2008*, Townsville, Australia: Global Coral Reef Monitoring Network and Reef and Rainforest Research Centre.

Yeemin, T. et al., 2012. Impacts of coral bleaching, recovery and management in Thailand. In *Proceedings of the 12th International Coral Reef Symposium*. Cairns, Australia.

Yeemin, T. et al., 2010. Status of coral reefs in Thailand following the 2010 coral bleaching event. In Kimura T & K. Tun, eds. *Status of Coral Reefs in East Asian Seas Region*. Ministry of the Environment, Japan, pp. 29–49.

Chapter 7: Multiscale Region-Specific Modelling and Forecasting of the Effect of Sea Surface Temperature on Coral Bleaching in the Indo-Pacific

7.1 Abstract

The coral reefs ecosystem is one of the most diverse and valuable ecosystems on Earth. Other than providing habitats and shelter for many marine organisms, coral reefs also play an integral role as the economic contributor especially in Tropical countries. For the past few decades, this ecosystem is critically threatened as a result of the mass coral bleaching event which relates to the warming of the ocean. Around the globe, specific indexes have been used to identify potential areas for coral bleaching. This study investigate the relationship between Sea Surface Temperature (SST) and coral bleaching using suitable statistical model in the Indo-Pacific region. The SST data was obtained from Coral Reef Temperature Anomaly Database (CoRTAD) while the coral bleaching record was downloaded from ReefBase, an online database records. The original CoRTAD data at 4 km spatial resolution and 4 other resampled SST at 16 km, 32 km, 64 km and 100 km were tested. The findings showed significant relationship between the probablity of coral bleaching and maximum monthly mean SST(MaxSST). The recommended spatial resolution which best fit the the model was 4 km with 12 km autocovariate. The results suggest that with a proper selection of spatial resolution size, coral bleaching probability mapping could be improve.

Key words — SST, space-time, coral bleaching, Indo-Pacific

7.2 Introduction

Coral reefs are among the most important ecosystems in the world (Mumby & Steneck 2008). Generally confined to tropical regions, this ecosystem creates essential habitat for a diversity of marine life. Coral reefs serve as nursery grounds to many marine organisms, where they can safely lay their eggs and raise their young. A conducive environment, sufficient sunlight and a plentiful supply of nutrients are the reasons why coral reefs are perfect for marine organisms. Plaisance et al. (2011) reported that within a 6.3 m^2 area they found 525 crustacean species, and they concluded that the high biodiversity of crustaceans in coral reefs was previously underestimated.

The total area of the world's tropical coral reefs is approximately 284,300 km^2 (Spalding et al. 2001). The vast majority of the coral reefs species can be found in the world's largest and richest area of coral reefs, commonly known as the Coral Triangle (CT). This large area is covered by six countries, namely Indonesia, Malaysia, Papua New Guinea, the Philippines, the Soloman Islands and Timor-Leste. These countries are working together to monitor and sustain the CT’s extraordinary marine and coastal resources, under the banner of the “CT6” which started in 2009. This initiave has created a strong conservation network across the CT (Pietri et al. 2015).

Coral reefs are considered dead when the algae that live on the calcium carbonate skeleton move out from the reefs leaving a white coral. The greatest threat to coral reefs are warming of the ocean water and ocean acidification. A predicted increase in temperature of 2^0C by 2050 to 2100 puts this ecosystem at the greatest future risk (Hoegh-Guldberg et al. 2007), while other important factors such as sedimentation, local pollution and illegal fishing in Marine Protected Areas (MPA) can also lead to coral death.

Generally, coral reefs status is monitored using the SCUBA diving, manta towing (English et al. 1997) and video transect techniques (Carleton & Done 1995) that are costly and time-consuming. In contrast, remote sensing has the advantages that it can provide complete coverage, at a particular spatial resolution, both synoptically and remotely such that large, often inaccessible, areas can be mapped (Hedley et al. 2016). The National Oceanic and Atmospheric Administration (NOAA), for example, operates a fleet of environmental satellites that has monitored the Earth since 1981. The daily satellite sensor data are available freely to the public. The derived variables predicted from the satellite sensor imagery include sea surface temperature (SST), forest fires, land cover etc., and these can be used in a wide range of applications such as forestry, agriculture, geology and oceanography. Given appropriate hardware and software, such satellite sensor data can support monitoring coral reefs effectively.

Since 2009, NOAA has continuously monitored and reported on the status of coral reefs around the globe using certain indices. These indices predict the threat of coral bleaching as a function of SST for different time periods. Since 2005, the NOAA Coral Reef Watch (CRW) programme has provided near-real time reef temperature conditions in the form of a Satellite Bleaching Alert (SBA) product. It effectively warns the public of the threat of coral bleaching (Liu et al. 2006). The NOAA CRW 50 km bleaching alert product has succesfully used to detect large scale coral bleaching occurrence but at some level, failed to capture small reefs bleaching. Based on high user request, NOAA then introduce a new 4 km bleaching alert area in May 2014 and the product is now under continous validation and development.

This research aimed to characterise the link between maximum monthly mean SST (MaxSST) and coral bleaching occurrence using an appropriate statistical model. Additionally, this research aimed to examine the impact of using different spatial data resolutions when modelling and predicting the probability of coral bleaching in the Indo-Pacific.

7.3 Materials and methods

7.3.1 Study site and data

The study area covers a section of the Indo-Pacific region (Figure 7-1) between Latitudes 16.5° South to 26.5° North and Longitudes 96.5° East to 165.5° East. There are two important areas in the region, the South China Sea which is commonly known to be a mass of connective economic tissue where global sea routes coalesce; and the Coral Triangle, the world's center for marine biodiversity (Veron, 2009).

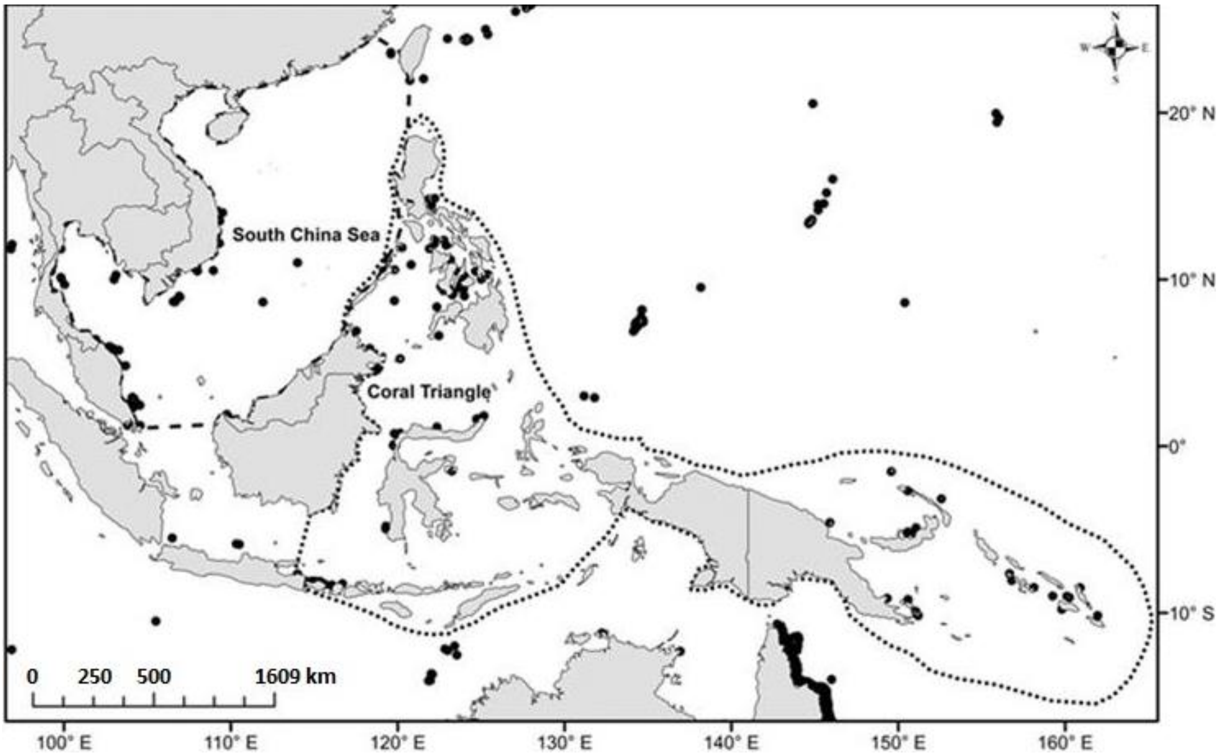


Figure 7-1. Map showing the central region of the Indo-Pacific which encompasses the South China Sea and Coral Triangle. The dark spots indicate the distribution of the coral bleaching record from 1983 to 2010 (ReefBase, 2012).

7.3.1.1 Sea surface temperature data

SST datasets were obtained from the Coral Reef Temperature Anomaly Database (CoRTAD) (http://www.nodc.noaa.gov/sog/cortad/). A total of 4,452 weekly time-series images of SST from January 1983 to December 2010 were downloaded, processed and entered into a geographical information system (GIS) environment for further analysis. The CoRTAD SST gap filled data was produced using 3x3 median spatial filter before piecewise Cubic Hermite Interpolating Polynomial (PCHIP) (Fritsch & Carlso 1980) taking care of the temporal fill. The CoRTAD is described in detail in Selig et al. (2010). The gap filled procedures was done by the data provider.

7.3.1.2 Coral bleaching data

Coral bleaching data were acquired from ReefBase, an online information system on coral reefs which provides essential coral bleaching data to the public for free. Currently ReefBase is hosted by the WorldFish Center, an organization that aims to reduce poverty and hunger by improving fisheries and aquaculture. The obtained data include: Reefbase GIS ID, Region, Subregion, Country, country code, Location, Latitude, Longitude, Month, Year, Depth, Severity Code, Bleaching Severity, Coral family, Coral species, Percentage affected, Bleaching duration, Mortality code, Mortality, Recovery code, Recovery, Survey type, Survey area, Water temperature, Other factors, Remarks, Source and reference code. The ReefBase database was built originally by the United Nations Environment Programme-World Conservation Monitoring Centre (UNEP-WCMC). The data were compiled and updated by Reefbase since 2002. According to the Reefbase database, there were 967 bleaching and non-bleaching records. However, only 852 records were suitable for use in this research as 115 records were located under the 'land mask' associated with the SST data.

7.3.2 Data pre-processing

A total of 156 weekly SST images were downloaded from CoRTAD (with a spatial resolution of 4 km). The annual maximum monthly mean SST (MaxSST) was then calculated for the 28 years from 1983 to 2010. The CoRTAD dataset at the 4 km spatial resolution comprises 1,570 columns and 978 rows and its latitudinal extent is from 96.5^{0}E 16.5^{0}N to 165.5^{0}E 26.5^{0}S. The 4 km spatial resolution data were also resampled using the Block Statistic using MEAN function to produce the annual MaxSST for the 16 km, 32 km, 64 km and 100 km spatial resolutions. An additional 12 km MaxSST dataset was produced using a "doughnut" shaped kernel filter with 3 x 3 pixel size (Xie et al. 2015) for use as an autocovariate in regression modelling.

The MaxSST together with the bleaching records were then entered into a GIS for further analysis. The coral bleaching data were recorded according to month and year to facilitate straightforward comparison of MaxSST and the year of coral bleaching. As mentioned in Section 2.1.2, any coral bleaching record without a MaxSST value due to the 'land mask', was omitted from the analysis. From 852 ReefBase records, there were 520 bleaching records and another 332 non-bleaching records. As the bleaching and non-bleaching record is binary (bleaching=1 and non-bleaching=0), this research used a logistic regression model to characterise the relation between bleaching occurrence and MaxSST. 716 coral bleaching records were common to all covariates and so this set was used in each logistic model for consistency.

7.3.3 Methods

7.3.3.1 Logistic regression (LR)

Logistic regression aims to estimate the probability associated with each event in a population according to a set of explanatory variables or covariates. It was first introduced and used by Verhulst to explain population growth (Press & Wilson 1978), while today it is applied to a very wide range of fields. One advantage of logistic regression is that one can include categorical and binary covariates.

For this research, logistic regression was used to characterise the link between a dependent variable (coral bleaching) and a covariate (MaxSST). The coral bleaching data are binary (1 for coral bleaching and 0 for non-bleaching). The logistic regression formula is given below:

$$ln(\frac{\hat{p}}{1-\hat{p}}) = \beta_0 + \beta_1 * X \qquad \text{Equation 7-1}$$

where the probability of coral bleaching, $Y = 1$, is given by $\hat{p}$ and the probability that coral bleaching does not occur, $Y = 0$, is given as $1 - \hat{p}$. Theoretically, we can estimate the probability $\hat{p}$ given X (where X is MaxSST) as:

$$\hat{p} = \frac{e^{\beta 0 + \beta 1 * X}}{1 + e^{\beta 0 + \beta 1 * X}} \qquad \text{Equation 7-2}$$

To determine the best fitting logistic regression model we used the Akaike Information Criterion (AIC) (Akaike 1973). As a general rule, the smaller the AIC the better the fit. The AIC can be represented as

$$\text{AIC} = 2K - 2\text{Log}(L) \qquad \text{Equation 7-3}$$

Where K is the number of predictors and L is the likelihood.

The logistic regression model was used to define the relationship between coral bleaching events and MaxSST in the survey region at the five different spatial resolutions. This was undertaken to investigate the most appropriate spatial resolution at which to fit such a model and predict coral bleaching. To extend the concept of varying the spatial resolution, as well as extend the model itself, we introduced an autocovariate term. This was calculated simply as the mean MaxSST of the neighboring pixels defined at a 4 km spatial resolution. This autocovariate was then added to the logistic regression model defined at 4 km as an additional fixed effect term. The rationale for investigating the use of an autocovariate is that it allows the model fitting process itself to determine the optimal weighting coefficients between the 4 km pixel central value of MaxSST and the mean of the neighbours. In this way, the logistic model with autocovariate has the potential to outperform the 4 km and 16 km counterpart models.

To assess the accuracy of the models, the receiver operating characteristic (ROC) curve was plotted and the fraction of observed data that were correctly classified was reported as the area under the curve (AUC) (Mason & Graham 2002). 70% of the data was used in the model and 30% for validation. AUC values from 0.7 to 0.9 are considered to indicate a well-fitting model.

7.4 Results

7.4.1 Logistic model

The best fitting model was produced with MaxSST defined at the 4 km spatial resolution with 12 km MaxSST as autocovariate, as shown in Figure 7-2. The other models are shown in Figure 7-3 to Figure 7-7. The relative goodness-of-fit of the all logistic models is reported in Table 7-1 which shows that the AIC for MaxSST 4 km and 12 km as autocovariate is the smallest. The area under the curve (AUC) for the model is 0.78 which indicates a good predictive ability. The full ROC curve is given in Figure 7-8.

Table 7-1. The AIC of the models fitted using the MaxSST covariate defined at spatial resolutions of 4 km, 16 km, 32 km, 64 km and 100 km. The model for the 4 km spatial resolution plus autocovariate is shown in bold.

Model	AIC
MaxSST 4 km	837.917
MaxSST 16 km	852.776
MaxSST 32 km	848.517
MaxSST 64 km	863.232
MaxSST 100 km	862.124
MaxSST 4km and autocovariate	**832.632**

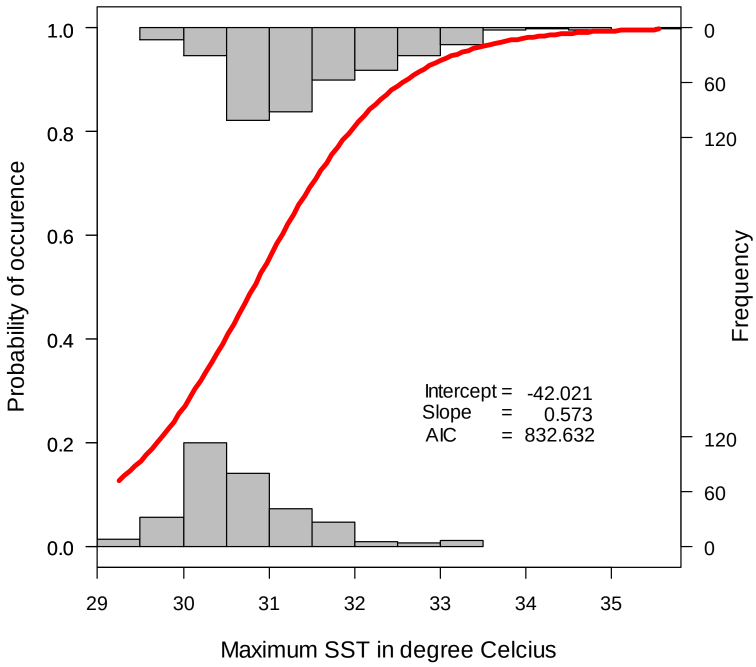


Figure 7-2. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 4 km and 12 km as autocovariate (1983 to 2010).

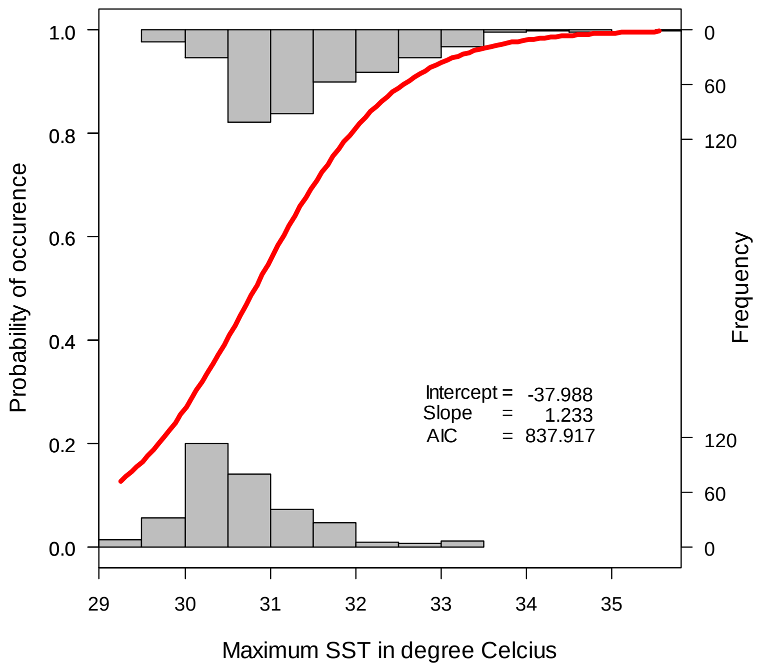


Figure 7-3. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 4 km (1983 to 2010).

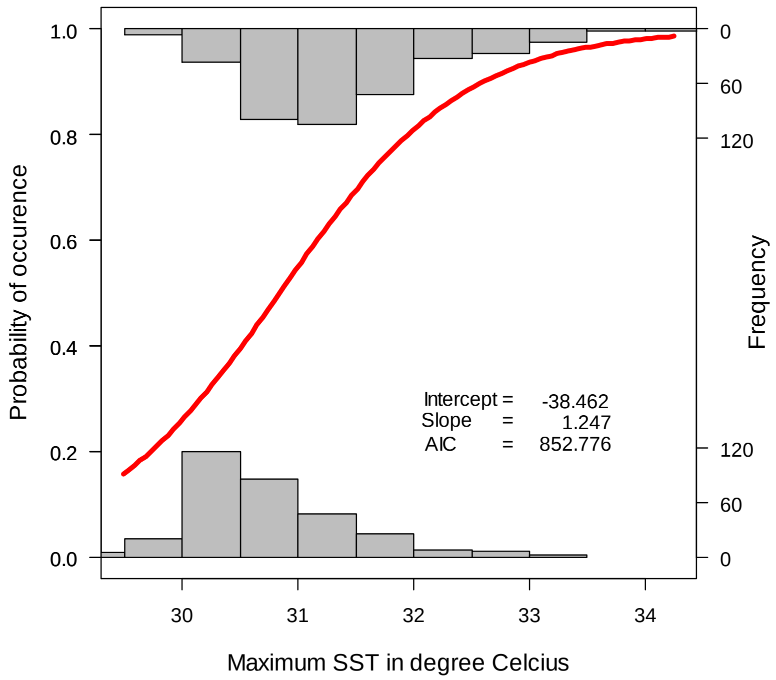


Figure 7-4. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 16 km (1983 to 2010).

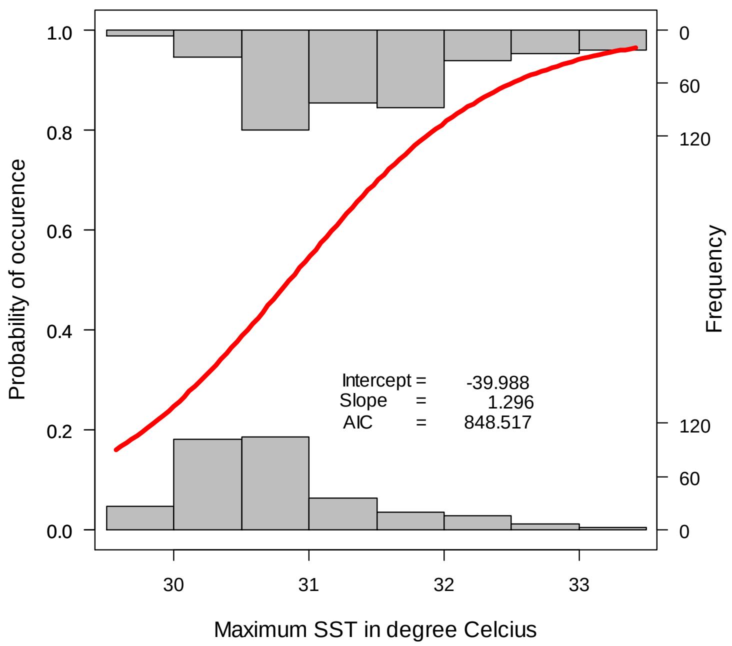


Figure 7-5. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 32 km (1983 to 2010).

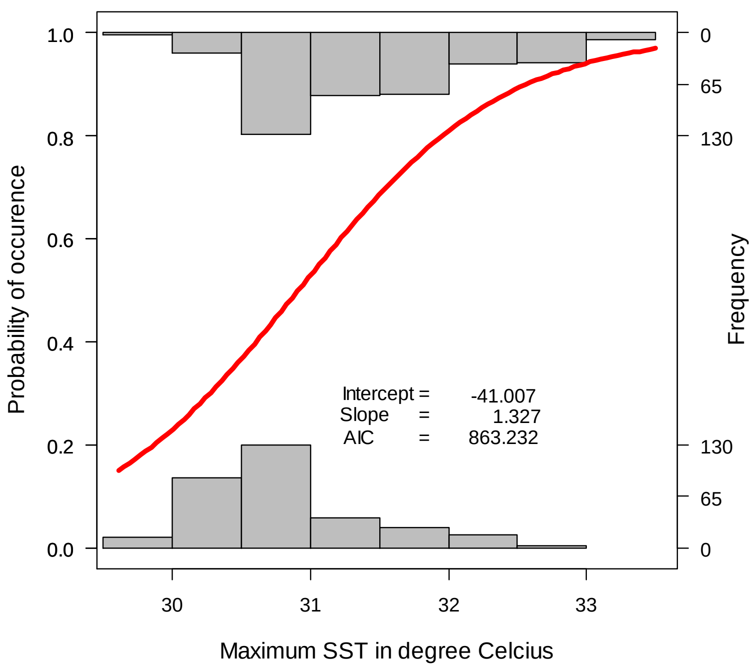


Figure 7-6. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 64 km (1983 to 2010).

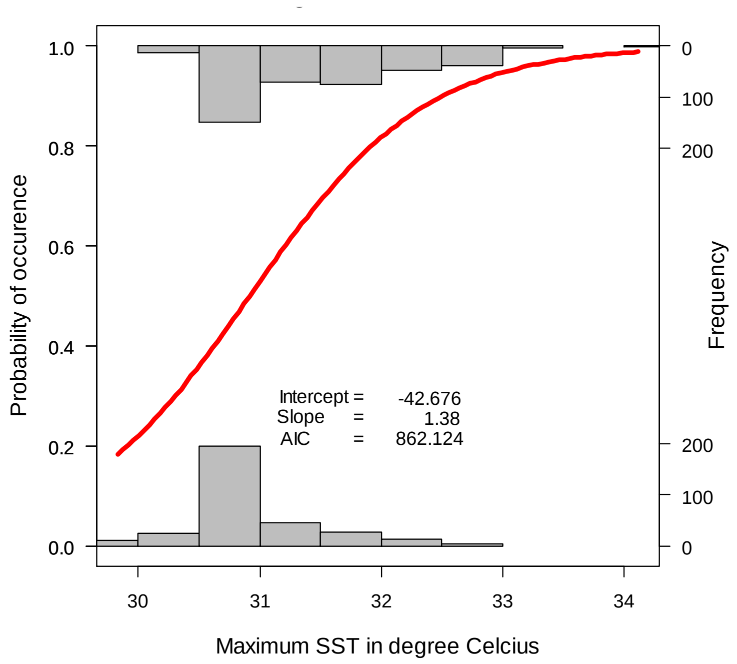


Figure 7-7. Logistic probability plot of coral bleaching occurrence against MaxSST at a spatial resolution of 100 km (1983 to 2010).

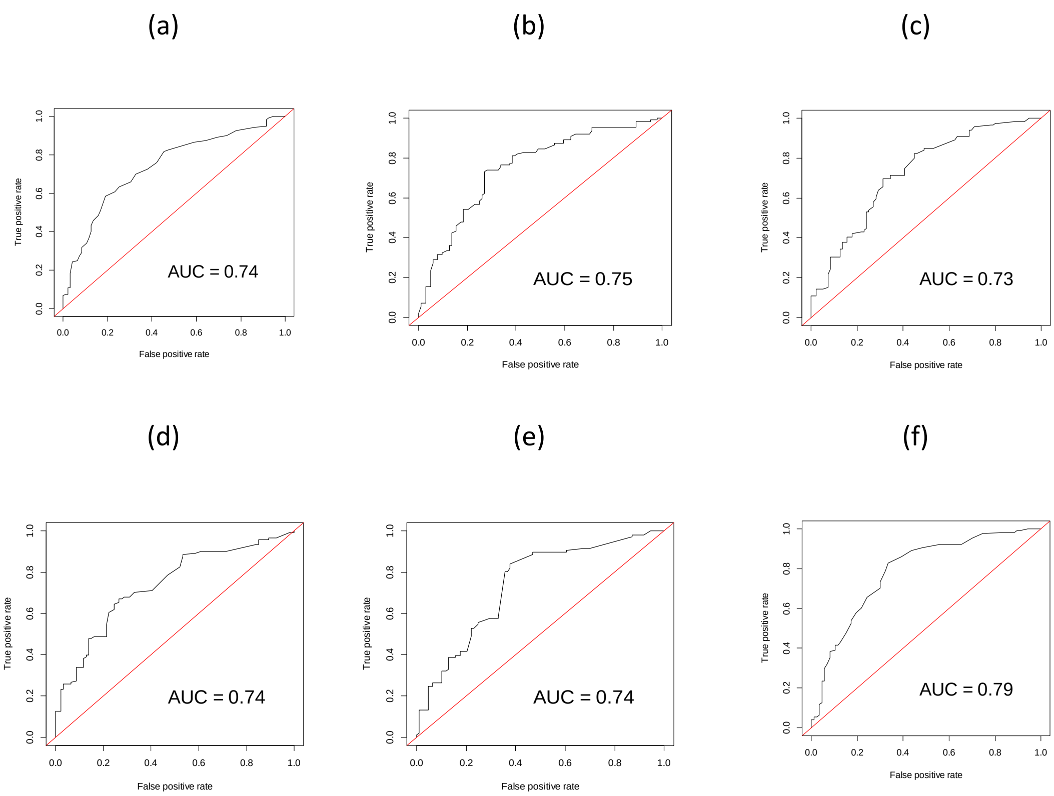


Figure 7-8 : The area under the curve (AUC) for the logistic regression model fitted using the MaxSST data at spatial resolutions of (a) 4 km, (b) 16 km, (c) 32 km, (d) 64 km (e) 100km and (f) 4 km with 12 km as autocovariate.

7.5 Discussion

Studies of the most appropriate spatial resolution to use for coral bleaching monitoring and forecasting are rare. Andréfouët et al. (2002) studied different scales of scanned aerial photographs from 10 cm, 50 cm, 1 m and 2 m to determine the most appropriate spatial resolution for monitoring coral bleaching over small areas in the Great Barrier Reef. The most appropriate spatial resolution reported was 10 cm, but the 40-80 cm spatial resolution was suggested as practicable considering the large number of data, processing time and accuracy requirements at 10 cm resolution. Intensive *in situ* measurements were made in March and April 1998 to validate the remote sensing classification. While this is an example of an attempt to define an appropriate spatial resolution for coral bleaching monitoring, for the purpose of monitoring coral bleaching around the globe (e.g., mass coral bleaching) this fine spatial resolution is not appropriate. Coarser spatial resolution data were also reported to be more cost effective compared to fine resolution data (Mumby & Edwards 2002).

The assessment and monitoring of coral status around the globe has been undertaken by NOAA through the Coral Reef Watch (CRW) programme since 2000. Based on the 50 km SST product, the CRW has continuously provided public users with a Bleaching Alert warning. However, due to its coarse spatial resolution, the monitoring of small reefs has been somewhat hampered. As stated by Berkelmans et al. (2004) and Weeks et al. (2008), the data at this spatial resolution regularly failed to predict the probability of coral reef bleaching across smaller areas (10 km across and below).

This research examined the use of multiscale remote sensing SST data in coral bleaching monitoring and forecasting. We examined MaxSST data at five different spatial resolutions (4 km, 16 km, 32 km, 64 km and 100 km) and observed the changes in the goodness-of-fit a logistic regression model with resolution. In parallel with the study conducted by (Mohammed et al. 2016) who discovered that the latest product from NOAA with a 5 km spatial resolution (Liu et al. 2014) was able to monitor and assess coral bleaching more effectively than at 50 km resolution, we anticipated that the original MaxSST CoRTAD data at the 4 km spatial resolution would provide the best fitting model. This had been confirmed by this research to some extent. Amongst the five spatial resolutions tested, the best fitting logistic model was found at the 4 km spatial resolution according to the AIC. A full comparison of the logistic model AIC and the AUC of ROC curve is shown in

Table 7-2. All models were categorised as good by the AUC.

Table 7-2 : Logistic model fit accuracy

	4 km	16 km	32 km	64 km	100 km
AIC	837.9	852.8	848.5	863.2	862.1
AUC	0.74	0.75	0.73	0.74	0.74

The variability in MaxSST at a spatial resolution of 4 km seems to be the most appropriate to predict the space-time variation in coral bleaching occurrence. Near-shore SST has been captured well by the 4 km data. Considering the spatial auto-correlation, we introduced a 4 km MaxSST autocovariate into the MaxSST 4 km logistic model. This refined the model with much improved AIC (832.6) and AUC (0.79).

The coarsening of the spatial resolution corresponds to spatial averaging, and it is well known that averaging of covariates can lead to greater correlation (e.g., due to an increase in the signal-to-noise ratio). For example, in remote sensing, classification accuracy is expected to increase (not decrease) with a coarsening of spatial resolution (Townshend, 1981). However, while the accuracy of classification increases, the information content of the prediction decreases because the spatial convolution means that less detail is presented in the resulting map. Therefore, the spatial resolution that one should choose will ultimately depend on the purpose of the regression modelling. Where the purpose is to present the most detailed maps of coral bleaching probability based on MaxSST (e.g., for use in fine resolution local monitoring) then we argue that it may be most appropriate to use the original CoRTAD 4 km spatial resolution data. Indeed, one recommendation from this research is that in such investigations a range of spatial resolutions should be considered and the best fitting model chosen.

The normal logistic regression does not taking into account the spatial autocorellation of the data. By ignoring the spatial autocorellation, one possible impact is it would lead to biased parameter estimates (Keitt et al. 2002). This was also reported by Miller et al. (2007) and Triantakonstantis et al. (2013). Holmes & Adams (2003) suggested that by taking into account several nearest neighbour values, using an autocovariate in a logistic model may futher improve the model. This method was found to be the best fitting model of those investigated here. The autotologistic regression fitted well with AIC= 0.82 and AUC = 0.79.

7.6 Conclusion

This research explored the ability to use the annual maximum monthly mean SST to predict coral bleaching in the Indo-Pacific region. In particular, using a logistic regression model we fitted five models with covariates defined at different spatial resolutions ranging from the 4 km resolution of the new CoRTAD dataset to 100 km, which envelopes the 50 km spatial resolution of longer-standing datasets from the Coral Reef Watch (CRW) programme. Using logistic regression, a highly significant relationship was found between coral bleaching and the annual maximum monthly mean SST in the Indo-Pacific region. From the five investigated spatial resolutions (4 km, 16 km, 32 km, 64 km and 100 km) the MaxSST at a 4 km spatial resolution provided the best fitting model and the greatest suitability for use in coral bleaching modelling for monitoring and forecasting purposes. However, the introduction of an autocovariate term improved the model fit further, suggesting a new alternative to use of the 4 km data directly when fitting models to predict the probability of coral bleaching. This suggests that researchers should consider carefully how best to handle the 4 km CoRTAD data prior to use in coral bleaching event monitoring and forecasting.

7.7 Acknowledgements

The authors would like to acknowledge NOAA National Centers for Environmental Information (formerly known as the National Oceanographic Data Center (NODC)for their data from their web site at http://www.nodc.noaa.gov/sog/cortad/. The authors would also like to thank Reefbase (http://www.reefbase.org) for the coral bleaching datasets.

7.8 REFERENCES

Andréfouët, S. et al., 2002. Choosing the appropriate spatial resolution for monitoring coral bleaching events using remote sensing. *Coral Reefs*, 21(2), pp.147–154. Available at: http://dx.doi.org/10.1007/s00338-002-0233-x.

Holmes, C.C. & Adams, N.M., 2003. Likelihood inference in nearest-neighbour classification models. *Biometrika*, 90(1), pp.99–112.

Keitt, T.H. et al., 2002. Accounting for spatial pattern when modeling organism-environment interactions. *Ecography*, 25(5), pp.616–625. Available at: http://www.blackwell-synergy.com/doi/abs/10.1034/j.1600-0587.2002.250509.x.

Kleypas, J., Buddemeier, R. & Gattuso, J.-P., 2001. The future of coral reefs in an age of global change. *International Journal of Earth Sciences*, 90(2), pp.426–437. Available at: http://dx.doi.org/10.1007/s005310000125.

Liu, G. et al., 2014. Reef-scale thermal stress monitoring of coral ecosystems: New 5-km global products from NOAA coral reef watch. *Remote Sensing*, 6(11), pp.11579–11606.

Miller, J., Franklin, J. & Aspinall, R., 2007. Incorporating spatial dependence in predictive vegetation models. *Ecological Modelling*, 202(3-4), pp.225–242.

Mohammed, S.S. et al., 2016. Performance evaluation of CRW reef-scale and broad-scale SST-based coral monitoring products in fringing reef systems of Tobago. *Remote Sensing*, 8(1).

Mumby, P.J. & Edwards, A.J., 2002. Mapping marine environments with IKONOS imagery: Enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment*, 82(2-3), pp.248–257.

Nancy, K. et al., 2010. Coral Reef Biodiversity. In D. M. Alasdair, ed. *Life in the Wold's Ocean: Diversity, Distribution, and Abundance*. Singapore: Wiley_Blackwell, pp. 65–78.

Townshend, J.R.G., 1981. The spatial resolving power of earth resources satellites. *Progress* *in Physical Geography*, 5(1), pp.32–55.

Triantakonstantis, D.P., Kalivas, D.P. & Kollias, V.J., 2013. Autologistic regression and multicriteria evaluation models for the prediction of forest expansion. *New Forests*, 44(2), pp.163–181.

Weeks, S.J. et al., 2008. Improved predictions of coral bleaching using seasonal baselines and higher spatial resolution. *Heron*, 53(4), pp.1369–1375.

Chapter 8: Discussion

8.1 Relevance of the study

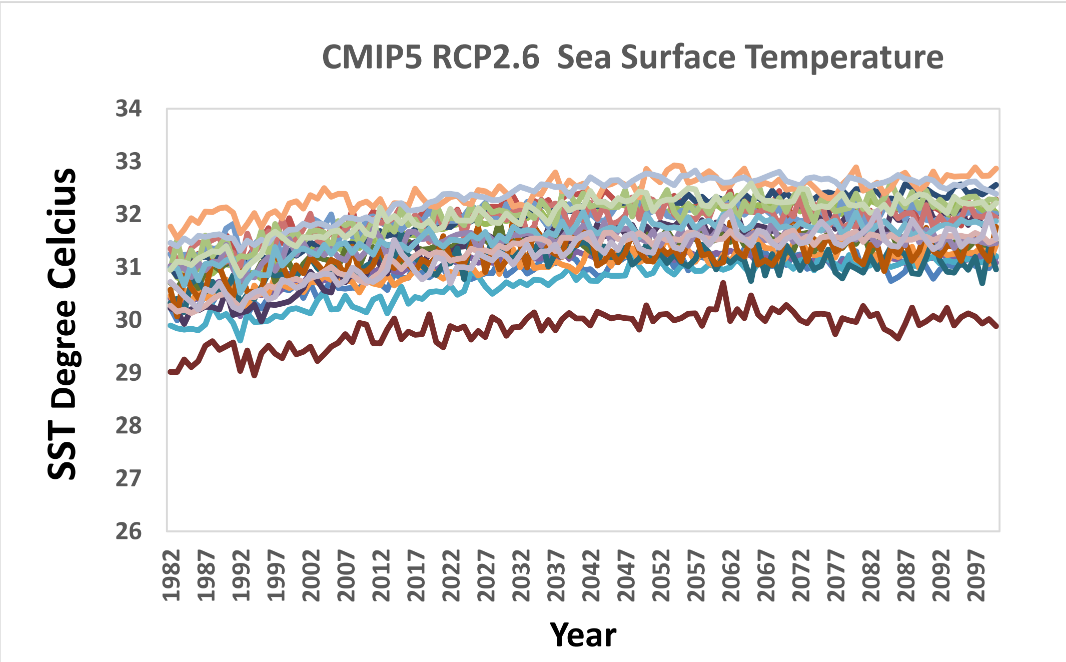
Coral reefs are very important to the ecosystem and need to be carefully conserved. Its prominent contribution to the human lives is undeniable, including from the socio-economic aspect where it serves as a tourist recreation area, marine organism habitat, or as a buffer to wave energy. Therefore, it is very unfortunate for us to neglect our coral reefs without proper monitoring and constant destruction as a destroyed coral reef area will take decades to recover completely depending on the extent of its destruction.

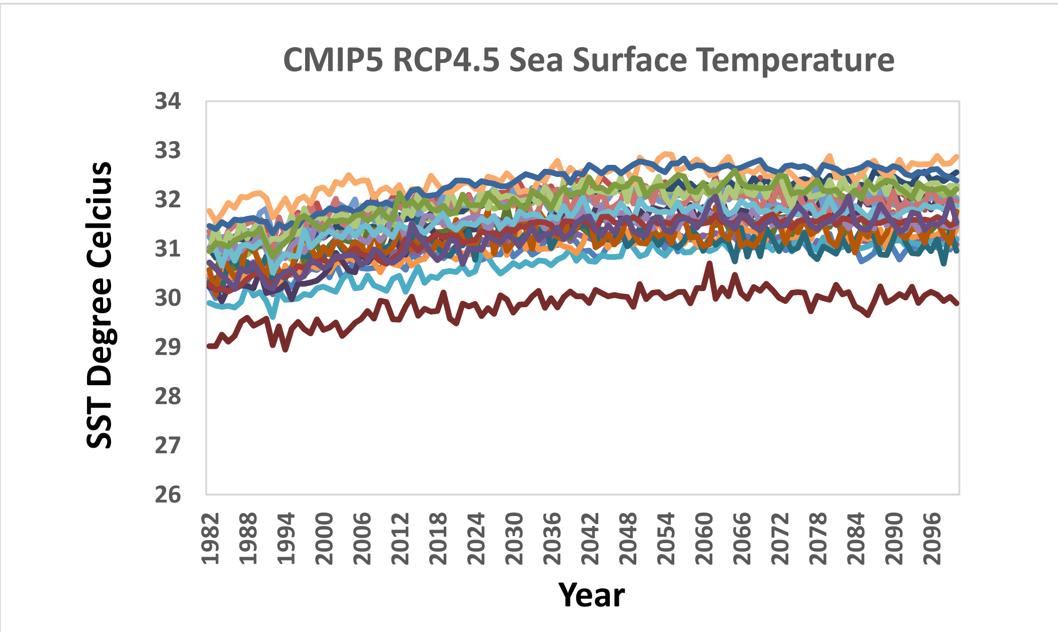
Generally, the potential threats to coral reefs can be categorised into global and local threats (Burke, 2012). In most developing countries, the use of inappropriate fishing gears such as fish bombs and trawlers contributes to the destruction of coral reefs. This is made even worse by the uncontrolled tourism industry where the large number of tourists who visited islands and Marine Protected Areas (MPA) for the purpose of snorkelling and scuba activities has resulted with the increase in the number of broken coral reefs. There are also reported cases of tourists who break and pick up corals to be brought back as a memento. These activities contribute to the deterioration of coral reefs.

Additionally, the warming ocean due to the increased concentration of carbon dioxide gas in the atmosphere has also given threats to coral reefs in the tropics. Hansen et al. (2016) stated that since the 19th century, the ocean temperature reached the highest level in 1940 and experienced a small annual change. Until then, it has begun to show a steady rise from 1970 until now. This creates a need to understand the climate change particularly within the area.

This thesis attempts to answer few questions. Is the ocean warming in the Coral Triangle and the South China Sea experiencing the same warming patterns as elsewhere? If the answer is yes, what is the rate of warming? Another important question is whether warming also affects the coral reefs life in the area. Can the satellite SST dataset be used to understand the coral bleaching phenomenon? If yes, what is the best spatial resolution?

Using the NOAA sea temperature data, this thesis found that there was an increase of 29-years sea temperatures from 1982 to 2010 in both areas of the Coral Triangle and the South China Sea despite differences in warming rates. Chapter 5 of this thesis adds to our understanding on the spatiotemporal trends of SST in the region. This is important as the last intensive investigation on sea warming in the region was conducted by Penaflor (2009) who reported SST trends in the CT from 1985 to 2006. Aside from reporting on the previous trends of SST, this study also investigates on how the temperature will be in the future. The SST data of the Coupled Model Intercomparison Project Phase 5 (CMIP5) under the Representative Concentration Pathway RCP2.6 has been used to understand the spatiotemporal SST in this area until the year 2100. The RCP2.6 scenario is chosen because it is the low emission scenario greenhouse gases concentration on the Earth. Despite using the lowest scenario, this study finds that the high probability of coral death in this region is as early as 2040, which is something to be aware of. To understand the magnitude of SST in other CMIP5 scenarios that might further affect the bleaching, we obtained CMIP5 datasets (one member per model) as shown in Figure 8-1.





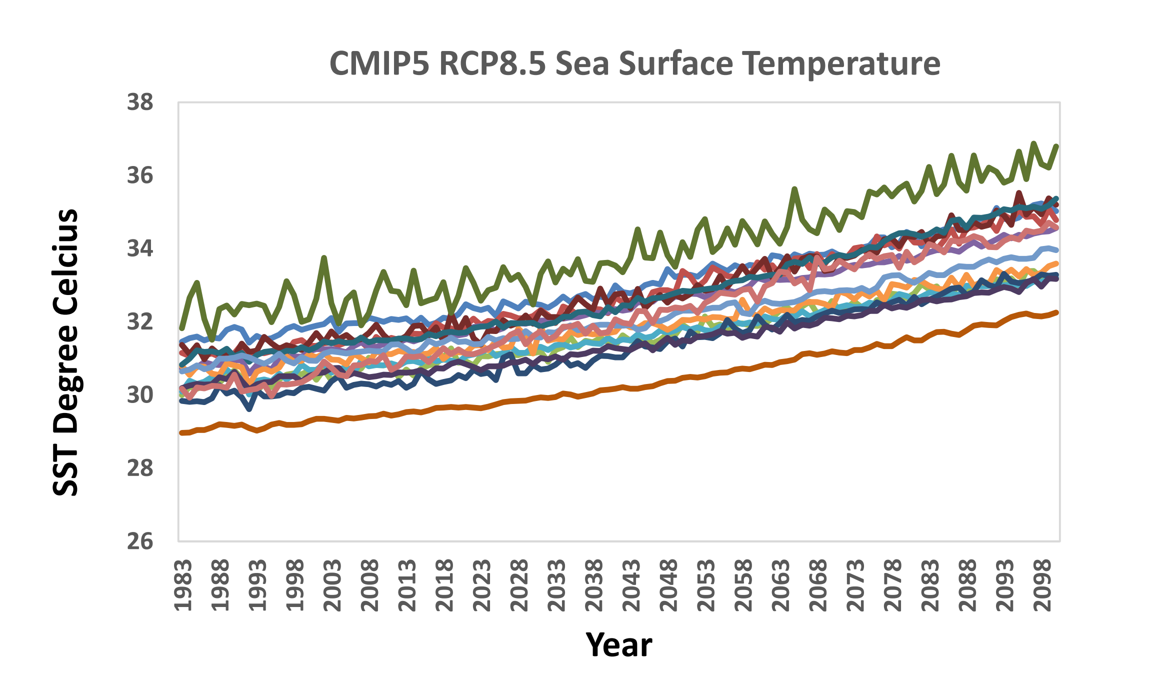


Figure 8-1. CMIP5 RCP2.6, RCP4.5 and RCP8.5 SST (one member per model)

Figure 8-1 clearly indicated a warming trend for all CMIP5 scenarios. A careful consideration however needs to be taken into account when using SST datasets from climate models. We can clearly see the variability of each model members. In certain cases, the temperature difference between models members are up to 3^{0}C in average. This is why the use of average SST across models is not recommended.

Ocean warming in the region is commonly linked to a phenomenon known as El Niño Southern Oscillation (ENSO). Every 3 to 7 years, the sea level in the Pacific equatorial area will experience warming (El Nino) and cooling (La Nina). The neutral phase of data is between the two. When El Nino occurs, the region will experience over-average warming and less rainfall while below average temperature and heavy rainfall will occur during the La Nina. Serious incidents of El Nino were reported in 1997/1998, 2002, 2005, and 2010.

Oceanic warming and cooling in the region could possibly link to coral bleaching events. This raises the question whether coral bleaching that happen in the area is a result of El Nino and whether a 25 km SST satellite data is able to show the relationship between temperature and coral bleaching events.

The only operating system in coral bleaching detection by the Coral Reef Watch which use the static threshold value. This thesis attempts to investigate whether the maximum annual temperature proposed by Logan (2013) can depict the maximum annual temperature-coral bleaching relationship.

Chapter 6 of this thesis addresses this knowledge gap. The findings show that the model used in this thesis is able to show a significant relationship between coral bleaching incidents with maximum annual temperature. The coral bleaching data used was obtained from the bleaching database (Donner, 2017). It is an extension of the existing Reefbase database with the addition of new data from researchers and reef managers. The Donner 2017 bleaching database is used as the majority of data in the Reefbase database is focused on areas where research work is happening (e.g. Caribbean and Galapagos). The lack of data on the Pacific Ocean is also significant in the Reefbase database where there are many coral reefs distribution. Doner (2017) reports on the presence of geographic biases in Reefbase's coral bleaching reporting. For example, despite having a total of 200 islands, there are only two coral bleaching reports in Fiji as compared to smaller areas like Panamas with 65 bleaching reports by volunteers and researchers. Therefore, in order to understand the frequency of mass coral bleaching over time, we could not solely rely on the Reefbase database.

In the modelling of coral bleaching events and maximum temperature, this study utilises the SST satellite data at 25 km spatial resolution. The researcher is aware that there are possibilities for the data to contain more than one report on coral bleaching within the 25 km2 radius. This situation is common as mass coral bleaching usually covers a large area. Hence, linking some of the bleaching records with a temperature value is deemed as acceptable.

In order to determine whether higher resolutions will give better results, this study had tested several spatial resolutions as reported in Chapter 7. The original SST data used in Chapter 7 is 4 km spatial resolution before being resampled to spatial resolutions of 16 km, 32 km, 64 km, and 100 km. As with the hypothesis, 4km data provides the best model decision. McLeod et al. (2010) report fine resolution data such as a few kilometres, giving a better opportunity to management at a regional scale.

8.2 Limitations and future work.

Coral bleaching events occurred not only because of the rising ocean temperature. Other stressors e.g wind speed, salinity, solar radiation, pH and barometric pressure also contributing to the events. Mass bleaching, the interest of this thesis however, was found to be the most significant variable by majority coral experts. Future works should focus on testing different approach in modelling coral bleaching.

Chapter 9: Conclusions

The association between ocean warming and coral bleaching is not new. It has been discussed and researched intensively at least since the mass coral bleaching that occurred as a result of the 1997/1998 El Nino. However, extensive studies across specific regions are less common, yet important. In relation to in-depth study of the relation between ocean warming and coral bleaching in the Indo-Pacific, this thesis has produced the following conclusions:

1. An ocean temperature trend in a significant area for coral reef, the Indo-Pacific region, was reported. A satellite remote sensing-derived product was used to characterise the SST spatio-temporal pattern from 1982 to 2010. Gap-filled OISSTv2 with 100 km spatial resolution was used to fit a linear regression. The future trend was then forecasted from 2010 to 2100 using the latest climate model data. Both historical and future trends were used to produce a warming trend in the South China Sea and the Coral Triangle for three SST variables namely MaxSST, MeanSST and MinSST. The warming trend reported in this study has important implications for coral and marine related studies.

2. The three SST variables were then fitted into a logistic regression model to characterise the relationship with coral bleaching. Coral bleaching records from 1979 to 2010 acquired from an online database were paired with SST data in the model. The logistic model of MaxSST and coral bleaching occurrence was reported to be significant. Based on this finding, historical coral bleaching probability maps were produced and showed good agreement with the current operational bleaching alert. The coral bleaching probability was then extended into the future. Using SST data from RCP2.6 CMIP5, annual MaxSST was produced and a logistic regression model was fitted. Decadal coral bleaching maps from 2020 to 2100 forecasted a worrying coral bleaching phenomenon, at least from now until year 2040. As the climate model forecasted a cooling period at the end of its simulation time, coral bleaching probability is also expected to be low at that time.

3. To answer a question whether a fine spatial resolution SST could produce a better model, this thesis tested a much finer spatial resolution, 4km compared to 100 km in the previous logistic model. Using the block statistic (windows neighbourhood pixels), four other spatial resolutions datasets were produced; 16 km, 32 km, 64 km and 100 km. Each dataset was then fitted by the

logistic model. The result shows that, the best spatial resolution to use in the logistic regression model is 4 km. The reasons for this were discussed above.

Overall, this thesis fulfilled the aims of characterising the spatio-temporal variation in SST in the Indo-Pacific region; characterising the relationship between SST and coral bleaching occurrence, and forecasting coral bleaching probability into the future; and determining the best spatial resolution of SST datasets for modelling coral bleaching in the region.

List of References

Akaike, H., 1973. Information theory & an extension of the maximum likelihood principle. B. N. Petrov & F. Csaki, eds. *2nd International Symposium on Information Theory*, pp.pp. 267–281.

Alien, M.R. et al., 1994. Global change detection. *Nature*, 370(6484), p.24. Available at: http://dx.doi.org/10.1038/370024b0.

Allen, G.R., 2008. Conservation hotspots of biodiversity and endemism for Indo-Pacific coral reef fishes. *Aquatic Conservation: Marine and Freshwater Ecosystems*, 18(5), pp.541–556. Available at: http://dx.doi.org/10.1002/aqc.880.

Atkinson, P.M. & Massari, R., 1998. GENERALISED LINEAR MODELLING OF SUSCEPTIBILITY TO LANDSLIDING IN THE CENTRAL APENNINES, ITALY. *Computers & Geosciences*, 24(4), pp.373–385. Available at: http://www.sciencedirect.com/science/article/pii/S0098300497001179.

Bellwood, D.R. & Wainwright, P.C., 2002. The history and biogeography of fishes on coral reefs. In P. F. Sale, ed. *Coral Reef Fishes*. Amsterdam: Academic Press, Elsevier, pp. 5–32.

Berkelmans et al., 2004. *A comparison of the 1998 and 2002 coral bleaching events on the Great Barrier Reef: spatial correlation, patterns, and predictions*, Berlin, ALLEMAGNE: Springer.

Berkelmans, R., 2002. Time-integrated thermal bleaching thresholds of reefs and their variation on the Great Barrier Reef. *Marine Ecology Progress Series*, 229, pp.73–82. Available at: http://www.int-res.com/abstracts/meps/v229/p73-82/.

Blackmore, T. et al., 2012. Correction of AVHRR Pathfinder SST data for volcanic aerosol effects using ATSR SSTs and TOMS aerosol optical depth. *Remote Sensing of Environment*, 116(0), pp.107–117. Available at: http://www.sciencedirect.com/science/article/pii/S0034425711002161.

Bouchet, P., 2006. The Magnitude of Marine Biodiversity. In C. M. Duarte, ed. *The Exploration of Marine Biodiversity: Scientific and Technological Challenges*. Fundación BBVA, pp. 31–64. Available at: http://books.google.co.uk/books?id=PqMfAQAAIAAJ.

Brander, K., 2010. Impacts of climate change on fisheries. *Journal of Marine Systems*, 79(3-4), pp.389–402.

Brander, L.M., Van Beukering, P. & Cesar, H.S.J., 2007. The recreational value of coral reefs: A meta-analysis. *Ecological Economics*, 63(1), pp.209–218. Available at: http://www.sciencedirect.com/science/article/pii/S092180090600557X.

Brown et al., 2002. Experience shapes the susceptibility of a reef coral to bleaching. *Coral Reefs*, 21(2), pp.119–126. Available at: http://dx.doi.org/10.1007/s00338-002-0215-z.

Brown, B.E., 1997. Coral bleaching: causes and consequences. *Coral Reefs*, 16(1), pp.S129–S138. Available at: http://dx.doi.org/10.1007/s003380050249.

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), p.e711. Available at: http://dx.plos.org/10.1371/journal.pone.0000711.

Burke, L. et al., 2012. *Reefs at Risk Revisited in the Coral Triangle*, Washington D.C, USA: World Resource Institute.

Burke, L.M. et al., 2002. *Reefs at Risk in Southeast Asia*, World Resources Institute, Washington, DC. Available at: http://books.google.co.uk/books?id=WScVAQAAIAAJ.

Burkepile, D.E. & Hay, M.E., 2008. Coral Reefs. In J. Editors-in-Chief: Sven Erik & F. Brian, eds. *Encyclopedia of Ecology*. Oxford: Academic Press, pp. 784–796. Available at: http://www.sciencedirect.com/science/article/pii/B9780080454054003232.

Burns, R.P. & Burns, R., 2008. *Business Research Methods and Statistics Using SPSS*, SAGE Publications. Available at: http://books.google.co.uk/books?id=bPvCRzBou3gC.

Cabrera, A.F., 1994. Logistic Regression Analysis in Higher Education : An Applied Perspective. In C. S. John, ed. *Higher education: Handbook of Theory and Research*. New York: Agathon Press, pp. 225–256.

Cao, X. et al., 2013. Evaluation of wildfire propagation susceptibility in grasslands using burned areas and multivariate logistic regression. *International Journal of Remote Sensing*, 34(19), pp.6679–6700. Available at: http://dx.doi.org/10.1080/01431161.2013.805280.

Carilli, J., Donner, S.D. & Hartmann, A.C., 2012. Historical Temperature Variability Affects Coral Response to Heat Stress. *PLoS ONE*, 7(3), p.e34418. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0034418.

Carpenter, K.E. et al., 2008. One-third of reef-building corals face elevated extinction risk from climate change and local impacts. *Science*, 321(5888), pp.560–563. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18653892.

Cesar, H., Burke, L. & Pet-Soeda, L., 2003. *The Economics of Worldwide Coral Reef Degradation*, The Netherlands: Cesar Environmental Economics Consulting (CEEC).

Clarke, A., 1990. Temperature and evolution: Southern Ocean cooling and the Antarctic marine fauna. In *Antarctic ecosystems*. Springer, pp. 9–22.

Coles, S.L. & Jokiel, P.L., 1992. Effects of Salinity on coral reefs. In Connell Des W. & Hawker D.W., eds. *Pollution in Tropical Aquatic Systems*. Boca Raton: CRC Press Inc, p. pp 147–166.

Corlett, G., 2013. SST definitions : The Group for High-Resolution Sea Surface Temperature (SST) (GHRSST) . , Version 12(23/01/). Available at: https://www.ghrsst.org/ghrsst-science/sst-definitions/.

Cox, D.D.R. & Snell, E.J., 1989. *The Analysis of Binary Data*, Chapman and Hall. Available at: http://books.google.co.uk/books?id=QBebLwsuiSUC.

De'ath, G. et al., 2012. The 27–year decline of coral cover on the Great Barrier Reef and its causes. *Proceedings of the National Academy of Sciences*, 109(44), pp.17995–17999. Available at: http://www.pnas.org/content/109/44/17995.abstract.

Dollar, S.J. & Grigg, R.W., 1981. Impact of a Kaolin Clay Spill on a Coral-Reef in Hawaii. *Marine Biology*, 65(3), pp.269–276. Available at: <Go to ISI>://A1981MV64200008.

Doney, S.C. et al., 2012. Climate Change Impacts on Marine Ecosystems. *Annual Review of Marine Science*, 4(1), pp.11–37.

Donlon, C. et al., 2009. The GODAE high resolution sea surface temperature pilot project. *Oceanography*, 2(3), pp.34–45.

Donlon, C.J. et al., 2002. Toward Improved Validation of Satellite Sea Surface Skin Temperature Measurements for Climate Research. *Journal of Climate*, 15(4), pp.353–369. Available at: http://dx.doi.org/10.1175/1520-0442(2002)015<0353:TIVOSS>2.0.CO;2.

Donner, S.D., 2011. An evaluation of the effect of recent temperature variability on the prediction of coral bleaching events. *Ecological Applications*, 21(5), pp.1718–1730. Available at: http://dx.doi.org/10.1890/10-0107.1.

Donner, S.D., 2009. Coping with Commitment: Projected Thermal Stress on Coral Reefs under Different Future Scenarios. *PLoS ONE*, 4(6), p.e5712. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0005712.

Donner, S.D. et al., 2005. Global assessment of coral bleaching and required rates of adaptation under climate change. *Global Change Biology*, 11(12), pp.2251–2265. Available at: http://dx.doi.org/10.1111/j.1365-2486.2005.01073.x.

Donner, S.D., Knutson, T.R. & Oppenheimer, M., 2007. Model-based assessment of the role of human-induced climate change in the 2005 Caribbean coral bleaching event. *Proceedings of the National Academy of Sciences of the United States of America*, 104(13), pp.5483–5488. Available at: http://europepmc.org/abstract/MED/17360373.

Douglas, A.E., 2003. Coral bleaching––how and why? *Marine Pollution Bulletin*, 46(4), pp.385–392. Available at: http://www.sciencedirect.com/science/article/pii/S0025326X03000377.

Eakin, C.M. et al., 2010. Caribbean Corals in Crisis: Record Thermal Stress, Bleaching, and Mortality in 2005. *PLoS ONE*, 5(11), p.e13969. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0013969.

Emery, W.J., 2003. AIR-SEA INTERACTION | Sea Surface Temperature. In R. H. James, ed. *Encyclopedia of Atmospheric Sciences*. Oxford: Academic Press, pp. 100–109. Available at: http://www.sciencedirect.com/science/article/B77C7-4B0C797-1B/2/f3eb223e65ba49df6b4924ae825870b0.

Emery, W.J. & Thomson, R.E., 2001. *Data Analysis Methods in Physical Oceanography*, Available at: http://www.sciencedirect.com/science/article/pii/B978044450756350006X.

Fitt, W. et al., 2001. Coral bleaching: interpretation of thermal tolerance limits and thermal thresholds in tropical corals. *Coral Reefs*, 20(1), pp.51–65. Available at: http://dx.doi.org/10.1007/s003380100146.

Galbraith, P.S. et al., 2012. Sea-surface temperature in relation to air temperature in the Gulf of St. Lawrence: Interdecadal variability and long term trends. *Deep Sea Research Part II: Topical Studies in Oceanography*, 77–80(0), pp.10–20. Available at: http://www.sciencedirect.com/science/article/pii/S0967064512000495.

GCRMN, 2010. *Status of Coral Reefs in East Asian Seas Region: 2010* G. C. R. M. Network, ed., Ministry of the Environment, Japan.

Gleeson, M.W. & Strong, A.E., 1995. Applying MCSST to coral reef bleaching. *Advances in Space Research*, 16(10), pp.151–154. Available at: http://www.sciencedirect.com/science/article/pii/027311779500396V.

Glynn, P.W., 1997. Bioerosion and coral reef growth: a dynamic balance. In C. Birkeland., ed. *Life and Death of Coral Reefs*. New York: Chapman and Hall.

Glynn, P.W., 1993. Coral reef bleaching: ecological perspectives. *Coral Reefs*, 12(1), pp.1–17. Available at: http://dx.doi.org/10.1007/BF00303779.

Glynn, P.W., 1996. Coral reef bleaching: facts, hypotheses and implications. *Global Change Biology*, 2(6), pp.495–509. Available at: http://dx.doi.org/10.1111/j.1365-2486.1996.tb00063.x.

Goodrum, G., K. B. Kidwell & W. Winston, 2009. NOAA KLM user's guide with NOAA-N,-P SUPPLEMENT : revised 2009. Available at: http://www.ncdc.noaa.gov/oa/pod-guide/ncdc/docs/klm/index.htm.

Goreau, T.J. & Hayes, R.L., 1994. Coral bleaching and ocean "hot spots. *Ambio*, 23(23), pp.176–180.

Halpern, B.S. et al., 2008. A Global Map of Human Impact on Marine Ecosystems. *Science*, 319(5865), pp.948–952. Available at: http://www.sciencemag.org/content/319/5865/948.abstract.

Harvell, C.D. et al., 2002. Climate warming and disease risks for terrestrial and marine biota. *Science*, 296(5576), pp.2158–2162.

Hatcher, B.G., 1997. Coral reef ecosystems: how much greater is the whole than the sum of the parts? *Coral Reefs*, 16(1), pp.S77–S91. Available at: http://dx.doi.org/10.1007/s003380050244.

Heron SF, Johnston L, Liu G, Geiger EF, Maynard JA, De La Cour JL et al (2016) Validation of reef-scale thermal stress satellite products for coral bleaching monitoring. Remote Sens 8:59. https://doi.org/10.3390/rs8010059

Hoegh-Guldberg et al., 2009. *The Coral Triangle and Climate Change: Ecosystems, People and Societies at Risk*, Brisbane, Australia: WWF Australia.

Hoegh-Guldberg, O., 1999. Climate change, coral bleaching and the future of the world's coral reefs. *Marine and Freshwater Research*, 50(8), pp.839–866. Available at: http://www.publish.csiro.au/paper/MF99078.

Hoegh-Guldberg, O. et al., 2007. Coral Reefs Under Rapid Climate Change and Ocean Acidification. *Science*, 318(5857), pp.1737–1742. Available at: http://www.sciencemag.org/content/318/5857/1737.abstract.

Hoeke, R.K. et al., 2011. Projected Changes to Growth and Mortality of Hawaiian Corals over the Next 100 Years. *PLoS ONE*, 6(3), p.e18038. Available at: http://dx.doi.org/10.1371%2Fjournal.pone.0018038.

Hooidonk, R. & Huber, M., 2012. Effects of modeled tropical sea surface temperature variability on coral reef bleaching predictions. *Coral Reefs*, 31(1), pp.121–131. Available at: http://dx.doi.org/10.1007/s00338-011-0825-4.

van Hooidonk, R. et al., 2013. Temporary refugia for coral reefs in a warming world. *Nature Clim. Change*, 3(5), pp.508–511. Available at: http://dx.doi.org/10.1038/nclimate1829.

Hopley, D., 2011. *Encyclopedia of Modern Coral Reefs: Structure, Form and Process*, Springer. Reef Building by John E. N. Veron. Available at: http://books.google.co.uk/books?id=5umXDDmqxwIC.

Hosmer, D.W. & Lemesbow, S., 1980. Goodness of fit tests for the multiple logistic regression model. *Communications in Statistics - Theory and Methods*, 9(10), pp.1043–1069. Available at: http://www.tandfonline.com/doi/abs/10.1080/03610928008827941.

Hubbard, D.K., 1997. Reefs as dynamic systems. In C. Birkeland., ed. *Life and Death of Coral Reef*. New York: Chapman and Hall.

IPCC, 2001. Climate Change 2001: Synthesis Report. A Contribution of Working Groups I, II, and III to the Third Assessment Report of theIntegovernmental Panel on Climate Change R. T.

Watson & C. W. Team, eds. , p.398.

IPCC, 2007. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change IPCC Core Writing Team, Pachauri, & A. R.K and Reisinger, eds. , p.104.

Iskandar, I., 2010. Seasonal and interannual patterns of sea surface temperature in Banda Sea as revealed by self-organizing map. *Continental Shelf Research*, 30(9), pp.1136–1148. Available at: http://www.sciencedirect.com/science/article/B6VBJ-4YJT5GV-1/2/f2b8cb2219c0f7e894ae3d039c4ff91e.

Just-Baringo, X. et al., 2013. Total Synthesis and Stereochemical Assignment of Baringolin. *Angewandte Chemie International Edition*, p.n/a–n/a. Available at: http://dx.doi.org/10.1002/anie.201302372.

Kleypas, J., Buddemeier, R. & Gattuso, J.-P., 2001. The future of coral reefs in an age of global change. *International Journal of Earth Sciences*, 90(2), pp.426–437. Available at: http://dx.doi.org/10.1007/s005310000125.

Kool, J.T. et al., 2011. Connectivity and the development of population genetic structure in Indo-West Pacific coral reef communities. *Global Ecology and Biogeography*, 20(5), pp.695–706. Available at: http://dx.doi.org/10.1111/j.1466-8238.2010.00637.x.

Lalli, C.M. & Parsons, T.R., 1997. *Biological Oceanography: An Introduction*, Elsevier, Butterworth Heinemann. Available at: http://books.google.co.uk/books?id=qjcUAQAAIAAJ.

Liu, G. et al., 2006. Overview of NOAA Coral Reef Watch Program's near-real-time satellite global coral bleaching monitoring activities. In *Proc. 10th Int. Coral Reef Sym.* Okinawa, Japan, pp. 1783–1793.

Liu, G., STRONG, A.E. & SKIRVING, W., 2003. Remote Sensing of Sea Surface Temperatures During 2002 Barrier Reef Coral Bleaching. *EOS*, 84(15), pp.137–144.

Logan, C.A. et al., 2012. A framework for comparing coral bleaching treshold. In *Proceedings of the 12th International Coral Reef Symposium*. Florida.

Manzello, D.P., Berkelmans, R. & Hendee, J.C., 2007. Coral bleaching indices and thresholds for the Florida Reef Tract, Bahamas, and St. Croix, US Virgin Islands. *Marine Pollution Bulletin*, 54(12), pp.1923–1931. Available at: http://www.sciencedirect.com/science/article/pii/S0025326X07003074.

Marshall, P.A. & Baird, A.H., 2000. Bleaching of corals on the Great Barrier Reef: differential susceptibilities among taxa. *Coral Reefs*, 19(2), pp.155–163. Available at: http://dx.doi.org/10.1007/s003380000086.

Maynard, J.A. et al., 2008. ReefTemp: An interactive monitoring system for coral bleaching using high-resolution SST and improved stress predictors. *Geophysical Research Letters*, 35(5), p.L05603. Available at: http://dx.doi.org/10.1029/2007GL032175.

McCLAIN, E.P., 1989. Global sea surface temperatures and cloud clearing for aerosol optical depth estimates. *International Journal of Remote Sensing*, 10(4), pp.763–769. Available at: http://www.informaworld.com/10.1080/01431168908903917.

McClain, E.P., Pichel, W.G. & Walton, C.C., 1985. COMPARATIVE PERFORMANCE OF AVHRR-BASED MULTICHANNEL SEA SURFACE TEMPERATURES. *J. Geophys. Res.*, 90(C6), pp.11587–11601. Available at: http://dx.doi.org/10.1029/JC090iC06p11587.

McClanahan, T. et al., 2007. Predictability of coral bleaching from synoptic satellite and in situ temperature observations. *Coral Reefs*, 26(3), pp.695–701. Available at: http://dx.doi.org/10.1007/s00338-006-0193-7.

McFadden, D., 1974. Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka, ed. *Frontiers in econometrics*. Academic Press, pp. 105–142.

McLeod, E. et al., 2010. Warming Seas in the Coral Triangle: Coral Reef Vulnerability and Management Implications. *Coastal Management*, 38(5), pp.518–539.

Meissner, T. & Wentz, F., 2006. Ocean Retrievals for WindSat. In *IEEE MicroRad, 2006*. pp. 119–124.

Minnett, P.J. et al., 2001. The Marine-Atmospheric Emitted Radiance Interferometer: A High-Accuracy, Seagoing Infrared Spectroradiometer. *Journal of Atmospheric and Oceanic Technology*, 18(6), pp.994–1013. Available at: http://dx.doi.org/10.1175/1520-0426(2001)018<0994:TMAERI>2.0.CO;2.

Molinski, T.F. et al., 2009. Drug development from marine natural products. *Nat Rev Drug Discov*, 8(1), pp.69–85. Available at: http://dx.doi.org/10.1038/nrd2487.

Muscatine, L., 1990. The role of symbiotic algae in carbon and energy flux in coral reefs. . In *Ecosystems of the World*. Amsterdam, The Netherlands: Elsevier Science Publishing Company, Inc., p. 550.

Nagelkerke, N.J.D., 1991. A note on a general definition of the coefficient of determination. *Biometrika*, 78(3), pp.691–692. Available at: http://biomet.oxfordjournals.org/content/78/3/691.abstract.

Nancy, K. et al., 2010. Coral Reef Biodiversity. In D. M. Alasdair, ed. *Life in the Wold's Ocean: Diversity, Distribution, and Abundance*. Singapore: Wiley_Blackwell, pp. 65–78.

Noyes, E.J. et al., 2006. The accuracy of the AATSR sea surface temperatures in the Caribbean. *Remote Sensing of Environment*, 101(1), pp.38–51. Available at: http://www.sciencedirect.com/science/article/pii/S0034425705004062.

O'Carroll, A.G. et al., 2012. Towards a bias correction of the AVHRR Pathfinder SST data from 1985 to 1998 using ATSR. *Remote Sensing of Environment*, 116(0), pp.118–125. Available at: http://www.sciencedirect.com/science/article/pii/S0034425711002173.

O'Carroll, A.G., Eyre, J.R. & Saunders, R.W., 2008. Three-Way Error Analysis between AATSR, AMSR-E, and In Situ Sea Surface Temperature Observations. *Journal of Atmospheric and Oceanic Technology*, 25(7), pp.1197–1207. Available at: http://dx.doi.org/10.1175/2007JTECHO542.1.

O'Carroll, A.G., Saunders, R.W. & Watts, J.G., 2006. The Measurement of the Sea Surface Temperature by Satellites from 1991 to 2005. *J. Atmos. Oceanic Technol.* , 23(11), pp.1573–1582.

Oliver, T.A. & Palumbi, S.R., 2011. Do fluctuating temperature environments elevate coral thermal tolerance? *Coral Reefs*, 30(2), pp.429–440. Available at: http://dx.doi.org/10.1007/s00338-011-0721-y.

Oommen, T., Baise, L. & Vogel, R., 2011. Sampling Bias and Class Imbalance in Maximum-likelihood Logistic Regression. *Mathematical Geosciences*, 43(1), pp.99–120. Available at: http://dx.doi.org/10.1007/s11004-010-9311-8.

Pandolfi, J.M. et al., 2011. Projecting Coral Reef Futures Under Global Warming and Ocean Acidification. *Science*, 333(6041), pp.418–422. Available at: http://www.sciencemag.org/content/333/6041/418.abstract.

Park, S. et al., 2013. Landslide susceptibility mapping using frequency ratio, analytic hierarchy process, logistic regression, and artificial neural network methods at the Inje area, Korea. *Environmental Earth Sciences*, 68(5), pp.1443–1464. Available at: http://dx.doi.org/10.1007/s12665-012-1842-5.

Peirce, C.S., 1884. The Numerical Measure of the Success of Predictions. *Science*, 4(93), pp.453–454. Available at: http://www.jstor.org/stable/1760565.

Peñaflor, E. et al., 2009. Sea-surface temperature and thermal stress in the Coral Triangle over the past two decades. *Coral Reefs*, 28(4), pp.841–850. Available at: http://dx.doi.org/10.1007/s00338-009-0522-8.

Peng, G. & Yanchen, B., 2008. Validation of AVHRR/MODIS/AMSR-E Satellite SST Products in the West Tropical Pacific. In *Geoscience and Remote Sensing Symposium, 2008. IGARSS 2008. IEEE International*. pp. IV – 942–IV – 945.

Porter, J.W. & Tougas, J.I., 2001. Reef Ecosystems: Threats to their Biodiversity. In A. L. Editor-in-Chief: Simon, ed. *Encyclopedia of Biodiversity*. New York: Elsevier, pp. 73–95. Available at: http://www.sciencedirect.com/science/article/pii/B0122268652002297.

Qiu, C. et al., 2009. Validation of AVHRR and TMI-derived sea surface temperature in the northern South China Sea. *Continental Shelf Research*, 29(20), pp.2358–2366.

Quinn, G.G.P. & Keough, M.J., 2002. *Experimental Design and Data Analysis for Biologists*, Cambridge University Press. Available at: http://books.google.co.uk/books?id=VtU3-y7LaLYC.

Reaka-Kudla, M.L., 1997. The global biodiversity of coral reefs: A comparison with rainforests. In M. L. Reaka-Kudla, D. E. Wilson, & E. O. Wilson, eds. *Biodiversity II: Understanding and Protecting Our Biological Resources*. National Academies Press, pp. 83–108. Available at: http://books.google.co.uk/books?id=MPp5RkhBrZEC.

Reed, P. & Wu, Y., 2013. Logistic regression for risk factor modelling in stuttering research. *Journal of Fluency Disorders*, 38(2), pp.88–101. Available at: http://www.sciencedirect.com/science/article/pii/S0094730X12000836.

Renema, W. et al., 2008. Hopping Hotspots: Global Shifts in Marine Biodiversity. *Science*, 321(5889), pp.654–657. Available at: http://www.sciencemag.org/content/321/5889/654.abstract.

Robinson, C.J., Gómez-Gutiérrez, J. & de León, D.A.S., 2013. Jumbo squid (Dosidicus gigas) landings in the Gulf of California related to remotely sensed SST and concentrations of chlorophyll a (1998–2012). *Fisheries Research*, 137(0), pp.97–103. Available at: http://www.sciencedirect.com/science/article/pii/S0165783612002755.

Robinson, I.S., 2010. *Discovering the Ocean from Space: The Unique Applications of Satellite Oceanography*, Springer. Available at: http://books.google.co.uk/books?id=u-CwzWN3Zg8C.

Robinson, I.S., 2004. *Measuring the Oceans from Space: The Principles and Methods of Satellite Oceanography*, Springer. Available at: http://books.google.ca/books?id=jk1fIo51uwMC.

Sagar, S., Kaur, M. & Minneman, K.P., 2010. Antiviral Lead Compounds from Marine Sponges. *Marine Drugs*, 8(10), pp.2619–2638. Available at: http://www.mdpi.com/1660-

3397/8/10/2619.

Saha, K., 2010. *Tropical Circulation Systems and Monsoons*, Berlin, German: Springer.

Schowengerdt, R.A., 2006. *Remote Sensing: Models and Methods for Image Processing*, Elsevier Science. Available at: http://books.google.co.uk/books?id=KQXNaDH0X-IC.

Schwarz, J.N. et al., 2010. Biophysical coupling in remotely-sensed wind stress, sea surface temperature, sea ice and chlorophyll concentrations in the South Indian Ocean. *Deep Sea Research Part II: Topical Studies in Oceanography*, 57(9–10), pp.701–722. Available at: http://www.sciencedirect.com/science/article/pii/S0967064509003853.

Selig, E.R., Casey, K.S. & Bruno, J.F., 2010. New insights into global patterns of ocean temperature anomalies: implications for coral reef health and management. *Global Ecology and Biogeography*, 19(3), pp.397–411. Available at: http://dx.doi.org/10.1111/j.1466-8238.2009.00522.x.

Sheppard, C.R.C., 2003. Predicted recurrences of mass coral mortality in the Indian Ocean. *Nature*, 425(6955), pp.294–297. Available at: http://dx.doi.org/10.1038/nature01987.

Skirving, W., Liu, G., et al., 2006. Extreme events and perturbations of coastal ecosystems. In L. L. Richardson & E. F. LeDrew, eds. *Remote sensing of aquatic coastal ecosystem processes*. Springer Netherlands, pp. 11–25. Available at: http://dx.doi.org/10.1007/1-4020-3968-9_2.

Skirving, W., Heron, M. & Heron, S., 2006. The Hydrodynamics of a Bleaching Event: Implications for Management and Monitoring. In *Coral Reefs and Climate Change: Science and Management*. American Geophysical Union, pp. 145–161. Available at: http://dx.doi.org/10.1029/61CE09.

Smith, A.H., Saunders, R.W. & Závody, A.M., 1994. The Validation of ATSR Using Aircraft Radiometer Data over the Tropical Atlantic. *Journal of Atmospheric and Oceanic Technology*, 11(3), pp.789–800. Available at: http://dx.doi.org/10.1175/1520-0426(1994)011<0789:TVOAUA>2.0.CO;2.

Spalding, M., 2009. Detecting and Monitoring Coral Bleaching Events. In M. H. Oppen & J. Lough, eds. *Coral Bleaching*. Springer Berlin Heidelberg, pp. 69–82. Available at: http://dx.doi.org/10.1007/978-3-540-69775-6_5.

Staskiewicz, G. et al., 2013. Logistic regression model for identification of right ventricular dysfunction in patients with acute pulmonary embolism by means of computed tomography. *European Journal of Radiology*, 82(8), pp.1236–1239. Available at: http://www.sciencedirect.com/science/article/pii/S0720048X13000715.

Strong, A.E. et al., 1997. Improved satellite techniques for monitoring coral reef bleaching. In *Proc 8th International Coral Reef Society Symposium*. Panama, pp. 1495–1498.

Strong, A.E. et al., 2011. NOAA's Coral Reef Watch program from satellite observations. *Annals of GIS*, 17(2), pp.83–92. Available at: http://dx.doi.org/10.1080/19475683.2011.576266.

Tittensor, D.P. et al., 2010. Global patterns and predictors of marine biodiversity across taxa. *Nature*, 466(7310), pp.1098–1101. Available at: http://dx.doi.org/10.1038/nature09329.

UNEP-WCMC, 2006. *In the Front Line: Shoreline Protection and Other Ecosystem Services from Mangroves and Coral Reefs.* , United Kingdom : UNEP-WCMC, Cambridge.

Veron, J.E.N. et al., 2009. Delineating the Coral Triangle. *Galaxea, Journal of Coral Reef Studies*, 11(2), pp.91–100.

Vilar del Hoyo, L., Martín Isabel, M.P. & Martínez Vega, F.J., 2011. Logistic regression models for human-caused wildfire risk estimation: analysing the effect of the spatial accuracy in fire occurrence data. *European Journal of Forest Research*, 130(6), pp.983–996. Available at: http://dx.doi.org/10.1007/s10342-011-0488-2.

Wang, L.-J., Sawada, K. & Moriguchi, S., 2013. Landslide susceptibility analysis with logistic regression model based on FCM sampling strategy. *Computers & Geosciences*, 57(0), pp.81–92. Available at: http://www.sciencedirect.com/science/article/pii/S0098300413001064.

Weeks, S.J. et al., 2008. Improved predictions of coral bleaching using seasonal baselines and higher spatial resolution. *Heron*, 53(4), pp.1369–1375. Available at: http://www.google.com.mx/search?client=safari&rls=es-es&q=Improved+predictions+of+coral+bleaching+using+seasonal+baselines+and+higher+spatial+resolution&ie=UTF-8&oe=UTF-8&redir_esc=&ei=juSgS-6VJMyztgfNgPXyBw.

Wilkinson, C., 2008. *Status of coral reefs of the world: 2008*, Townsville, Australia: Global Coral Reef Monitoring Network and Reef and Rainforest Research Centre.

Winter, A. et al., 1998. Sea surface temperatures and coral reef bleaching off La Parguera, Puerto Rico (northeastern Caribbean Sea). *Coral Reefs*, 17(4), pp.377–382. Available at: http://dx.doi.org/10.1007/s003380050143.

Yeemin, T. et al., 2012. Impacts of coral bleaching, recovery and management in Thailand. In *Proceedings of the 12th International Coral Reef Symposium*. Cairns, Australia.

Yilmaz, I., 2009. Landslide susceptibility mapping using frequency ratio, logistic regression, artificial neural networks and their comparison: A case study from Kat landslides (Tokat—Turkey). *Computers & Geosciences*, 35(6), pp.1125–1138. Available at: http://www.sciencedirect.com/science/article/pii/S0098300408002665.

Zhang, Z. et al., 2013. Logistic regression models based on the ratio models of plasma amino acids for diagnosis of hepatitis B associated hepatic fibrosis. *Journal of Clinical and Experimental Hepatology*, 3(1, Supplement), p.S77. Available at: http://www.sciencedirect.com/science/article/pii/S0973688313004131.

Appendix A

Example of ReefBase Coral Bleaching Records (Asia) – page 1

ID	REGION	SUBREGION	COUNTRY	LOCATION	LAT	LON	MONTH	YEAR	DEPTH	SEVERITY_CODE	BLEACHING_SEVERITY
6762	Asia	Southeast Asia	Malaysia	Anemone Reef	4.29389	113.82620	8	2009	12m	1	Low
6763	Asia	Southeast Asia	Malaysia	Anemone Reef	4.29230	113.82578	8	2009	11m	2	Medium
6918	Asia	Southeast Asia	Malaysia	Aur Islan, Johor	2.47000	104.51000	7	2009	3	0	No Bleaching
6949	Asia	Southeast Asia	Malaysia	Aur Island	2.47000	104.53000	5	2009	3.5	0	No Bleaching
6950	Asia	Southeast Asia	Malaysia	Aur Island	2.46000	104.49000	5	2009	2.5	0	No Bleaching
6952	Asia	Southeast Asia	Malaysia	Aur Island	2.47000	104.51000	7	2009	7.9	0	No Bleaching
6919	Asia	Southeast Asia	Malaysia	Aur Island, Johor	2.44000	104.55000	7	2009	10	0	No Bleaching
6920	Asia	Southeast Asia	Malaysia	Aur Island, Johor	2.46000	104.49000	7	2009	9.4	0	No Bleaching
29411	Asia	Southeast Asia	Malaysia	Aur islands	2.49500	104.48700	5	2010	5 m	0	No Bleaching
29412	Asia	Southeast Asia	Malaysia	Aur islands	2.45900	104.48700	5	2010	10 m	0	No Bleaching
[illegible]	[illegible]	[illegible]	[illegible]	Bodgaya Dead End	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]

Appendix B

Example of ReefBase Coral Bleaching Records (Asia) – page 3

CORAL_FAMILY	CORAL_SPECIES	PERCENTAGE_AFFECTED	BLEACHING_DURATION	MORTALITY_CODE
Acroporidae, Poritidae, Fungiidae, Mussidae	Branching acropora, Porites cylindrica, P. lutea, Psammocora digitata, fungia, lobophyllia			
Poritidae, Mussidae, Acroporidae	Porites, Symphyllia , Acropora,	<10%	Start in June 2002	0
Poritidae, Acroporidae, Merulinidae	Porites, Encrusting, Acropora, Hydnophora	<10%	Start in June 2002	1
	Acropora spp, massive corals especially patches of Porites			3
	Sea anemonies			0
	barrel sponges (bleached white and sponges disintegrated)			3
Poritidae	Porites sp.	63-100%		

Appendix C

Example of ReefBase Coral Bleaching Records (Asia) – page 3

MORTALITY	SURVEY_TYPE	WATER_TEMPERATURE	OTHER_FACTORS	REMARKS	SOURCE
	line intercept transect, annually 5 permanently marked line transect 10 x 1 m (photograthy)	exceeding 30.1C		no widespread bleaching	Dunne, R.P. & B.E. Brown. 2001. The influence of solar radiation on bleaching of shallow water reef corals in the Andaman Sea, 1993-1998. Coral Reef 20:201-210
23 of monitored colony show partial mortality	line intercept transect, annually 5 permanently marked line transect 10 x 1 m (photograthy)		annual bleaching	extensive solar bleaching	Dunne, R.P. & B.E. Brown. 2001. The influence of solar radiation on bleaching of shallow water reef corals in the Andaman Sea, 1993-1998. Coral Reef 20:201-210
23 of monitored colony show partial mortality	line intercept transect, annually 5 permanently marked line transect 10 x 1 m (photograthy)		annual bleaching	extensive solar bleaching	Dunne, R.P. & B.E. Brown. 2001. The influence of solar radiation on bleaching of shallow water reef corals in the Andaman Sea, 1993-1998. Coral Reef 20:201-210
	line intercept transect, annually 5 permanently marked line transect 10 x 1 m (photograthy)	exceeding 30.1C		extensive bleaching	Dunne, R.P. & B.E. Brown. 2001. The influence of solar radiation on bleaching of shallow water reef corals in the Andaman Sea, 1993-1998. Coral Reef 20:201-210
				Extent Unspecified; Exposure to air caused mortality. Mortality	ReefBase
				Prominent on Faviids and restricted to specific areas of colonies. Lesions appeared on the western surface of reef flat corals corresponding with sun altitude and	ReefBase
					ReefBase
				Extent Unspecified; As a result of this exposure, areas of bleached tissue formed on the west-facing	ReefBase