Improving Coral Bleaching Predictions for Malaysian Reefs Through Improved Understanding of Satellite Sea Surface Temperature (SST) Accuracy and Reef Resilience

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Statement of the Contribution of Others

Nature of Assistance	Contribution	Names, Titles (if relevant), and Affiliations of Co-Contributors
Intellectual support	Proposal writing, Thesis writing	Prof Scott Heron, A/Prof Chun Hong Tan, Prof Morgan Pratchett, Dr Putu Liza Mustika
Data Sources	Used publicly available remote sensing satellite data from NOAA	National Oceanic and Atmospheric Administration (NOAA)
Data Sources	Used publicly available *in-situ* temperature data from AquaLink	AquaLink (Private Organization specializing in oceanic data collection)
Data Sources	Requested past data from Reef Check Malaysia's coral bleaching survey in 2015 to 2017	Reef Check Malaysia (RCM)
Data Sources	Used publicly accessible data documenting a reef resilience survey conducted in 2021	Universiti Malaysia Terengganu (UMT) research team
Data Sources	Used a report describing the 2011 Malaysian reef resilience study published by the Department of Marine Park Malaysia (DMPM)	Conducted in collaboration with government agencies, international organizations, and local NGOs
Data analysis	Python programming	Prof Scott Heron, Wesley Loh, Kang Zheng Lee

Abstract

Coral reefs in Malaysia face significant threats from environmental and human pressures, which could potentially impact their resilience. To address this issue, this study aims to enhance the understanding of coral bleaching predictions and the factors affecting coral reef resilience, to support better management strategies. While previous research and monitoring methods in Malaysia have primarily focused on past impacts, their limited capability to monitor ocean conditions in real-time hinders the prediction of coral health and resilience. Therefore, this study aims to (1) assess the accuracy of remote sensing satellite predictions for the coral bleaching response, (2) investigate the factors influencing bleaching prediction accuracy in Malaysian coral reefs for enhanced predictive modeling, (3) compare the resilience potential of coral reef sites in Malaysia to inform management strategies.

Three primary datasets were analyzed throughout the study, each contributing to different chapters: (a) *in-situ* temperature records from 2021 to 2022, used in Chapter 2 to validate remote sensing sea surface temperature (SST) and real-time SST; (b) remote sensing satellite observations (from 1985 to 2022) encompassing marine physical properties such as SST, cloud fraction, wind speed, and ocean turbidity, used in both Chapter 2 for comparing *in-situ* temperature records, and in Chapter 3 for analyzing factors affecting bleaching predictions; (c) field observations documenting coral bleaching events from 2015 to 2017, used in both Chapter 2 for comparing satellite predictions with actual bleaching events, and in Chapter 3 for analyzing survey sites across 31 Malaysian islands clustered into groups.

Comparison of *in-situ* and satellite-derived SST datasets from 2021 to 2022 revealed that the satellite data achieved an accuracy of up to 92% throughout the year in Peninsular Malaysia (PM) and East Malaysia. However, satellite-based predictions of coral bleaching events exhibited moderate accuracy, ranging between 50% and 56% compared with observed coral bleaching events. Distinct patterns in marine physical properties across Malaysia characterize three distinct seasons throughout the year. From November to February, the period typically marks the lowest SST levels, highest wind speeds, and turbidity levels, while the period from March to June signifies the highest SST levels, lowest wind speeds and turbidity levels. Additionally, July to October stands out as the period characterized by the highest cloud fraction, which leads to the lowest correlation between satellite-derived and *in-situ* SST, making the satellite-derived measurements less reliable compared to other seasons. Incorporating reef resilience scores from 2011 helped explain the moderate accuracy of satellite-based coral bleaching predictions, as higher coral bleaching percentages even under low heat stress conditions in reefs with lower resilience scores. Updating reef resilience scores using the 2021 dataset may provide additional insight for conservation and management of specific islands, with lower resilience sites typically associated with higher levels of development and tourism. Furthermore, 31 Malaysian islands were clustered into 12 distinct smaller clusters based on temperature variation analysis of seasonal patterns in marine physical properties, revealing seasonalities that can inform reef management strategies related to environmental conditions.

In summary, this study emphasizes the significance of accurate satellite monitoring, the role of physical factors in coral bleaching predictions, and the use of resilience scores to refine coral bleaching predictions. These findings offer practical recommendations for improving the management and conservation of Malaysian coral reefs, including recognizing seasonal variations, considering differences in reef resilience, and adopting a more comprehensive approach in the future that integrates satellite data with other monitoring methods to better assess the impacts of environmental and human pressures.

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Chapter 1. General Introduction

1.1 Importance and Environmental Threats to Coral Reefs

Coral reefs are essential for the well-being of millions of people worldwide, providing direct benefits such as seafood, fishing, and tourism income, as well as indirect services like coastal protection, especially for communities in developing countries that rely for sustenance and livelihood (Moberg & Folke, 1999; Shah, 2021; Van den Hoek & Bayoumi, 2017). A quarter of all marine species depend on coral reef ecosystems for the functions of nursery and reproduction (Reimchen, 2002; Sanciangco et al., 2013), which supports gleaning and fishing activities (Allemand & Osborn, 2019; Allen, 2008). The tourism industry benefits significantly from activities such as snorkelling and diving. For instance, in the Asia-Pacific (APAC) coral reef ecosystems contribute $25 billion annually to the regional economy, with reef tourism as the primary driver at $19.5 billion, followed by artisanal fisheries ($2.4 billion) and industrial fisheries (Bartelet et al., 2024). The West Buleleng Conservation Zone (WBCZ) in Bali, Indonesia, is valued at approximately US$12,114,408 annually, or US$18,602 per hectare, including both direct use and non-use values (Windayati et al., 2022). Beyond their economic contributions, coral reefs reduce storm damage costs by over $4 billion annually, prevent increased flooding that would otherwise affecting an estimated 81% more people living along reef coastlines each year, and offer significant wave energy reduction (Beck et al., 2018; Ferrario et al., 2014).

Nevertheless, coral reef ecosystems are experiencing severe decline due to various environmental stressors (Downie et al., 2024; Good & Bahr, 2021). The growing effects of climate change, including rising sea temperatures and more extreme weather events (Cai et al., 2021; Eghbert et al., 2017), are resulting in an increasing frequency of coral bleaching and mortality (Figueiredo et al., 2022; Klein et al., 2024; Munday et al., 2009). Coral bleaching is a stress response in which the coral host expels zooxanthellae and/or pigments, leaving the white coral skeletons much more visible beneath the translucent coral tissues (Douglas, 2003; Sikorskaya & Imbs, 2020). Corals will die under extended periods of stress; however, if normal conditions return, bleached corals may regain their algae and corresponding pigmentation (Berkelmans & van Oppen, 2006; Sampayo et al., 2008).

The primary cause of bleaching is rising ocean temperatures (Hughes, Kerry, et al., 2018) . Due to a 0.5°C increase in global sea surface temperature (SST) over the past decade, coral bleaching has become more frequent and intense, driven by rising temperatures, prolonged heat stress, and other environmental stressors (Doshi et al., 2012; Horwitz & Fine, 2014; Sully et al., 2019). The 2015 El Niño contributed to the largest recorded global mass coral bleaching event, during which more than 75% of global tropical coral reefs experienced bleaching-level heat stress between 2014 and 2017 (Hughes, Kerry, et al., 2018). In the Great Barrier Reef, the 2015 El Niño event resulted in an estimated 91.1% of 1,156 surveyed reefs experiencing bleaching of shallow-water coral, compared with extents of 55.3% of 638 surveyed reefs in 1998 and 57.6% of 631 reefs in 2002 (Hughes et al., 2017). In the same year, as a result of the El Niño event, the central Pacific coast of Mexico recorded a rise in bleached and dead corals, which then led to an increase in algae in 2018 (Nava et al., 2021). From April 2015 to May 2016, coral reefs off Jarvis Island, a small island midway between Hawaii and the Cook Islands, experienced severe coral mortality, with island-wide coral cover declining by more than 95% within a year (Vargas-Ángel et al., 2019). Similarly, after the 2015 El Niño event, bleaching of more than 30% of coral cover across Seychelles' reefs, significantly reducing coral cover on Curieuse Island (from 49% to 22%), and Praslin (from 42% to 13%) - an overall loss of approximately 28% (Gardner et al., 2019).

Coral bleaching can also be driven by various environmental factors beyond temperature stress, including ocean acidification, reduced cloud cover and seasonal variation. Ocean acidification is a term used to describe a reduction in the pH of seawater resulting from the oceans' extensive uptake of atmospheric carbon dioxide (CO_2) (Figuerola et al., 2021; Gattuso & Hansson, 2011). Ocean acidification has risen by around 30% since the onset of the twentieth century changing pH from 8.2 to 8.1, and pH level is projected to potentially reach 7.8 by 2100 (Figuerola et al., 2021). Under conditions of ocean acidification, the coral species *Acropora millepora* expel more than half of their zooxanthellae, resulting in decreased zooxanthellae photosynthesis and respiration (Kaniewska et al., 2012). This leads to heightened coral oxidative stress and metabolic inhibition, ultimately causing a reduction in coral growth in both volume and surface area (Kaniewska et al., 2012; Martins et al., 2022). Ocean acidification negatively impact tissue regeneration in various coral species, particularly slower-growing ones like *Porites sp.* and *Favia favus*, potentially compromising their resilience and recovery following physical disturbances (Horwitz & Fine, 2014). In addition, seasonal climatic variability, such as monsoon-driven shifts in wind, wave energy, and ocean currents, may exacerbate or mitigate local thermal conditions and influence bleaching severity (Chenoli et al., 2018; Fadila et al., 2023). Extreme weather events, including storms and cyclones, can also disturb coral reef environments, compounding physiological stress and impairing recovery capacity (Fabricius et al., 2008; Safuan et al., 2020).

Reduced cloud cover allows more solar radiation to reach the ocean surface, leading to increased SST Heightened solar radiation intensifies thermal stress on corals, increasing the likelihood of bleaching events (Leahy et al., 2013; Li et al., 2021; Zhao et al., 2021).

Other environmental factors such as cyclones or tropical storms, nutrient runoff from land, and reduced seawater levels, also threaten corals. Cyclones or tropical storms, which are intense low-pressure systems that develop over warm ocean waters, represent another major threat to coral reefs due to their associated strong winds and heavy rainfall (Singh & Roxy, 2022). For instance, the impact of tropical cyclone Pabuk on Malaysian coral reefs in 2019 led to significant reductions in live coral cover, increased dead coral cover, and depth-dependent damage (Safuan et al., 2020). Nutrient runoff is the term used to describe nutrients from land, such as nitrogen and phosphorus, introduced to water bodies. The impact of nutrient enrichment on coral calcification and resistance has been linked to the ratio of nitrogen speciation phosphorus availability, as imbalances in high nitrogen with limited phosphorus can increase physiological stress and reducing coral resistance (Burkepile et al., 2020; Fernandes de Barros Marangoni et al., 2020; Shantz & Burkepile, 2014). Additionally, extreme low tides in Indonesia during the 2015 El Niño event produced the subaerial exposure exposure of corals led to extensive coral bleaching and mortality, with lowest sea levels in 12 years to 85% mortality on reef flats and affecting nearly 30% of Bunaken reefs (Elvan Ampou et al., 2017).

1.2 The Role of *In-Situ* Observations in Coral Reef Monitoring

As concerns grow about coral reefs' health and resilience, consistent monitoring is required, involving systematic and continuous observation of various parameters to generate data on diverse ecological aspects (Obura et al., 2019). This monitoring helps assess reef health, track environmental changes, identify threats, and guide conservation and management strategies (Obura et al., 2019). Among the numerous long-term monitoring methods available, two key global approaches are *in-situ* temperature loggers and visual surveys by divers that provide high-quality data (Emslie et al., 2020).

In-situ temperature sensors, strategically positioned in the ocean, capture changes in the seawater temperature over time and provide measurements at various depths. This enables the rapid identification of areas susceptible to heat stress, assisting researchers in protecting and preserving vulnerable coral reef ecosystems (Hendee et al., 2020). Organizations like AquaLink and the Australian Institute of Marine Science (AIMS) contribute significantly to this effort to global and Australia. AquaLink, a private organization, has deployed temperature data loggers at both shallow and bottom levels across more than 500 global sites. These loggers are integrated into solar-powered smart buoys, enabling the collection of real-time hourly temperature readings (Gray, 2020). AIMS, an Australian government organization dedicated to marine research, operates a comprehensive program to monitor environmental parameters across the Great Barrier Reef, including seawater temperature. Temperature loggers have been deployed at various reef sites and at various time since 1991, these temperature loggers recording seawater temperatures every 5 to 10 minutes and cover reef-slope depths from 5-9 m to around 20 m (Australian Institute of Marine Science, 2017).

Visual surveys, conducted by trained observers or divers, involve assessing reef conditions such as benthic distribution, coral health, and documenting coral bleaching events (Wetz et al., 2020). These surveys can be categorized into in-water observational data collection and recordings for later analysis. Monitoring coral reefs through in-water data surveys enables the collection of detailed and accurate information on reef conditions over large areas, thus offering a comprehensive understanding of the health and dynamics of coral ecosystems globally (Kuo et al., 2022; Teague et al., 2022; Urbina-Barreto et al., 2021). Recording techniques include the capture of photo quadrats and video transects that are subsequently analysed in the laboratory.

Organizations such as Reef Check (RC), AIMS, and the New Heaven Reef Conservation Program (NHRCP) are examples of organisations contributing to this effort by employing visual surveys. Reef Check (RC) Foundation, a non-profit organization founded in 1996, focuses on conducting visual surveys and training local volunteer citizen researchers and divers through the broader Reef Check Program. Collaborating with citizen researchers in over 95 nations, RC conducts over 600 surveys annually, engaging around 8,000 divers to track the condition of global coral reefs (Reef Check Foundation, 2024). AIMS' Long-Term Monitoring Program assesses the status and trends of reefs within the Great Barrier Reef World Heritage Area through annual surveys covering 80 to 130 reefs over 35 years (Australian Institute of Marine Science, 2022). NHRCP, since its inception in 2007, has become a premier marine conservation program in Thailand, offering diverse Conservation Diver Courses, collaborating with Thai governmental bodies, and engaging over 1,500 trained observers (New Heaven Reef Conservation Program, 2023, April 20).

1.3 The Role of Remote Sensing Satellite in Coral Reef Monitoring

A successful, long-term strategy for coral reef conservation relies on the continuous monitoring of global reefs and changes in oceanic conditions to inform management and conservation efforts. Alongside *in-situ* observations, incorporating advanced technologies like remote sensing satellites has become an important component of effective reef monitoring (Burke et al., 2011; Hedley et al., 2016). Although remote sensing does not offer the same level of precision and detail as an *in-situ* observations, its capability for assessing broad-scale patterns is complemented by its span of entire geographical areas (Hedley et al., 2016). By using satellite imagery, researchers can effectively monitor large-scale environmental parameters important for understanding reef health and resilience, including SST, wind patterns, cloud cover, and ocean turbidity (Burns et al., 2022; Tarun Teja et al., 2014; Williamson et al., 2022)

CoralTemp is a satellite remote sensing SST product developed by NOAA (National Oceanic and Atmospheric Administration) to aid in monitoring the health of coral reefs globally. This product has provide daily global SST data at 5-km spatial resolution from 1985 to the present. The use of night-time-only SST measurements minimizes effects of daytime warming and solar glare (Petrenko et al., 2022; Pryamitsyn et al., 2022). *CoralTemp* SST stands out as a premier daily global SST product that delivers consistent results, therefore forming a cornerstone for the development of precise climatology (Gomez et al., 2020). Understanding long-term climate patterns and trends allows scientists to create reliable climatological models and enhance the ability to monitor coral reef health worldwide (Hartmann, 2015).

CoralTemp supports monitoring of coral bleaching risk through several metrics (Skirving et al., 2020). The SST Anomaly metric reports deviations from expected SST values for each location and specific date (Liu et al., 2014; Liu et al., 2013). A positive SST Anomaly value signifies that the SST was either warmer or colder than expected for that location on the relevant date. The Coral Bleaching HotSpot metric indicates current heat stress, identifying regions where SST surpasses the average temperature of the annual warmest month, also known as the Maximum Monthly Mean (MMM) (Liu et al., 2003; Skirving et al., 2006). The Degree Heating Week (DHW) metric quantifies the cumulative severity and duration of heat stress by summing the Coral Bleaching HotSpot stress in a region across the preceding 12 weeks (Liu et al., 2013; Skirving et al., 2006). DHW accumulates HotSpot values of 1°C or more (i.e., SST values above climatological MMM by at least 1°C) and therefore has a unit of °C-weeks (Liu et al., 2013). Key thresholds for DHW have been established through prior research: values above 4°C-weeks are typically associated with ecologically significant coral bleaching, while values surpassing 8°C-weeks are linked to ecologically significant coral mortality (Heron et al., 2016; Liu, 2006). On the Great Barrier Reef, a recent study suggested that lower DHW values of 2-3°C-weeks can lead to bleaching, with approximately 30–40% of corals experiencing bleaching and showing signs of die when DHW values reach 3-4°C-weeks (Hughes et al., 2017; Hughes, Kerry, et al., 2018). An exposure of 6°C-weeks led to a regional-scale change in the composition of coral assemblages (Hughes, Kerry, et al., 2018). Furthermore, when DHW values exceeded 8°C-weeks, 70% to 90% of corals were bleached (Hughes et al., 2017). The data and metrics of the *CoralTemp* product suite can be accessed through the NOAA Coral Reef Watch website at (https://coralreefwatch.noaa.gov/product/5km/indices.php).

Satellite-based monitoring of cloud properties is important in modern climate research and atmospheric studies, as it supports efforts in coral reef monitoring. The Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS) NASA Level-3 (L3) monthly Cloud Properties product, also known as CLDPROP_M3_VIIRS_SNPP, is part of an ongoing effort to maintain long-term records inherited from both the Moderate Resolution Imaging Spectroradiometer (MODIS) and VIIRS technologies. This product encompasses various cloud properties, including both Cloud-Optical Property (COP) and Cloud-Top Property parameters, and uses a consistent algorithm applicable to both MODIS and VIIRS data, ensuring continuity through shared spectral channels (Platnick et al., 2021). The product is derived by aggregating the daily SNPP/VIIRS D3 Cloud Properties product

(CLDPROP_D3_VIIRS_SNPP) into a global gridded dataset, and includes 128 science datasets with 837 variables. These parameters cover Cloud-Top Properties, Cloud-Optical Properties, and Solar and Sensor Angles, each associated with statistical variables such as mean, standard deviation, pixel count, and histograms. The product has provide monthly and daily cloud properties data with a 1.0° spatial resolution since 2012, aiding research and applications dependent on accurate cloud data (Meyer et al., 2020). This dataset can be accessed through the NASA website at https://ladsweb.modaps.eosdis.nasa.gov/search/.

Monitoring of wind using satellite products can also support the assessment and management of coral reef ecosystems by providing data on wind speed that affect reef health and resilience. The Blended Sea Winds product of NOAA's NCEI (NBS v2.0) is a satellite remote sensing product that has provide sea surface wind information with a 0.25° spatial resolution on a 6-hour timestep since 1987. The product represents wind speed at a 10 m height above the sea surface in a neutral atmosphere (Saha & Zhang, 2022). Integrating data from multiple satellite sources and employing advanced blending techniques results in a high level of accuracy and reliability (Price et al., 2023; Zhang et al., 2006). Over the years, the operational observation of sea surface wind speed has evolved from a single satellite in 1987 to a constellation of five or more satellites by 2000 (Saha & Zhang, 2022; Zhang et al., 2006). NBS v2.0, which builds upon the previous version (v1.0), improves accuracy in high wind delineation by incorporating random-error-based weighted averaging with spatial-temporal interpolation (Saha & Zhang, 2022). This comprehensive dataset has been instrumental in enhancing the understanding of the wind patterns and the potential impact on several factors including precipitation, cloud cover, ocean currents, and wave activity at the survey sites. The relevant Blended Sea Winds data can be accessed at https://www.star.nesdis.noaa.gov/data/pub0015/coastwatch/blended/wind/scien-ce/uvcomp/.

Ocean colour satellite data products contribute to understanding coral reef ecosystem dynamics by offering information about water quality, primary productivity, and the health of marine ecosystems. The VIIRS Ocean Colour multi-sensor daily merge product combines ocean colour data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensors on the Suomi National Polar-orbiting Partnership (SNPP) and National Oceanic and Atmospheric Administration (NOAA)-20 satellites. These sensors capture visible, near infrared, and shortwave infrared light. From these, ocean colour properties are calculated including chlorophyll-a concentration (chlor-a) and water turbidity parameters of Kd(PAR) and Kd(490) (Liu & Wang, 2019; Wang et al., 2013). With a 0.04° spatial resolution and spanning from 2018 to the present, this dataset provides daily diffuse attenuation coefficients, which represent the Kd products, offering insights into light propagation and attenuation within the ocean. This dataset can be accessed through the Ocean Colour Level 3 VIIRS Multi-Sensor website at https://coastwatch.noaa.gov/cwn/products.html/.

1.4 Coral Reef Resilience

Coral resilience refers to the capacity of coral reefs to survive, withstand, and recover from environmental disturbances while maintaining their ecosystem functions. Coral reef resilience has been extensively considered through two key components: resistance and recovery (*sensu* (McClanahan et al., 2012)). Resistance is the capacity of coral reefs to endure environmental stressors and pressures without significant degradation or loss of function (Grimsditch & Salm, 2005; Obura & Grimsditch, 2009). At the individual coral colony level, this involves mechanisms such as adaptations and symbiotic relationships with zooxanthellae that help corals maintain their health and integrity in the face of challenges (Morikawa & Palumbi, 2019; Palumbi et al., 2014). These changes may become apparent at the reef scale when triggered by broad changes in environmental conditions, recovery refers to the ability of coral reefs to restore their structure and function after being subjected to disturbances (Obura & Grimsditch, 2009; Shaver et al., 2022). This process may involve recruitment of new coral colonies, regrowth of damaged coral structures, and restoration of ecosystem services over time (Shaver et al., 2022). Together, the interplay between resistance and recovery mechanisms determines the overall resilience of coral reef ecosystems, influencing their ability to persist in dynamic and changing environments (Lam et al., 2020; McClanahan et al., 2012; Obura & Grimsditch, 2009).

Resilience-based management (RBM) has been proposed to enhance the ability of coral reef ecosystems against environmental pressures, thereby ensuring the supplying of numerous benefits to both human communities and marine biodiversity (McLeod et al., 2019). RBM aims to identify both current and anticipated factors impacting ecosystem functionality and to prioritize, implement, and adjust management strategies accordingly. This involved identifying resilience factors and supporting individuals in learning and sharing knowledge, encouraging innovation, and adapting responses to changing drivers and processes, to enhance ecosystem resilience (Folke et al., 2016; McLeod et al., 2019; Mumby et al., 2014). The specific objectives of RBM can vary depending upon the unique circumstances of the local context, including local baselines, stakeholder requirements, and the desired system state.

Table 1.1:

A Summary of 11 Resilience Factors Analyses to be the Most Important (among 61 candidates) for Coral Reefs. Adapted from (McClanahan et al., 2012)).

Resilience Factor	Perceived importance of Resilience (0 to 20)	Scientific Proof of Resilience (-10 to +10)	Feasibility (0 to 10)
Resistant coral species	15.6	7.2	8.0
Temperature variability	14.0	6.1	7.7
Nutrient runoff	13.3	5.4	5.6
Sedimentation	12.6	5.6	6.7
Coral diversity	12.4	4.8	7.1
Herbivore biomass	11.8	5.0	7.4
Physical human impacts	11.7	4.8	6.4
Coral disease	11.6	3.8	6.4
Macroalgae	11.5	4.7	8.5
Recruitment	11.4	4.9	6.7
Fishing pressure	11.4	4.4	7.0

Sixty-one variables were identified as contributing to coral resilience and used as the basis for developing an assessment protocol to evaluate the success of coral reef conservation management (Obura & Grimsditch, 2009). Several countries have implemented this assessment protocol as a part of standardized tools in the management of coral reef resilience conservation. A study reviewing 65 reef resilience assessments across 44 countries showed that 52% of these assessments effectively informed coral reef management strategies, highlighting the practical importance and effectiveness of using resilience-based management to strengthen coral reef ecosystems (McLeod et al., 2021). Among 61 resilience variables, 11 were prioritized as the most important coral resilience factors, based on an analysis of the perspectives of 28 coral reef experts to ensure effective coral reef management (McClanahan et al., 2012) (Table 1.1). Each factor was evaluated based on three criteria: (1) Perceived Importance (0–20), reflecting expert opinions on its significance; (2) Scientific Proof (-10 to +10), indicating the strength of empirical evidence; and (3) Feasibility (0–10), representing the practicality of assessing and managing the factor. However, those authors also noted that additional research attention was required beyond these factors that may influence the selection of priority resilience factors (at least for individual locations).

1.5 Coral Reefs in Malaysia

Malaysia is located within the South China Sea (SCS) region, regarded as Southeast Asia's primary coral reef hotspot. The SCS region encompasses approximately 12,000 km² of world's coral reef area and hosts an estimated around 570 identified coral species (Burke et al., 2002; Huang et al., 2014; Huang et al., 2015). Within this extensive coverage, Malaysia has a significant presence, featuring a coral reef area of around 4, 000 km² that is renowned for its high richness of scleractinian reef corals (501 known coral species) (Affendi & Rosman, 2012; Burke et al., 2002; Fenner, 2001; Huang et al., 2016; Waheed et al., 2012). Geographically, Malaysia comprises two major landmasses: Peninsular Malaysia (PM) and East Malaysia (EM), bordered by different seas (Figure 1.1).

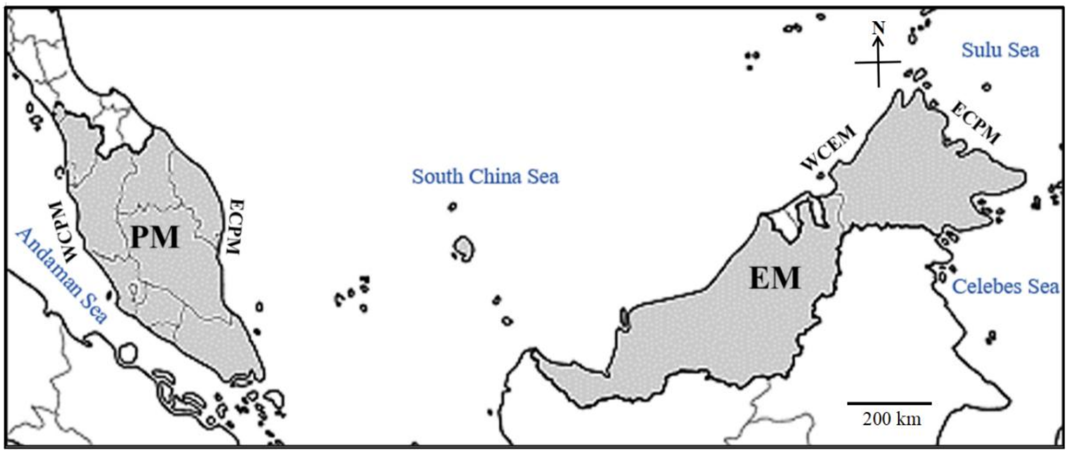


Figure 1.1. Map of Malaysia.The left shaded area represents Peninsular Malaysia (PM), while the right shaded area represents East Malaysia (EM). WC denotes the West Coast, and EC represents the East Coast of each area.

Malaysian coral reefs exhibit varying diversity along different coastlines (Figure 1.1). The west coast of PM (WCPM) is bordered by the Andaman Sea, while the South China Sea (SCS) lies between the east coast of PM (ECPM) and the west coast of EM (WCEM). The east coast of EM (ECEM) shares boundaries with the Sulu Sea and the Celebes Sea. These geographical distinctions give rise to diverse coral reef compositions in each region. WCPM contains 56 documented species within 0.5% of Malaysia's total coral reef area; ECPM has 398 species within 3.0% of the Malaysia's coral reef area; 248 species have been documented in WCEM within 14.1% of the total coral reef area; there are 382 known species in ECEM within 82.4% of Malaysia's coral reef area (Huang et al., 2014; Leem et al., 2022; Waheed, 2016).

Malaysian coral reefs are a biodiversity hotspot and an important area for conservation, supporting high species richness, rare species, and a variety of endangered species (Huang et al., 2016; Safuan et al., 2022). Within the SCS region, Malaysia hosts approximately 88% of the coral species classified as endangered, thus underscoring its significance in coral conservation efforts (Burke et al., 2002; Huang et al., 2016; Waheed, 2016). These reefs also contribute significantly to the country's reef tourism and fisheries sectors. The annual economic contribution of Malaysia's coral reefs amounted to approximately US$1.5 billion between 2008 and 2012, with around 40% attributed to tourism and 60% to fisheries, representing 0.6% of Malaysia's GDP (Bartelet et al., 2024).

Malaysian coral reefs experience natural seasonal variability and also face various associated threats. Malaysia experiences two main monsoon seasons: the Southwest (SW) Monsoon and the Northeast (NE) Monsoon. The SW Monsoon occurs from May to August/September brings drier conditions compared to the NE Monsoon, especially to the WCPM which experiences less wind and rain due to the shielding effect of Sumatra (Masseran & Razali, 2016; Moslim et al., 2021; Suhaila et al., 2010). In contrast, the NE Monsoon, prevailing from November to February/March, brings northeasterly winds that particularly affecting Malaysia's ECPM and EM . During this period, especially in November and December, around 50% of the annual rainfall occurs in four to six episodes of heavy rain due to monsoon surges from northerly and easterly winds (Fadila et al., 2023; Fakaruddin et al., 2020). The strong winds and resulting waves and currents can cause coral colonies to dislodge and break (Fabricius et al., 2008; Ibrahim et al., 2000). For example, Tropical Storm Pabuk which impacted the southern region of the SCS in 2019, brought winds exceeding 80 kph. As a result, the live coral cover (LCC) at ECPM, Pantai Pasir Cina and Pulau Bidong, decreased from 47.9% to 28.75%, while dead coral cover increased from 26.3% to 65.09%, with the most substantial reduction in live coral cover observed at depths of 3 m (Safuan et al., 2020). Furthermore, the occurrence of El Niño events create challenges for Malaysian coral reefs. In 2010, an El Niño event resulted in widespread coral bleaching across various Malaysian islands, leading to increased coral mortality and economic losses (Doshi et al., 2012; Guest et al., 2012; Tan & Heron, 2011). Approximately half of the hard corals experienced bleaching, with two-thirds of affected colonies turning completely white and affecting depths of up to 20 m in Redang Island (Tan & Heron, 2011). Malaysia also experiences a monsoon transition period before and after each monsoon. During this transition, wind direction fluctuates, and relatively weak wind conditions prevail (Chenoli et al., 2018; Masseran & Razali, 2016).

Malaysian coral reefs in different coastline presents unique challenges influenced by varying physical properties of the seas and levels of development (Burke et al., 2002). In WCPM, muddy sands and mud dominate the bottom sediment creating less conducive environments for coral growth due to higher turbidity levels and reduced light penetration (Mubin et al., 2023; Thia-Eng et al., 2000). Urban pressures such as land rehabilitation, tourism, and international shipping further exacerbate threats to these coral reefs (Burke et al., 2002; Leem et al., 2022; Thia-Eng et al., 2000). Conversely, ECPM exhibits the highest coral cover in Malaysia, attributed to the establishment of Malaysian Marine Parks and clear water environments (Leem et al., 2022; Reef Check Malaysia, 2022). However, threats from agricultural activities, coral reef development projects, and tourism persist, leading to physical damage and environmental changes (Burke et al., 2002; Lachs et al., 2019; Leem et al., 2022; Statista Research Department, 2022). EM consists of two states, Sabah and Sarawak (Figure 1.1). Sabah, encompassing the northern part of the WCEM and ECEM, suffers from overfishing and lack of protection with only a small fraction of its coral reefs under marine park designation (Asian Development Bank, 2014; Burke et al., 2011; Zakariah et al., 2007). Over 60% of coral reefs in Sabah have suffered damage due to overfishing and destructive practices (Asian Development Bank, 2014). Sarawak, located in the southern part of the WCEM, experiences high sedimentation rates, hindering coral settlement and promoting algal growth (Burke et al., 2011).

Malaysian government and civil society have been actively involved in marine biodiversity conservation since the 1980s. The designation of Marine Protected Areas (MPAs) is a key strategy in accordance with the IUCN's objective of marine biodiversity conservation (Yacob et al., 2012; Yeo, 2004). Of the 47 MPAs in Malaysia, 42 are located in PM under the auspice of the Ministry of Natural Resources and Environment, with the remainder in EM established under the Sabah Parks Enactment. Reef Check Malaysia (RCM) is a non-governmental organisation that was formally established in 2007 (but active for a decade prior) to focus on coral reef conservation in Malaysia. RCM monitors over 200 coral reefs annually, with more than 2,000 surveys conducted, and has been actively involved in reef management and conservation initiatives for over 15 years (Reef Check Malaysia, 2022). RCM undertakes quantitative *in-situ* observations of coral reefs in MPAs with a focus on abundance of benthic communities, the health status of coral reefs, and the coral bleaching events.

An overview of studies conducted in Malaysia indicated that research on coral in Malaysia had increased since the 2000s (Misman et al., 2023). Through distribution maps and discussions of techniques employed, the study underscored that most research has occurred in the ECPM with three main approaches: visual assessment, remote sensing, and geochemical analysis. Visual assessment studies constitute the majority and exhibit diverse objectives, ranging from understanding coral status, species richness, coral disease prevalence, and distribution patterns to detailed mapping efforts. Remote sensing studies primarily focus on mapping coral reefs using satellite imagery and other advanced techniques. Geochemical analyses delve into the concentration of chemical elements in the water, examining their potential impact on coral health. The overview emphasized the need for future research to explore other Malaysian reef areas, diversify characterization techniques, and conduct more studies in under-researched locations.

1.6 Research Objectives and Thesis Structure

Whilst the monitoring protocol of RCM is effective in assessing the bleaching condition of Malaysian coral reefs, it only offers insight into past impacts. This limitation underscores the necessity for complementary methods that offer near-real-time monitoring of ocean conditions to identify contemporary or emerging threats. Satellite remote sensing has been used effectively to monitor ocean conditions that cause mass coral bleaching (Obura et al., 2019). However, the application of satellite remote sensing together with the quantitative *in-situ* observation to monitor coral reefs is still a relatively new research activity in Malaysia. While similar approaches have been used in other regions, Malaysia's coral reefs present unique challenges due to the specific geographic, climatic, and ecological conditions of the region (Castillo & Lima, 2010; Hedley et al., 2016; Kavanaugh et al., 2021; Mills et al., 2024). Therefore, it is important to better understand the reliability and accuracy of satellite-derived data, particularly its ability to predict coral bleaching responses accurately in Malaysian waters. This research aims to address this, focusing on enhancing the understanding and predicting Malaysian coral bleaching events, supporting management efforts.

The main body of the thesis is structured in four chapters. Chapter 2 addresses the first objective: assess to the accuracy of satellite remote sensing predictions by comparing them with *in-situ* observations to improve the understanding of satellite-based predictions for coral bleaching responses (Figure 1.2). Understanding the reliability of satellite-derived data in capturing SST provides the foundation for calculating thermal stress – the primary indicator for predicting of coral bleaching events (Hughes, Kerry, et al., 2018). Chapter 3 examines obejective 2 and 3, explore to the role of resilience factors (e.g., reef resilience score, cloud cover, wind speed and turbidity) that may influence or improve the accuracy of bleaching predictions based on satellite-derived SST data in Malaysian coral reefs. Through this investigation, the potential for refining predictive modelling approaches and enhancing the ability to predict coral bleaching impacts is discussed, together with assessing the resilience potential of coral reef sites to support conservation efforts. Chapter 4 provides a general discussion of the results and their implications for coral reef conservation efforts in Malaysia, aiming to improve the understanding of Malaysian coral bleaching prediction. The research aims to contribute to the development of more accurate predictions and improved outcomes to support the sustainable management and conservation of Malaysian coral reefs in the face of ongoing environmental challenges.

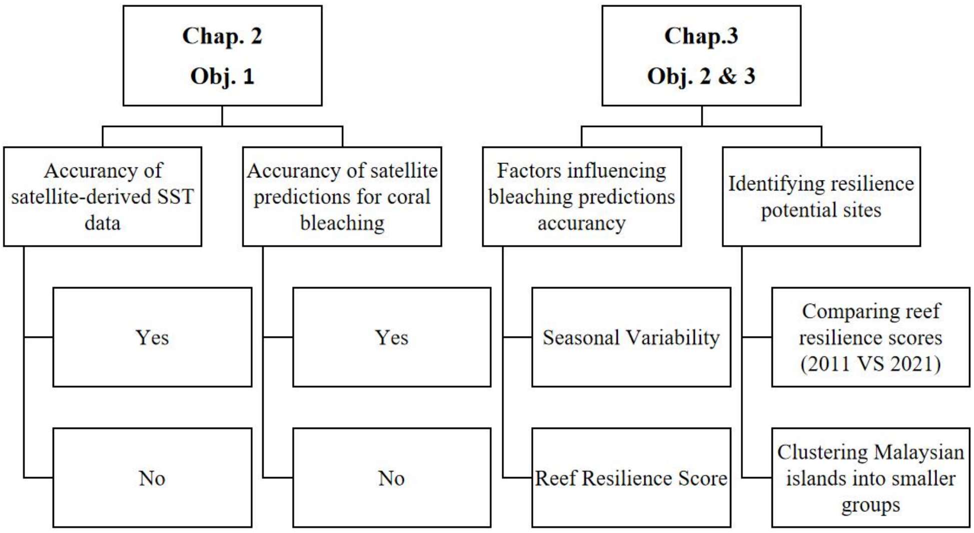


Figure 1.2. The thesis structure.

Chapter 2: Evaluating Remote Sensing Satellite Predictions for Coral Bleaching Response in Malaysia

2.1 Introduction

Rapidly changing environmental conditions, attributable to anthropogenic climate change (A. K et al., 2023; Garcia-Soto et al., 2021; Hansen & Stone, 2016), represent the foremost threat to coral reef ecosystems (Cartwright et al., 2021; Fourney & Figueiredo, 2017; Gobler, 2020; Tout et al., 2015). Moreover, the effects of climate change are compounding and conflating pre-existing disturbances and threats to coral reef ecosystems (Baum et al., 2023; Cartwright et al., 2021), resulting in widespread and accelerating habitat degradation (Duarte et al., 2020; Safuan et al., 2020; Tebbett et al., 2023). The foremost effect of changing environmental conditions on coral reefs is mass coral bleaching and corresponding coral mortality (Hughes et al. 2018), which is mainly and increasingly caused by severe marine heatwaves (Baum et al., 2023; Donovan et al., 2021; Leggat et al., 2019; Yadav et al., 2023).

While mass coral bleaching has been reported across much of the world's coral reefs since 1998 (Wilkinson 1998), the first documented mass bleaching on coral reefs in Malaysia occurred in 2010 (Tan & Heron, 2011). In 2010, severe coral bleaching (in which at least 50% of corals exhibited bleaching) was recorded across a wide range of islands, with significant bleaching recorded to depths of up to 20 m (Tan & Heron, 2011). Since 2010, research on the health status of coral reefs and benthic community composition in Malaysia has increased. For example, in Tioman Island, coral species displayed varying susceptibilities to bleaching, with branching *Porites* being the most affected, while massive coral taxa experienced comparatively lower mortality rates (Guest et al., 2012). Additionally, a significant reduction in growth rates of *Porites lutea* corals at Tinggi Island in 2010 was considered likely to be a result of the thermally-induced bleaching event (Ong et al., 2022).

Given the inexorable link between temperature and mass coral bleaching ((Gardner et al., 2019; Hughes, Anderson, et al., 2018; Hughes et al., 2017; Nava et al., 2021; Vargas-Ángel et al., 2019), see also Chapter 1.1), satellite remote sensing data on sea surface temperature (SST) may provide valuable insights into the spatial and temporal dynamics of environmental conditions that directly influence the status and trends in coral reef health ((Burke et al., 2011; Burns et al., 2022; Hedley et al., 2016; Tarun Teja et al., 2014; Williamson et al., 2022), see also Chapter 1.3). More importantly, it is the accumulation of heat stress (the duration and magnitude of thermal anomalies above the long-term summertime maximum monthly temperatures), measured as Degree Heating Weeks (DHW or °C-weeks), rather than the absolute temperature that generally influences the incidence and severity of mass coral bleaching. Global guidance for heat stress is that significant coral bleaching is predicted at DHW values at and above 4°C-weeks, while values exceeding 8°C-weeks indicate ecologically significant coral mortality (Heron et al., 2016; Liu, 2006). In a recent study on the Great Barrier Reef, bleaching was observed at DHW values of 2°C-weeks to 3°C-weeks (Hughes et al., 2017; Hughes, Kerry, et al., 2018). However, the resulting incidence and severity of mass coral bleaching may also be moderated by local environmental conditions and coral species resilience (Carturan et al., 2022; Keighan et al., 2023; Lyu et al., 2022; Sully & Woesik, 2020). It is also apparent that satellite-derived estimates of SST will not necessarily reflect the true extent of accumulated heat stress in some habitats due to turbidity level of water and cloud cover (Benas et al., 2020; Zhang et al., 2018).

The accuracy of satellite remote sensing data is important to ensure reliable information for effective management decisions. A previous study provided sea and land temperature data for Penang Island, Malaysia, from 2016 to 2018, and found a positive correlation ($R^2 > 0.5$) when comparing the NASA remote sensing satellite data with AccuWeather's temperature forecasts (Md Kamaludin et al., 2022). In areas where satellite-derived estimates of SST have been directly compared to *in-situ* and ongoing measurement of ambient temperature, there is often a high correlation, highlighting the reliability of satellite data (Corlett et al., 2006; Gomez et al., 2020; Kuleli & Bayazit, 2020). However, few studies have compared satellite-derived and *in-situ* SST measurements in Malaysia. Previous assessment of the seawater temperature derived from satellite and *in-situ* measurement is limited to one specific island . The study found differences of 0.63°C ± 0.26°C between datasets for a specific island in a two-year timeframe (2019 and 2020) (Szereday & Affendi Yang, 2022). This highlights the need for broader and longer-term remote sensing and *in-situ* observations to assess the reliability of satellite data in Malaysia, and to evaluate the effectiveness of the DHW metric in understanding and predicting bleaching events, as well as supporting targeted reef management strategies.

2.2 Research Objectives

The specific research objectives for this chapter are twofold:

1. To compare remote sensing satellite data to *in-situ* measurements of SST for coastal environments in Malaysia. Temperature data have been recorded *in-situ* by AquaLink from 2021 to 2022, along with satellite-derived SST data covering the same period on four islands - three located in Peninsular Malaysia (PM) and one in East Malaysia (EM).

2. To test predictability of the incidence and severity of mass coral bleaching by comparing historical SST data to documented occurrences of mass coral bleaching in Malaysia. This includes field coral bleaching observations conducted by RCM from 2015 to 2017 and satellite-derived SST datasets covering the same period across 31 islands.

2.3 Methodology

2.3.1 Study Area

The datasets derived from *in-situ* temperature measurements, field coral bleaching observations and satellite-derived SST data were analyzed to evaluate the accuracy of remote sensing satellite heat stress models in predicting coral bleaching responses in Malaysia. *In-situ* temperature measurements were gathered from four study sites Malaysia from 2021 to 2022 (the red dots in Figure 2.1). Concurrently, field coral bleaching observations (the blue dots in Figure 2.1) were collected from 31 islands, 132 study sites, and 188 survey times across Malaysia from 2015 to 2017..

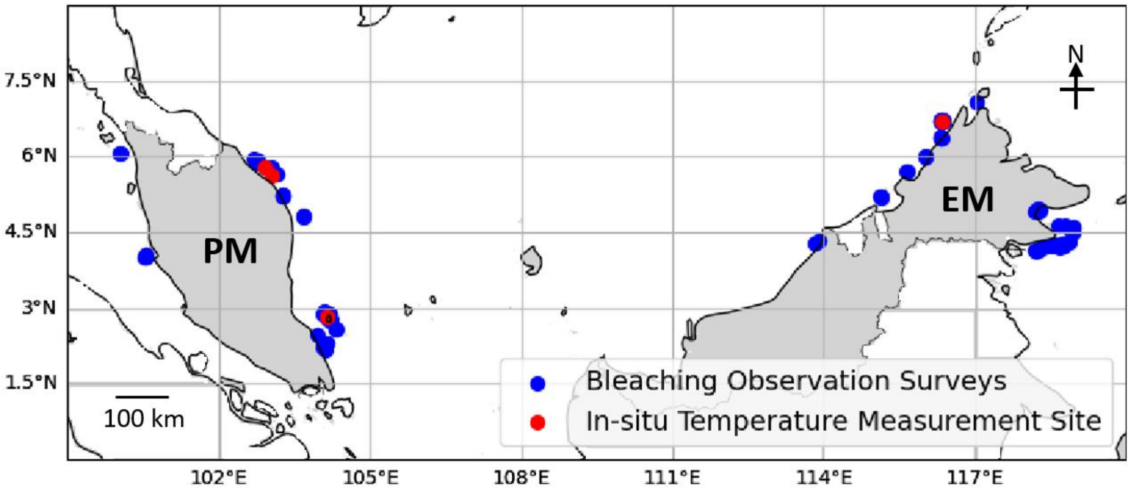


Figure 2.1. Map of study sites in Malaysia. Four *in-situ* measurement sites (red) are complemented by 132 locations of bleaching observation surveys (blue), spanning Peninsular Malaysia (PM) and East Malaysia (EM).

2.3.2 Data Sources

2.3.2.1 *In-situ* Temperature Data Loggers

This study made use of long term, open access, *in-situ* temperature data loggers that were installed and managed by AquaLink, a private organization specializing in oceanic data collection and analysis. AquaLink uses a combination of sensor technology, satellite imagery, and machine learning techniques to facilitate real-time monitoring of Malaysian coral reefs (Gray, 2020). In 2021, AquaLink deployed four temperature data loggers, each equipped with temperature sensors at two depths, across four sites in Malaysia (Table 2.1). The duration of logger deployment varied due to local regulations (Gray, 2020). The *in-situ* surface and deep hourly temperature measurements acquired from 2021 to 2022 were used to evaluate the accuracy of satellite-derived SST datasets and understand temperature variations at different depths to corals. However, publicly available documentation on their calibration process or accuracy assessments is limited. While this study assumes the loggers provide reliable measurements, a direct evaluation of their accuracy is beyond the scope of this thesis. Future studies could consider comparing AquaLink loggers with other *in-situ* temperature instruments to assess measurement consistency and potential biases.

Table 2.1**:**

Summary of Surface and Depth Sensor Placement Information at Study Sites in Peninsular Malaysia (PM) and East Malaysia (EM; Figure 2.1)

Study sites	**Surface sensor depth (m)**	**Deep sensor depth (m)**	**Development Period and Data Taken (Month & Year)**	**Number of days (N)**
Pantai Pasir Cina, PM	1	9	Mar 2021 - Sep 2022	547
Pulau Lang Tengah, PM	1	15	Oct 2021 - Dec 2022	448
Tekek Reef, PM	1	10	Feb 2021 - Aug 2022	530
Mantanani Reef, EM	1	6	Nov 2021 - May 2022	193

2.3.2.2 Field Coral Bleaching Observations

Reef Check Malaysia (RCM), a Malaysian non-profit organization established in 2007, has consistently conducted coral reef surveys throughout Malaysia, averaging 200 surveys annually. These data were chosen as the primary observations source for coral bleaching due to RCM's extensive experience in this field and its consistent application of the globally recognized Reef Check Protocol method (Hodgson, 1999; Reef Check Malaysia, 2021) for more than 15 years.

During annual coral reef surveys, coral bleaching was assessed using a Point Intercept Transect (PIT) method Reef Check Protocol and recorded using the Bleaching Watch Survey Reporting Form. The PIT method involves the placement of a 100 m transect tape parallel to the shoreline at the selected sites. This transect is divided into four 20 m segments, separated by 5 m gaps (Hodgson, 1999; Reef Check Malaysia, 2021). Trained divers swim along the transect to record the extent of coral bleaching responses as a percentage of colonies. The collected data were later transferred into a form which included the following information: survey dates, site details, percentages of coral bleaching, type of affected corals, and morphological attributes.

The heat stress event that was part of El Niño in 2014 triggered a global mass coral bleaching event that persisted from 2015 to 2017, representing the third and most extensively documented

Global Coral Bleaching Event (Oliver et al., 2018; Sully et al., 2019). For this reason, field coral bleaching observations conducted between 2015 and 2017 were selected for this study. During this period, RCM conducted 188 survey trips to record coral bleaching responses in 132 sites across 31 islands in Malaysia. The observed bleaching responses formed the fundamental dataset for the coral bleaching response analyses undertaken in this study.

2.3.2.3 Satellite-derived SST Dataset

The *CoralTemp* SST dataset, which provides daily global satellite data at a 0.05° spatial resolution from 1985 to the present, was used to compare SST data from 2021 to 2022 for four satellite pixels with *in-situ* SST measurements. In addition, the *CoralTemp* SST from 2015 to 2017 and Maximum Monthly Mean (MMM) values for 68 satellite pixels were extracted for heat stress calculations, to calculate satellite predictions of coral bleaching events (DHW; see Chapter 1.3). The relevant data were accessed at *CoralTemp* on the NOAA Coral Reef Watch website at https://coralreefwatch.noaa.gov/product/5km/index_5km_composite.php

2.3.3 Statistical Analysis

2.3.3.1 **Statistical Comparisons between *In-situ* Temperature and Satellite-derived SST**.

Time series graphs were created to illustrate detailed temperature profiles and patterns by comparing *in-situ* hourly surface and deep temperature measurements with daily satellite-derived SST. Additionally, time series graphs illustrating temperature bias were constructed using a two-week rolling average of the differences between in-situ hourly temperature records and daily satellite SST across the four study sites from 2021 to 2022. The selection of a two-week timeframe was based on the timing of the spring-neap cycle, aiming to capture variations in temperature dynamics over short-term tidal fluctuations, thus contributing to a more comprehensive understanding of temperature dynamics (SuYin et al., 2019).

The accuracy of remote sensing satellites in capturing SST was assessed using Python-based descriptive statistics, accuracy metrics, and scatter plots by comparing them with *in-situ* surface temperature measurements. *In-situ* hourly surface temperature were averaged to a daily scale and compared with daily satellite-derived SST. Descriptive statistics summarize temperature data, providing insights into temperature trends and assessing temperature data variabilities

(Alemu & Dioha, 2020). The range of descriptive statistics analyzed included minimum and maximum temperatures for each temperature measurement, standard deviation, and the average of standard deviation. Accuracy metrics were used to enable benchmarking and method comparison in context of temperature data, allowing for alignment with broader academic communities and standardizes the evaluation process (Kumar et al., 2021). R-squared (R^2), the square of the correlation coefficient, quantified the proportion of variance in *in-situ* measurements explained by satellite data, providing insight into how well the satellite data predicted *in-situ* values (Gomez et al., 2020; Masud-Ul-Alam, 2022; Onyutha, 2022). P-values assessed the statistical significance of these relationships, indicating the likelihood that the observed correlations were due to chance (Edwards et al., 2021). Meanwhile, scatter plots, a preferred tool for anomaly detection, facilitated a visual and qualitative comparison between satellite-derived and *in-situ* SST data (Gomez et al., 2020; Masud-Ul-Alam, 2022). The selected accuracy metrics and scatter plot statistics for this study are outlined in Table 2.2 (Gomez et al., 2020; Paloschi & Noernberg, 2021).

Table 2.2*:*

Summary of Accuracy Metrics Interpretation and Scatter Plot Statistics (Edwards et al., 2021; Gomez et al., 2020; Paloschi & Noernberg, 2021)

Metric	Description	Interpretation for low magnitude	Interpretation for high magnitude
Mean bias	Average difference between measurements. Positive values indicate cooler *in-situ* SST; negative values indicate cooler satellite-derived SST.	Better alignment between measurements.	Greater divergence between measurements.
Standard deviation (SD) of the Bias	Quantifies variability in measurement differences.	Consistent variations in measurements.	Inconsistent variations in measurements.
Root mean squared (RMSE)	Magnitude of differences between measurements.	Close match between observed and predicted values.	Difference between observed and predicted values is high.
Spearman's correlation coefficient	Measures the strength and direction of relationships.	Near 0, weak or negligible linear correlation.	Higher negative values (near -1) suggest a pronounced inverse relationship; high positive values (near +1) indicate a positive association.
R-square (R^2)	Represents the proportion of variance explained by one dataset relative to another.	Low R^2 indicates a weaker relationship and lower predictive accuracy.	High R^2 suggests a strong relationship and better predictive accuracy.
P-value	Assesses the statistical significance of the observed relationship.	A high p-value (> 0.05) suggests the relationship may be due to random chance.	A low p-value (< 0.05) indicates that the relationship is statistically significant and unlikely due to random variation.

2.3.3.2 Statistical Analyses between Field Coral Bleaching Observations and Satellite Predictions

This study employed Python-based scatter plots, and confusion matrices for comparisons between field coral bleaching observations and satellite predictions of coral bleaching. The analyses focused on validating satellite-derived heat stress predictions expressed in Degree Heating Week (DHW) thresholds against field coral bleaching observations (Liu et al., 2013; Skirving et al., 2006). Coral bleaching predictions are based on DHW thresholds calculated using the *CoralTemp* Maximum Monthly Mean (MMM). DHW begins to accumulate when SST exceeds 1°C above climatological MMM. A widely accepted threshold for heat stress indicates that significant coral bleaching is expected when DHW reach or exceed 4°C-weeks, while values exceeding 8°C-weeks are associated with significant coral mortality (Heron et al., 2016; Liu, 2006). However, a recent study on the Great Barrier Reef (Hughes et al., 2017) reported bleaching occuring at lower DHW values, ranging from 2°C-weeks to 3°C-weeks. Here, both 4°C-weeks and 2.5°C-weeks are evaluated as specific DHW thresholds for identifying satellite-predicted bleaching events in Malaysia. Out of 188 field coral bleaching observations over three years, 139 observations were strategically selected based on their temporal proximity to the maximum DHW recorded up to the date of the survey for each year and each satellite pixel. Bleaching surveys from the beginning of each year until 30 days after the date of the highest DHW recorded up to the survey date, which signals the last accumulation of heat stress before the survey, were included.

Scatter plot analysis, which included measurements of R^2 and p-values, provided visual insights into the correlation between DHW and field coral bleaching observations. R^2 quantified the proportion of variance explained by DHW predictions relative to the field observations (Alfaris et al., 2024; Li et al., 2016; McClanahan et al., 2007), while p-values were calculated to assess the statistical significance of these correlations (Kayanne, 2017). Confusion matrices were used to assess prediction performance in terms of accuracy, precision, and recall (Lin et al., 2023). Accuracy measures the overall proportion of correct satellite predictions aligning with actual bleaching events; precision emphasizes the reliability of positive predictions, indicating the extent to which predicted bleaching events were clustered; recall refers to the model’s ability to correctly identify bleaching events when they occurred, highlighting its effectiveness in detecting true positive cases (Hildebrand et al., 2022; Phillips et al., 2024). Within these matrices, four variables are determined: True Positive (TP), indicating correct satellite predictions of coral bleaching instances; True Negative (TN), indicating the correct identification of coral bleaching absence; False Positive (FP), indicating incorrect bleaching predictions; and False Negative (FN), indicating failure to predict bleaching when it occurred. Two DHW thresholds were considered: by using DHW thresholds of 2.5°C-weeks (Hughes et al., 2017) and 4°C-weeks (Heron et al., 2016; Liu, 2006). Counts of TP, TN, FP, and FN were used to calculate three key metrics to evaluate the reliability and effectiveness of satellite predictions compared with field coral bleaching observations (Lin et al., 2023):

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

Malaysia is bordered by different seas along its four coastlines (Figure 2.1; see also Chapter 1.5), and the study sites can generally be categorized by their longitudinal positions. Study sites located between longitudes 100° and 102° correspond to the west coast of PM (WCPM). Sites between 102° and 104° represent the northern part of the east coast of PM (ECPM), while those from 104° to 106° fall within the southern part of the east coast. Moving to EM, study sites between longitudes 113° and 115° are located on the southern part of the west coast of EM (WCEM), while those from 115° to 117° lie further north along the same coastline. Study sites positioned between 117° and 119° are situated along the east coast of EM (ECEM).

2.3.4 Python Programming Language

Python programming language was used in the execution of various tasks within this study, including map drawing, data manipulation, sorting, calculations, and statistical procedures. Python was selected due to its user-friendly learning curve, adaptability, and a strong ecosystem of libraries (Dekkati, 2021; Farshidi et al., 2021) for conducting data analytics and facilitating well-informed decision-making in the context of this research (Colliau et al., 2017; Nagpal & Gabrani, 2019). The analysis in this study leveraged standard Python libraries, such as pandas for handling and structuring large tabular datasets, including daily SST time series from both satellite and in-situ sources; numpy and scipy for basic statistics (e.g., calculating means, standard deviations, and linear regressions);and matplotlib and seaborn for generating visualizations such as time series graphs, seasonal plots, and scatterplots with regression lines and confidence intervals.

Satellite-derived SST data (1985–2022) in NetCDF format using the netCDF4 library, allowing for efficient extraction and manipulation of multi-dimensional climate variables by latitude, longitude, and time. *In-situ* SST measurements from AquaLink (2021–2022) were resampled, and aggregated using PANDAS, and subsequently compared to satellite-derived SST to assess consistency across methods. Spatial visualizations, including maps of study areas, were created using folim library, enabling the integration of spatial data with interactive mapping tools. Temporal comparisons of SST with historical coral bleaching data (RCM 2015–2017) were also conducted, using pandas and datetime functionalities to align bleaching event dates with satellite SST records from 31 island sites across Malaysia.

2.4 Results

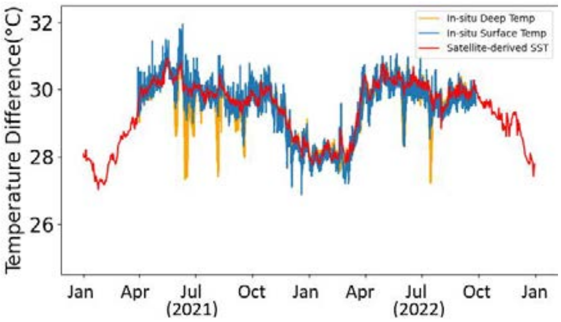
2.4.1 *In-situ Temperature and Satellite-derived SST Time Series and Bias*

The satellite-derived SST exhibited variations ranging from 26°C to 31°C (red in Figure 2.2), while *in-situ* surface temperature demonstrated a broader range of 25°C to 32°C (blue in Figure 2.2). Seasonal temperature showed a cooling phase from November to February, followed by warming from March to May. Between these, stable temperatures were observed – a consistent warm period occurred from May to October, contrasting with a cooler period from November to March. The highest temperatures were observed from the end of April to the end of June, while the lowest temperatures occurred from the end of December to the beginning of March, consistent in both satellite-derived and *in-situ* surface temperature data. Pantai Pasir Cina and Pulau Lang Tengah had similar satellite-derived SST time series, consistent with their close proximity (Figure 2.1).

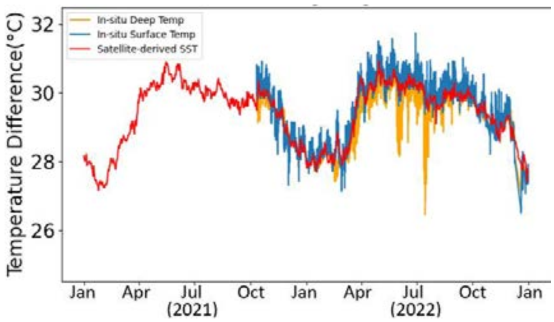
In-situ deep seawater temperature also ranged from 25°C to 31°C at the study sites between 2021 and 2022 (orange Figure 2.2). A difference between *in-situ* surface and deep seawater temperature variability was observed during the warm climate months, which span from May to October for all locations. Pulau Lang Tengah and Tekek Reef are study sites where deep seawater temperature variability is observed not only during the warm period but also during the seasonal warming from March to May. The interaction between SST and *in-situ* deep seawater was prominent during the cooler period from November to March, as indicated by overlapping regions of orange and blue indicating mixing patterns (Figure 2.2).

The two-week rolling average temperature bias time series graphs reveal fluctuations between *in-situ* and satellite-derived SST temperature (Figure 2.3). Generally, differences between *in-situ* surface and satellite-derived SST measurements were within 1°C (blue in Figure 2.3). The largest variations were observed during the seasonal cooling from November to February at Pantai Pasir Cina and Pulau Lang Tengah, while the largest variations were observed during seasonal warming from March to May at Mantanani Reef and Tekek Reef.

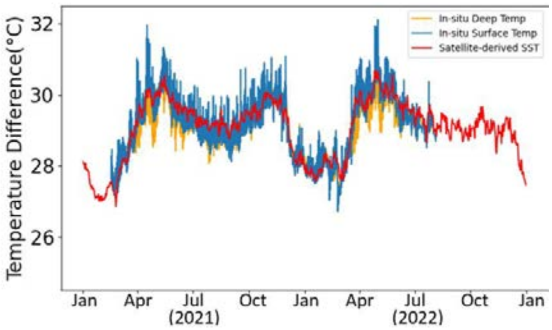
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(C) Mantanani Reef, EM

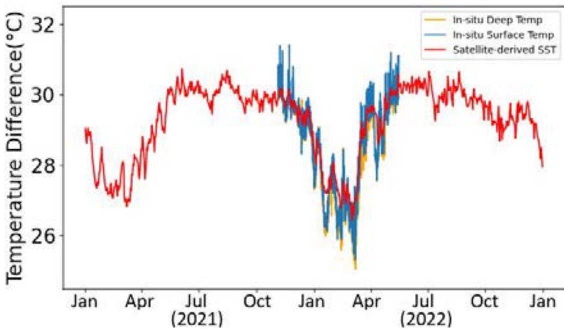
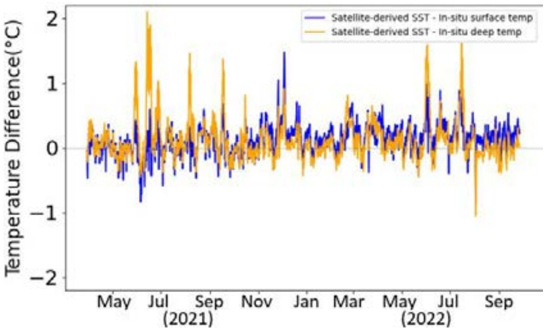
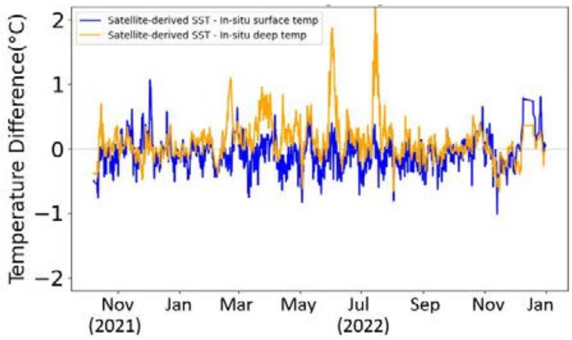


Figure 2.2. Temperature time series for different islands in Malaysia.Temperature time series were derived from satellite-derived daily SST (red), *in-situ* surface (blue) and *in-situ* deep (orange) hourly temperature data from 2021 to 2022 for four locations in Peninsular Malaysia (PM) and East Malaysia (EM) – A: Pantai Pasir Cina, PM (1 & 9m). B: Pulau Lang Tengah, PM (1 & 15 m). C: Tekek Reef, PM (1 & 10 m); D: Mantanani Reef, EM (1 & 6 m).

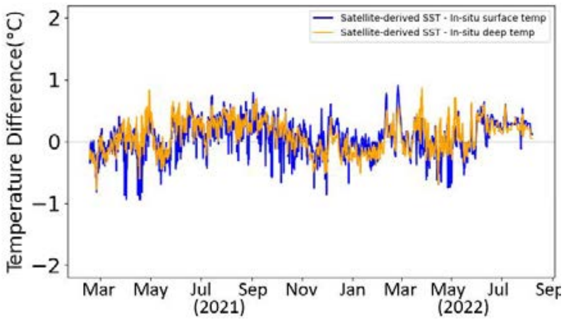
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

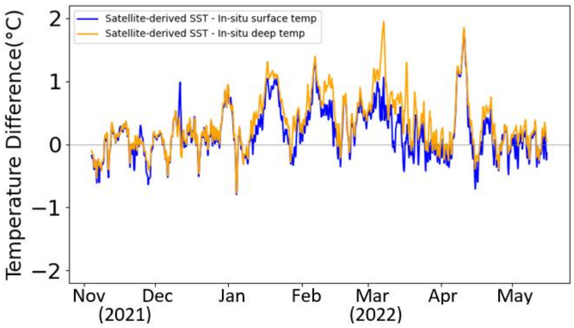


Figure 2.3. Temperature bias (satellite minus *in-situ*) for shallow (blue) and deep (orange) *in-situ* measurementsat four islands in PM and EM, with a two-week rolling average applied. A: Pantai Pasir Cina, PM. Panel B: Pulau Lang Tengah, PM. Panel C: Tekek Reef, PM; Panel D: Mantanani Reef, EM.

Temperature differences between two-week rolling average satellite-derived SST and *in-situ* deep seawater (orange in Figure 2.3) were larger during the warm period from May to October, with the most significant differences from the end of April to the end of June. Pulau Lang Tengah had the largest fluctuation, while Tekek Reef showed the smallest fluctuation. Noting the geographical proximity of Pantai Pasir Cina and Pulau Lang Tengah, Pantai Pasir Cina (deep logger at 10 m) had a lower fluctuation than Pulau Lang Tengah (15 m depth). Conversely, during the cooler period from November to February, temperature differences between satellite-derived SST and *in-situ* deep seawater were smaller, with the least significant differences occurring from December to January.

2.4.2 Accuracy Assessment of In-situ Surface and Satellite-derived SST

Maximum and minimum SST values, along with the temperature range, provide insights into the temperature variability at each study site. The study sites collectively exhibit a temperature range from 25°C to 32°C (Table 2.3). Pantai Pasir Cina, Pulau Lang Tengah, and Tekek Reef had relatively consistent temperature patterns, with *in-situ* surface measurements ranging from 26.7°C to 31.3°C. Mantanani Reef despite a smaller dataset, demonstrated a broader range from 25.70°C to 30.66°C. Standard deviation (SD) values were closely aligned for all sites, suggesting similarly variable temperature, except at Mantanani Reef that had a higher variability (but note the shorter deployment). *In-situ* surface measurements had consistently higher maximum temperatures than corresponding satellite values across all sites. The average SD provides a general sense of overall temperature variability across the sites, with values of 0.8°C to 1.2°C.

Table 2.3**:**

Descriptive Statistics of In-situ Daily Surface Temperature and Satellite-derived Daily SST for Peninsular Malaysia (PM) and East Malaysia (EM) – Number of Days of the Data Collection (N), Minimum Temperature (Min), Maximum Temperature (Max), Standard Deviation (SD) and Average SD of the SST Values

Study site	**SST measurements**	**N (days)**	**Min (°C)**	**Max (°C)**	**SD (°C)**	**Average SD (°C)**
Pantai Pasir Cina, PM	*In-situ*	547	27.40	31.26	0.82	0.80
	Satellite		27.76	30.95	0.77	
Pulau Lang Tengah, PM	*In-situ*	448	26.78	31.30	0.92	0.88
	Satellite		27.40	30.93	0.84	
Tekek Reef, PM	*In-situ*	530	27.16	31.14	0.84	0.82
	Satellite		26.86	30.67	0.80	
Mantanani Reef, EM	*In-situ*	193	25.70	30.66	1.33	1.22
	Satellite		26.45	30.57	1.10	

Accuracy metrics of Mean Bias, SD of the Bias, Root Mean Square Error (RMSE), Spearman correlation coefficient, R-squared and p-values were used in comparing the satellite-derived SST data with *in-situ* measurements (Table 2.4). Mean Bias was positive for Pantai Pasir Cina (0.13°C), Tekek Reef (0.05°C), Mantanani Reef (0.18°C), indicating warmer satellite-derived SST. Pulau Lang Tengah exhibited a marginal negative Mean Bias (-0.07°C), implying a tendency for warmer *in-situ* temperature. The standard deviation (SD) of the Bias values were consistent for PM sites, ranging from 0.23°C at Pantai Pasir Cina to 0.28°C at Tekek Reef. In contrast, Mantanani Reef in EM exhibited a higher SD (0.39°C). RMSE values suggested a close match between observed and predicted values for PM sites, distinct from Mantanani Reef in EM (0.43°C), which had a notably smallest dataset (N=193, Table 2.3).

The Spearman Correlation Coefficient showed a strong degree of association between *in-situ* and satellite-derived SST measurements, with high values across all sites (0.90 to 0.96) and highest at Mantanani Reef (Table 2.4). Mantanani Reef had the highest correlation coefficient ($R^2 = 0.9434$), highlighting the strong linear relationship between the temperature datasets. The three PM sites (Pantai Pasir Cina, Pulau Lang Tengah, and Tekek Reef) displayed similarly high correlation. The p-values for all sites were found to be less than 0.0001, indicating a high level of statistical significance.

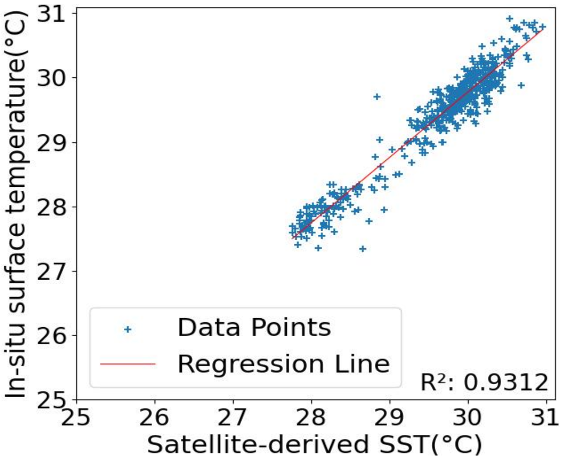
Table 2.4:

Accuracy Metrics for Study Sites – Mean Bias (satellite minus in-situ), Standard Deviation (SD) of the Bias, Root Mean Square Error (RMSE), Spearman Correlation Coefficient, R-squared ***(R^2), and p-value***

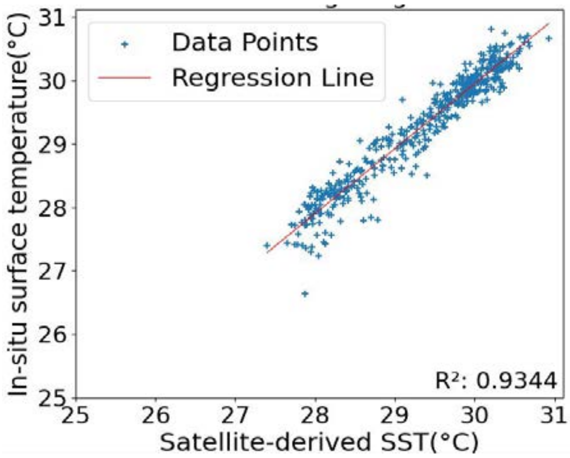
Study Site	**Mean Bias (°C)**	**SD of the Bias (°C)**	**RMSE (°C)**	**Spearman Correlation**	**R^2**	**p-value**
Pantai Pasir Cina, PM	0.13	0.23	0.26	0.90	0.9312	<0.0001
Pulau Lang Tengah, PM	-0.07	0.26	0.27	0.95	0.9344	<0.0001
Tekek Reef, PM	0.05	0.28	0.28	0.95	0.9176	<0.0001
Mantanani Reef, EM	0.18	0.39	0.43	0.96	0.9434	<0.0001

Strong and statistically significant relationships were observed between *in-situ* and satellite-derived SST measurements at all study sites, with R-squared values ranging from 0.92 to 0.94, across a range of 25°C and 32°C (Figure 2.4). A low density of points in the mid-range temperatures (between 28.5°C and 29.5°C) was observed in all study sites. The higher data density occurred at temperatures between 29.5°C and 30.5°C. Despite this variation in data density, all sites demonstrated high correlation coefficients, indicating strong linear relationships between the temperature datasets.

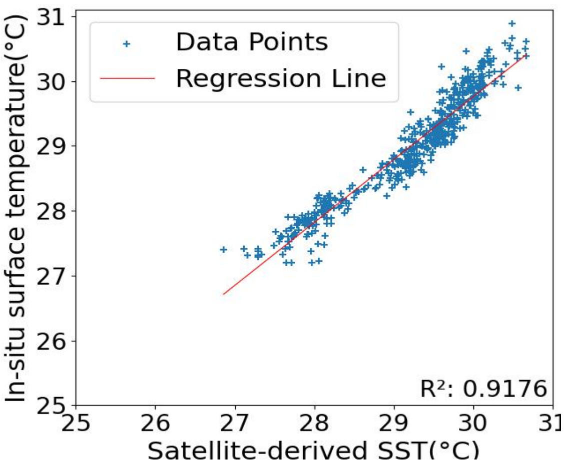
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

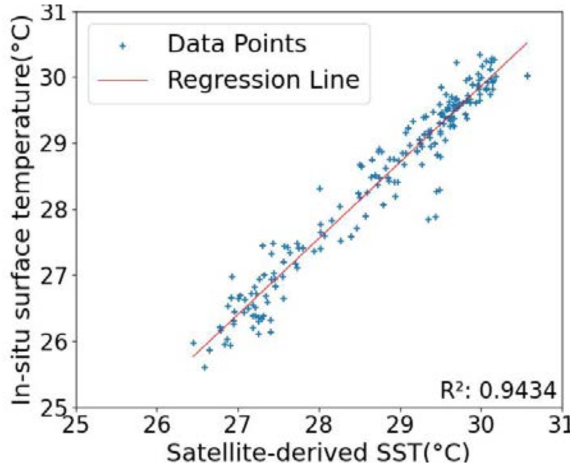


Figure 2.4. Correlation between satellite-derived SST and *in-situ* SST. The scatter plot shows the correlation between satellite-derived SST and *in-situ* SST for each site during the period from 2021 to 2022. Peninsular Malaysia (PM) – A: Pantai Pasir Cina, B: Pulau Lang Tengah, C: Tekek Reef, D: Mantanani Reef.

2.4.3 Evaluation of Field Coral Bleaching Observations and Satellite Prediction Accuracy

Coral bleaching observations (N=139 surveys) were generally in fewer than 20% of coral colonies, with only four surveys—conducted along the East Coast Peninsular Malaysia (ECPM) (between 102° and 106° longitude)— recording bleaching of over 40% of coral colonies across these years (Figure 2.5). Corresponding year-to-date maximum DHW values from 68 satellite pixels ranged from 0 to 5.5°C-weeks. Linear regression showed a high statistical significance ($p<0.0001$) despite a high degree of variability, with an R^2 value of 0.1387between coral bleaching observations and DHW. Of note was the presence of high coral colony bleaching (>10%) in surveys that corresponded with low DHW values (<0.2°C-weeks).

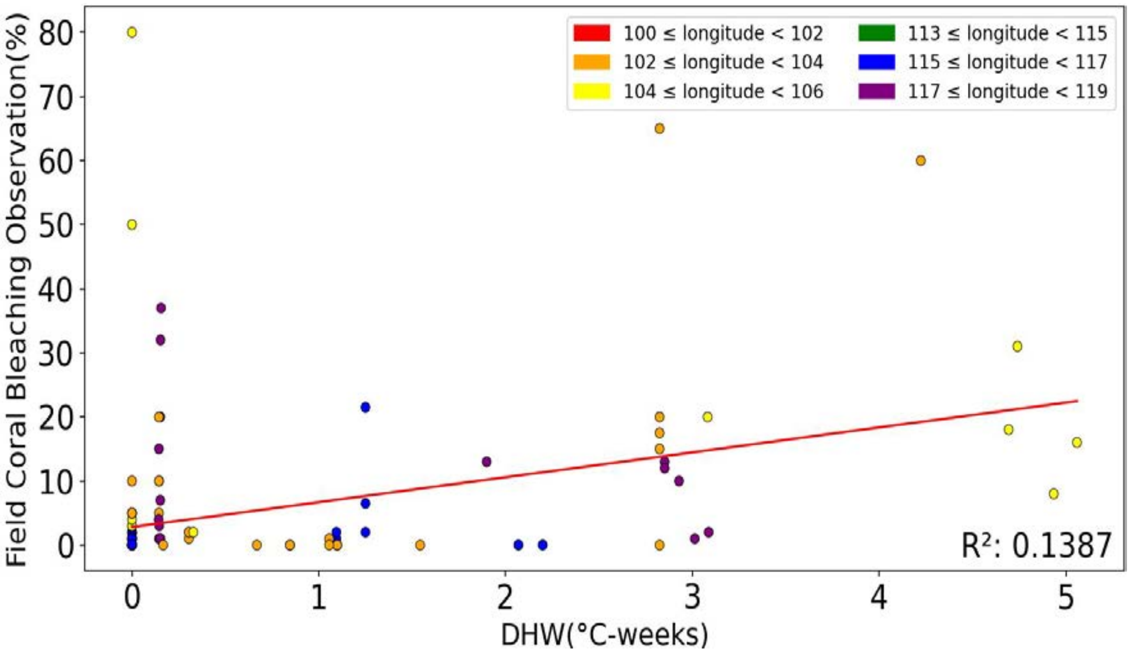


Figure 2.5. Scatter plot for satellite-derived DHW and observed coral bleaching (% of colonies).

Existing thresholds for heat stress (DHW) were evaluated for the Malaysian data using confusion matrices. For the 4°C-weeks satellite DHW threshold five true positive observations (correctly predicted bleaching events) and 65 true negative (correctly predicted absence of bleaching) instances resulted in 50% accuracy, 1.0 precision, and 0.07 recall (Figure 2.6). For the DHW threshold of 2.5°C-weeks there were 15 true positive observations and 64 true negative instances, resulting in 56% accuracy, 0.85 precision, and 0.23 recall. For both thresholds, there was a significant proportion of false negatives (i.e., bleaching observed below the DHW threshold considered).

(A) DHW: 4 °C-weeks (B) DHW: 2.5 °C-weeks

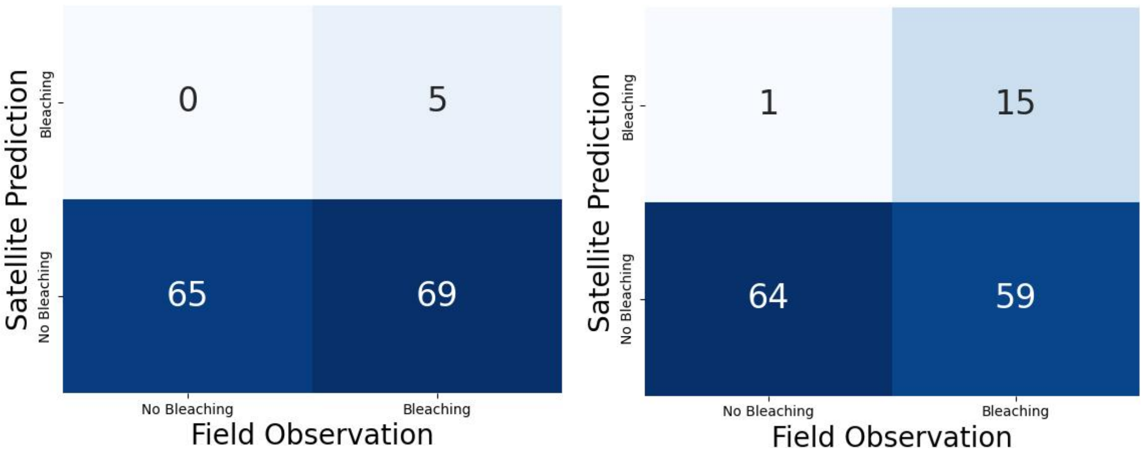


Figure 2.6. Confusion matrix for satellite and field coral bleaching observations. The confusion matrix represents the comparison between DHW thresholds (4 °C-weeks and 2.5 °C-weeks) and field coral bleaching observations.

2.5 Discussion

2.5.1 Insights into Satellite-derived SST and In-situ Seawater Temperature in Malaysia Region

The consistently narrow SST range of 25°C to 32°C observed here and in previous studies (McClanahan et al., 2007; Meyer et al., 2020) aligns with consistent Malaysia's equatorial location. Corroborating previous studies (Chenoli et al., 2018; Mubarak et al., 2022; Sun et al., 2020; Wong et al., 2016), the results of this study underscore the substantial effect of monsoon seasons on seawater temperature, with seasonal variations apparent.

Malaysia experiences two primary monsoon seasons: the Southwest (SW) Monsoon, from May to August/September, brings drier conditions, while the Northeast (NE) Monsoon, from November to February/March, brings northeasterly winds that significantly impact the East Coast of Peninsular Malaysia (ECPM) and East Malaysia (EM). The four *in-situ* temperature measurement sites within ECPM and EM during the 2021–2022 period experienced a warming phase during the SW Monsoon and a cooling phase during the NE Monsoon. This pattern aligns with the annual influence of the NE Monsoon, which typically dominates the region's seasonal temperature cycles (Fakaruddin et al., 2020; Samat et al., 2021).

Sub-surface temperature sensors, at depths ranging from 6 m to 15 m, revealed temperature differences between surface and deep seawater, with minimal variations observed during the NE Monsoon season compared to the SW Monsoon season. A >1.5°C temperature difference was previously observed below 15 m for northern locations in ECPM and below 40 m at more southern ECPM locations during the NE monsoon (Akhir et al., 2011; Akhir et al., 2014; Saadon et al., 1999). Similar temperature differences have also been observed below 35 m for WCPM (Mansor et al., 2023; Roseli & Akhir, 2014). In contrast, during the SW monsoon periods, a >1.5°C difference from surface temperatures was observed at closer to the surface: >10 m depth for northern ECPM, and >20 m for central and southern ECPM (Akhir et al., 2011; Akhir et al., 2014; Saadon et al., 1999); and >10 m depth for WCPM (Roseli & Akhir, 2014). Data analysed here confirm these previous findings for northern and southern ECPM, with a shallower thermocline in the north than in southern ECPM. Further investigations into deeper water temperatures in EM are needed, as research in this region has been limited compared to PM. These studies would improve understanding of the environmental characteristics of Malaysia's diverse reef distributions across different seas and depths. In contrast, observations from the NE monsoon seasons of 2021-2022 indicate a change from stratification to vertical mixing. During this period, temperature differences between surface and deeper waters (1–15 m) remained within 1°C, suggesting active mixing of shallow and deeper seawaters. These observations also suggest water mixing of shallow and deeper seawaters during the NE monsoon season, driven by the strong winds and currents typical of tropical monsoon climates (Ooi et al., 2013).

2.5.2 The Reliability of Satellite-derived SST Datasets

CoralTemp demonstrated a strong positive relationship with *in-situ* SST measurement in Malaysia, consistent with previous studies (Gomez et al., 2020; Szereday & Affendi Yang, 2022), by using the same satellite-derived SST measurement. The strong relationship between satellite-derived and *in-situ* SST measurements is supported by the calculated bias, RMSE, Spearman correlation coefficients, scatter plots and p-value (*sensu* (Gomez et al., 2020; Szereday & Affendi Yang, 2022). While the study confirmed the overall accuracy of satellite-derived SST measurements in Malaysia throughout the year, there was limited capacity to examine within season variations.

Previous studies observed that cloud cover and wind speed in different seasons may impact the agreement between the two SST measurement methods, potentially due to their interference with radiometric signals and sea surface roughness (Rascle et al., 2020; Sun et al., 2023). Nonetheless, larger temperature biases apparent during the SW monsoon season reveal the importance of considering varying surface and deeper seawater temperatures, as these differences reduce heat stress for deeper-growing coral. To better understand satellite accuracy in Malaysian seawaters factors such as cloud cover, turbidity, or other environmental variables should be investigated, particularly during different seasons. Investigating these remaining gaps will contribute to a better understanding of the factors influencing satellite-derived SST measurements and their reliability in monitoring coral reef ecosystems.

2.5.3 The Accuracy of Satellite Predictions of Coral Bleaching

Moderate accuracy of satellite-derived coral bleaching predictions was observed in this study, with DHW-based predictions achieving only 50–56% accuracy. Although sea surface temperature (SST) data from satellite observations were highly accurate, temperature alone does not directly determine bleaching events. The Degree Heating Weeks (DHW) metric, which accumulates heat stress exceeding a set threshold, does not fully account for other environmental and biological factors that influence bleaching susceptibility.

Despite this limitation, a positive correlation was found between satellite-derived DHW and field-observed coral bleaching percentages, reinforcing that thermal stress is a key driver of bleaching events (De et al., 2022; Hughes, Anderson, et al., 2018; McClanahan et al., 2012). However, the strength of this correlation indicates that DHW alone is not a reliable predictor, as bleaching responses vary due to additional ecological and oceanographic influences.

Accuracy improved with lower DHW thresholds, with 4°C-weeks and 2.5°C-weeks examined to identify satellite-predicted bleaching events. Consistent with previous studies (DeCarlo, 2020), lowering the DHW threshold from 4°C-weeks to 2.5°C-weeks improved accuracy, increasing True Positives while reducing False Negatives. However, this also led to an increase in False Positives, suggesting that lower thresholds may overestimate bleaching risk in some cases. Our findings show that DHW thresholds of 2.5°C-weeks achieved an accuracy of 56%, representing a 6% improvement over DHW thresholds of 4°C-weeks, which achieved 50% accuracy.

Given these findings, alternative DHW calculation methods have been explored in previous studies to improve bleaching prediction accuracy. Research suggests that adjusting the HotSpot threshold—such as using MMM + 0°C instead of MMM + 1°C—and modifying the accumulation window from 12 weeks to 8–9 weeks could enhance predictive performance (DeCarlo, 2020; Lachs et al., 2021). Similarly, an OISST-based threshold of MMM + 0.8°C has been shown to improve accuracy in certain regions (Eakin et al., 2012). While these refinements may be valuable, this study did not focus on threshold optimization. Instead, it aimed to assess how additional environmental factors, beyond heat stress alone, contribute to bleaching variability.

The findings emphasize the need to integrate other ocean physical properties into bleaching predictions, rather than relying solely on DHW-based temperature stress. Chapter 2 builds on this by incorporating seasonal oceanographic variables (e.g., cloud cover, wind speed, and turbidity) and assessing reef resilience to improve predictive accuracy. These factors may help explain why some reefs bleach under lower thermal stress while others show resistance despite prolonged exposure to high temperatures. Future studies could evaluate whether combining regional-specific DHW thresholds with environmental variables offers a more reliable approach for predicting bleaching in Malaysia's reefs.

2.6 Conclusion

This chapter has explored the reliability of satellite-derived sea surface temperature (SST) datasets and the accuracy of satellite predictions for coral bleaching events in Malaysia. A high correlation between *in-situ* and satellite-derived SST data indicated the reliability of satellite SST in this region. The results highlight the effect of monsoon seasons on seawater temperature, underscoring the importance of understanding seasonal variations in environmental conditions for effective coral reef management. However, the accuracy of satellite heat stress in predicting coral bleaching observations was found to be moderate. Whilst DHW thresholds serve as useful indicators of coral bleaching susceptibility, additional environmental factors beyond heat stress, may also inform coral reef management strategies. By addressing remaining knowledge gaps and incorporating multi-factorial approaches, future research can deepen understanding of coral reef ecosystems and support the development of conservation strategies to protect these important marine habitats.

Chapter 3: Reef Resilience Factors and Potential in Malaysian Coral Reefs

3.1 Introduction

Coral bleaching is a generalized stress response (Baker et al., 2015; Hendee et al., 2020), which may be caused by a range of environmental pressures, with impacts that also depend on the resilience of coral communities and vary by region (e.g., (Guest et al., 2012)). While previous studies have largely focused on temperature as the main cause of broad-scale mass coral bleaching (Dalton et al., 2020; Hughes, Anderson, et al., 2018; Leggat et al., 2019; Lyu et al., 2022; McClanahan et al., 2012; Vargas-Ángel et al., 2019), localised coral bleaching may also be influenced by changes in nutrient and acidity of the seawater, anthropogenic pollutants ((Burkepile et al., 2020; Horwitz & Fine, 2014; Safuan et al., 2020), see also Chapter 1.1). Additionally, there is also significant spatiotemporal variation in the responses of corals exposed to changing environmental conditions, due to local factors that may moderate bleaching responses (e.g., waves and currents, as well as turbidity and UV exposure (Wooldridge, 2009)). Moreover, bleaching responses vary among corals due to differential resilience, which varies within and among coral taxa (Burn et al., 2023; Guest et al., 2012).

Coral resilience is the capacity of coral populations and/ or communities to endure stress and/or recover from disturbances (Lam et al., 2020; McClanahan et al., 2012; Obura & Grimsditch, 2009). Resilience is influenced by a range of intrinsic and extrinsic factors, shaped by various factors including the presence of resistant coral species, herbivore biomass, macroalgae abundance, recruitment rates and fishing pressure, as outlined by the IUCN (Obura & Grimsditch, 2009). Coral resilience factors may vary between study sites, even within the same island, due to differences in coral species composition, coral morphology, and seasonal variability in ocean physical properties (Maynard et al., 2018; Maynard et al., 2015; Raj et al., 2021; Sakai et al., 2018). For instance, in Pulau Tioman (Malaysia), massive coral taxa showed greater resistance with lower mortality rates during 2010 thermal anomaly, while branching *Porites* were the most affected (Guest et al., 2012).This contrast with Pulau Weh (Sumatra) where *Acropora* and *Pocillopora* experienced the highest mortality (Guest et al., 2012). In Kāne'ohe Bay (Hawaii), *Porites compressa* displayed greater resilience, with faster pigment recovery and lower mortality than *Montipora capitata*, despite experiencing higher bleaching prevalence during thermal stress (Matsuda et al., 2020). Contrasting patterns were observed in the Great Barrier Reef, where massive *Porites* became increasingly susceptible to bleaching as severity increased, while juvenile *Montipora* and *Pocillopora* exhibited weaker resilience compared to their adult counterparts (Burn et al., 2023). Furthermore, taxa like *Cyphastrea, Turbinaria*, and *Galaxea* were relatively unaffected by bleaching, while *Millepora spp*. experienced 85% mortality, underscoring the variability in taxon-specific responses (Marshall & Baird, 2000). In Western Australia, the turbid reef site Somerville exhibited greater resilience to heat stress during a 2021 marine heatwave compared to the clearwater site Bundegi (Zweifler et al., 2024).

Malaysia, with its two major landmasses and four coastlines, is bordered by different seas. Each coastline hosts diverse coral species, contributing to considerable range in diversity across the coastline (Huang et al., 2014; Leem et al., 2022; Waheed, 2016). Being a tropical country, Malaysia experiences monsoon seasons that create distinct dry and wet periods, influencing coral reef ecosystems (Fabricius et al., 2008; Ibrahim et al., 2000). Each coastline faces unique challenges due to differences in oceanic conditions and levels of human activity. The west coast of Peninsular Malaysia (WCPM) is characterized by high turbidity levels (Mubin et al., 2023; Thia-Eng et al., 2000), the east coast of Peninsular Malaysia (ECPM) is significantly impacted by tourism and monsoon-related changes (Burke et al., 2002; Lachs et al., 2019; Leem et al., 2022; Statista Research Department, 2022), while East Malaysia faces pressures from overfishing and tourism (Asian Development Bank, 2014; Burke et al., 2011). In the previous chapter, the four islands represented by four 0.05° spatial resolution satellite pixels, were used to investigate the correlation between *in-situ* and satellite-derived SST. Additionally, 31 islands represented by a total of 68 0.05° spatial resolution satellite pixels, were analyzed to assess the accuracy of satellite heat stress predictions. These analyses formed the foundation for understanding the spatial variability in coral reef heat stress across Malaysia. This chapter builds on the previous work by exploring the influence of seasonal variability in oceanic properties and the incorporation of reef resilience scores to further enhance coral bleaching predictions.

3.2 Research Objectives

The specific research objectives for this chapter are threefold:

1. To establish baseline information and metrics that support future improvements in coral bleaching predictions by integrating resilience factors, including seasonal variability in ocean physical properties (e.g: SST, cloud cover, wind speed, and turbidity) and reef

resilience score. The satellite SST data obtained from *CoralTemp* for four islands (used in the previous chapter) from 2021 to 2022 extended back to 1985 and inclusive of all years up to 2022, incorporating additional ocean physical properties to identify seasonal patterns. Additionally, the reef resilience assessment reports from three marine parks conducted in 2011, have been incorporated to improve the accuracy of the satellite predictions.

2. To compare the reef resilience scores between 2011 and 2021 and assess the potential conservation strategies based on resilience of Malaysia's coral reef sites. The dataset from revisiting these three marine parks in 2021 allows for the recalculation of resilience scores, potentially new and valuable insights for the conservation and management of specific islands in Malaysia.

3. To use the findings from this study to support conservation efforts in Malaysia by grouping 31 islands into smaller clusters based on temperature variability. These clusters, identified through a cluster analysis of temperature patterns, provide a foundation for future in-depth analysis of physical properties to support more effective reef management. The islands included in this analysis were previously used for coral bleaching observations conducted by RCM between 2015 and 2017 (as referenced in the previous chapter).

3.3 Methodology

3.3.1 Study Area

The study area includes coral reef sites from 31 islands across Malaysia. For the analysis, data from four islands were used to explore possible seasonal patterns of sea surface temperature (SST), cloud fraction, wind speed, and turbidity in Malaysia (the four pixels are represented by the red dots, while the remained 64 pixels are represented by blue dots in Figure 3.1. Additionally, datasets from 132 study sites across 31 islands were then subject to a cluster analysis based on temperature variability, with the intention of grouping them into smaller clusters. Furthermore, reef resilience assessment reports from three marine parks, conducted in 2011 and revisited in 2021 (represented by the green dots in Figure 3.1) were incorporated to potentially enhance the accuracy of satellite predictions and to reassess the reef resilience scores.

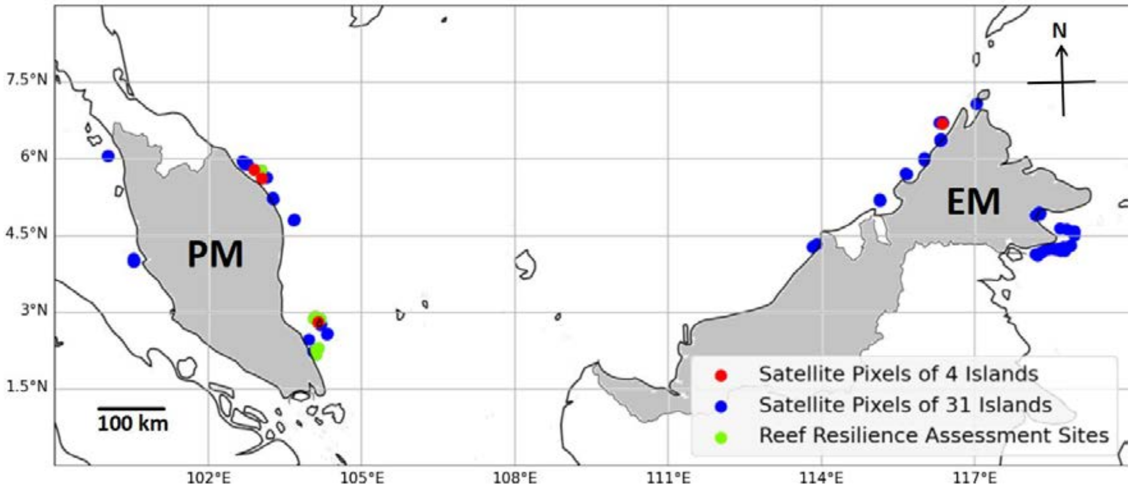


Figure 3.1. Map of study sites in Malaysia. The map displays Peninsular Malaysia (PM) on the left with shading denoting its geographical extent, while East Malaysia (EM) is depicted on the right, similarly shaded to indicate its geographical boundaries.

3.3.2 Data Sources

3.3.2.1 Satellite-derived Datasets (SST, Cloud Fraction, Wind Speed, Turbidity)

In the previous chapter, the four islands used to investigate the correlation between *in-situ* and satellite-derived SST, along with the 31 islands analyzed for the accuracy of satellite heat stress predictions were shared overlapping satellite pixels. The satellite SST data obtained from *CoralTemp* covering the periods 2015–2017 and 2021–2022, has now been extended back to 1985 through 2022 using the same method described in Chapter 2.3.2.3. *CoralTemp* provides daily global SST satellite data with a 0.05° spatial resolution from 1985 to the present, and the SST dataset for this study spans 68 satellite pixels. The relevant data were accessed at CoralTemp on the NOAA Coral Reef Watch website at https://coralreefwatch.noaa.gov/product/5km/index_5km_composite.php.

Additionally, satellite-derived datasets on physical properties, such as cloud cover, wind speed, and turbidity, for these 31 islands were incorporated with different spatial resolutions (Table 3.1). The extraction of data from the four islands (located in both Peninsular Malaysia (PM) and East Malaysia (EM)) was used to enhance the understanding of seasonal patterns in

Malaysia, while the data from 31 islands provided information to support efficient management strategies.

Table 3.1:

Summary Information of Satellite-Derived Source Datasets

Product Name	**Data**	**Spatial Resolution**	**Temporal Coverage**	**Data Selected**
CoralTemp	SST	0.05°	Daily	From 1985 to 2022
	SST climatology	0.05°	Monthly	
CLDPROP_M3_VIIRS_SNPP	Cloud Fraction	1.0°	Monthly	From 2012 to 2022
Blended Sea Surface Winds	Wind speed	0.25°	6-hours	From 2000 to 2022
Ocean Colour Level 3 VIIRS	Ocean turbidity	0.04°	Daily	From 2018 to 2022

NASA SNPP VIIRS Level-3 monthly Cloud Properties (CLDPROP_M3_VIIRS_SNPP), a satellite remote sensing product developed by merging data from NASA and NOAA sensors, provides monthly cloud properties datasets with a spatial resolution of 1.0° from 2011 to the present. The dataset provides cloud optical thickness and cloud fraction data that are useful for establishing correlations between cloud characteristics and their potential impacts on precipitation patterns within the study area (Platnick et al., 2019). Of the cloud-related variables, cloud fraction was the only property available throughout the year and was therefore selected for use in our analysis. Data from overlapping satellite pixels for the period 2012 to 2022 were used to assess historical patterns. This dataset was accessed via the NASA website https://ladsweb.modaps.eosdis.nasa.gov/search/.

NOAA NCEI Blended Sea Surface Winds ("Seawinds") provides sea surface wind information at a spatial resolution of 0.25° on a 6-hour period from 1987 to the present. Developed by

NOAA, the Seawinds dataset from multiple satellite sources uses advanced blending techniques to ensure a high level of accuracy and reliability (Price et al., 2023). Notably, the operational observation of sea surface wind speed had evolved from a single satellite in 1987 to a constellation of five or more satellites by 2000 (Saha & Zhang, 2022; Zhang et al., 2006). In this study, historical data from 2000 to 2022 were used to evaluate historical wind patterns for four islands study sites. To visualize the data effectively, monthly averages were calculated by taking the mean of all 6-hour wind speed values within each month. This approach allows for a clearer representation of wind speed trends in the time series graph. The relevant data were accessed via https://www.star.nesdis.noaa.gov/data/pub0015/coastwatch/blended/wind/science-/uvcomp/.

The NOAA Ocean Color Level 3 VIIRS multi-sensor product provides daily diffuse attenuation coefficient data with a spatial resolution of 0.04° from 2018 to the present. Developed by NOAA, this dataset has been instrumental in understanding the propagation and attenuation of light within the ocean, facilitating the analysis of turbidity dynamics (Liu & Wang, 2019; Wang et al., 2013). Daily- median diffuse attenuation coefficient data from 2019 to 2022 were used to understand ocean turbidity levels in the vicinity of the overlapping satellite pixels. However, due to missing satellite data during this four-year period at the survey sites, there are occasional gaps in the dataset. To ensure consistency, the median value of data within 0.25° of the study site was calculated and used. This method was justified by selected due to the relatively consistent nature of turbidity at this spatial scale. Access to the source dataset was from the Ocean Color Level 3 VIIRS Multi-Sensor website at https://coastwatch.noaa.gov/cwn/products.html/.

3.3.2.2 Coral Reefs Resilience Report 2011

A report published by the Department of Marine Park Malaysia (DMPM) describes the 2011 Malaysian reef resilience study conducted in collaboration with government agencies, international organizations, and local NGOs. The DMPM, a Malaysian government agency, is dedicated to managing and conserving 42 marine parks to support protection of nationally important marine biodiversity and resources, with a particular focus on coral reefs (Talib et al., 2004). The report specifically covered three marine parks, encompassing four islands—Pulau Redang, Pulau Tioman, Pulau Sibu, and Pulau Tinggi—located on the east coast PM (ECPM).

A total of 18 survey sites were assessed in Pulau Redang, 15 sites in Pulau Tioman, and 10 sites in the marine park encompassing both Pulau Sibu and Pulau Tinggi.

The methodology employed the Resilience Assessment of Coral Reefs protocol which was developed by the IUCN working group on Climate Change and Coral Reefs to assess reef resilience to climate change and thermal stress (Obura & Grimsditch, 2009). Resilience scores were assigned based on 61 indicators grouped into nine categories, including benthic composition, coral condition, coral population structure, connectivity, fish communities, anthropogenic impacts, and management effectiveness. Each variable was evaluated using a Likert-like scale ranging from 1 (low resilience) to 5 (high resilience), with intermediate levels indicating varying degrees of reef health and adaptive capacity. These scores were then integrated to produce an overall reef resilience score for each marine park in 2011. The capacity of the total reef resilience score to enhance the accuracy of coral bleaching predictions evaluated, and to assess the potential of Malaysia's coral reef resilience sites in this study.

3.3.2.3 Coral Bleaching Field Observations

Forty survey trips were conducted at 19 study sites, previously described in Chapter 2.3.2.2 to undertake field observations of coral bleaching. Of the 188 Reef Check Malaysia (RCM) surveys described in Chapter 2.3.1, 40 of those overlapped with locations in the 2011 Resilience Report. In summary, these RCM surveys were conducted as four 20-m point-intercept transects, where the extent of coral bleaching responses was recorded as a percentage of colonies. Out of 40 over three years, 33 observations were strategically selected based on their temporal proximity to the maximum DHW recorded up to the date of the survey for each year and each satellite pixel. Bleaching surveys from the beginning of each year until 30 days after the date of the highest DHW recorded up to the survey date, which signals the last accumulation of heat stress before the survey, were included.

3.3.2.4 Coral Reefs Resilience Dataset 2021

A publicly accessible raw dataset, produced by the Universiti Malaysia Terengganu research team, documents a reef resilience survey conducted in 2021 (Tan et al., 2023) using the same Resilience Assessment of Coral Reefs protocol as the 2011 study described in Chapter 3.3.2.2.

This protocol, developed by the IUCN working group on Climate Change and Coral Reefs, is designed to assess reef resilience to climate change and thermal stress (Obura & Grimsditch, 2009). This survey revisited several of the original sites and focused on four marine parks, covering five islands—Pulau Redang, Pulau Tioman, Pulau Sibu, Pulau Tinggi, and Pulau Perhentian—located on the ECPM. In total, 12 survey sites were assessed in Pulau Redang (10 of which overlapped with the 2011 sites), 12 sites in Pulau Tioman (all revisited from 2011), 11 sites in the marine park encompassing Pulau Sibu and Pulau Tinggi (5 overlapping sites), and 11 sites in Pulau Perhentian.

The 2021 survey updated 16 of the 61 reef resilience variables assessed in 2011, focusing on four groups: benthic composition, coral condition, coral associates, fish groups, and anthropogenic impacts. Using this information, reef resilience scores were re-calculated from the raw dataset following the protocol. To recalculate the reef resilience scores for 2021, the updated scores for these 16 variables were combined with the original 2011 scores for the remaining 45 variables, maintaining consistency across the dataset. The new resilience scores were again assigned on a Likert-like scale of 1 to 5, providing an updated of the total reef resilience score of 2021 for each marine park. The relevant data can be accessed on Zenodo website at https://doi.org/10.5281/zenodo.8045623 .

3.3.3 Statistical Analysis

3.3.3.1 Understanding Environmental Factors in Malaysia

Seasonal patterns across the four islands, previously used to investigate the correlation between *in-situ* and satellite-derived SST in the previous chapter, were analyzed using historical data on SST, cloud fraction, wind speed, and turbidity. Time series graphs depicting seasonal profiles and historical trends for each variable were used to calculate monthly means of these satellite-derived physical parameters over the study period. The relationships among the variables for the four islands were analyzed using Pearson correlation to quantify the strength and direction of the linear relationships (Wang et al., 2020; Zhang et al., 2020). The Pearson correlation coefficient, ranging from -1 to 1, indicates the degree of association, with values closer to 1 or -1 representing stronger correlations and 0 indicating no linear relationship. Additionally, scatter plots were generated to compare satellite-derived SST with *in-situ* measurements by using observed seasonal patterns to assess the accuracy of the satellite-derived SST data.

3.3.3.2 Understanding Coral Bleaching Correlations with Reef Resilience Scores 2011

To assess the relationship between coral bleaching field observations and reef resilience, the resilience scores of three marine parks in 2011 were evaluated. This analysis helps explain how different resilience levels impact the extent of coral bleaching under environmental stress. The average (AVG) and standard deviation (SD) of the 2011 reef resilience scores for three marine parks combined were calculated. Using the modified method of relative classifications for resilience scores created by (Maynard et al., 2018), the average and SD of the resilience scores were then used to categorize the resilience scores into four groups:

- high (scores ≥ 1 SD above the AVG),
- medium-high (AVG ≤ scores < 1 SD above the AVG),
- medium-low (1 SD below the AVG ≤ scores <AVG); and
- low (scores < one SD below the AVG).

R-Scatter plots were created to facilitate visual and quantitative comparisons between Degree Heating Week (DHW) thresholds (horizontal axis) and field coral bleaching observations (vertical axis) for the forty survey trips that overlapped with locations from the 2011 Resilience Report. (Gomez et al., 2020; Masud-Ul-Alam, 2022). R-squared (R^2) was used to quantify the proportion of variance explained by DHW predictions (Gomez et al., 2020; Masud-Ul-Alam, 2022; Onyutha, 2022), while p-values were calculated to assess the statistical significance of these correlations (Edwards et al., 2021). Each data point on the plot was color-coded according to its resilience group (high: green, medium-high: orange, medium-low: yellow, or low: red), thereby providing insight into how different resilience levels correspond to coral bleaching observations under various DHW thresholds.

3.3.3.3 Updated Reef Resilience Scores for 2021 and Comparative Analysis with 2011

The 2021 reef resilience dataset was used to update and compare coral reef resilience scores in 2011 across three marine parks. The average (AVG) and standard deviation (SD) of the 2011 and 2021 reef resilience scores were calculated individually for each of the three marine parks. Using the same classification method as in Chapter 3.3.3.2, the updated resilience scores were categorized and color-coded into four groups (high: green, medium-high: orange, medium-low:

yellow, or low: red). This consistent classification allowed for a direct comparison of resilience scores between 2011 and 2021 for each marine park.

3.3.3.4 Clustering Malaysian Islands by Temperature Variations

To evaluate temperature variations across Malaysian islands, field coral bleaching observations from 2015 to 2017 were analyzed alongside satellite-derived SST data. Field coral bleaching observations for 31 islands conducted by RCM from 2015 to 2017 covered 68 satellite pixels from the NOAA *CoralTemp* dataset. To assess spatial patterns in temperature variation across these islands, the *CoralTemp* Monthly Mean (MM) SST dataset was used (as described in Chapter 2.3.2.3). The average of MM SST for each of the 31 islands was calculated based on one or more satellite pixels. These island-level averages were then analyzed using a One-way Analysis of Variance (ANOVA) (Connelly, 2021; Liu et al., 2021) to distinguish whether observed differences exceed what might occur, thereby providing a method for assessing temperature pattern variability.

To further investigate these patterns, K-means clustering was employed to identify clusters among the 31 Malaysian islands (*sensu* (Shaltout, 2019)) based on monthly-mean (MM) *CoralTemp* SST data. This method iteratively assigns data points to clusters as well as adjusts centres for stability and minimizing distances within clusters (MacQueen, 1967; Raudsepp, 2021) and has previously been used to group environmental data such as SST, by identifying patterns of similarity (Shaltout, 2019). Initially, all 31 islands were considered as a single cluster. The K-means approach identifies a subset of one or more islands as a separate (second) cluster based on its distinct seasonal temperature variation. By running the k-means clustering algorithm repeatedly, the number of clusters was increased from one up to fifteen, revealing distinct groups based on a metric of "Temperature Variation" between clusters. The temperature variation within the clusters ranged from 1.61°C for two clusters to 0.24°C for fifteen clusters. After evaluating the balance between temperature variation and geographic proximity, 12 clusters were determined to be the most appropriate grouping for the 31 islands, achieving an average temperature variation of 0.33°C per cluster. Time series graphs depicting seasonal profiles for each variable in each of the 12 clusters were then constructed to visualize monthly means of the satellite-derived physical porperties over the study period. These variables include cloud cover, wind speed, turbidity, and SST, each represented in a separate graph.

3.3.4 Python Programming Language

Following the previous chapter, this section continues with the Python programming language as a statistical analysis tool. Standard Python libraries such as pandas, numpy, scipy, matplotlib, and netCDF4 were employed to create graphs, calculate means, standard deviations, and Pearson correlations. The netCDF4 library was particularly used to extract and process multi-dimensional satellite datasets in NetCDF format, facilitating temporal and spatial slicing of large-scale environmental data. To examine seasonal variability and interannual trends, pandas and numpy were used for data resampling, and time-series manipulation, while matplotlib and seaborn supported the generation of publication-quality figures to visualize variability and patterns across the four sites. Additionally, the scikit-learn library was used to conduct a K-means cluster analysis, grouping the 31 islands into smaller clusters based on temperature variability. Incorporation of reef resilience assessment reports from 2011 and revisits in 2021 involved recalculating resilience scores using site-specific metrics and indicators, with summary statistics computed via numpy and correlation analyses conducted using scipy.

3.4 Results

3.4.1 Ocean Physical Properties of Four Malaysian Islands

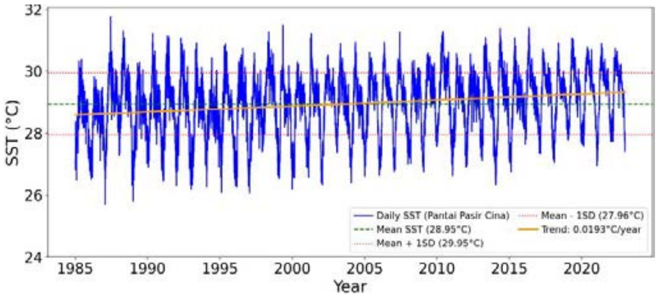
The satellite-derived data for sea surface temperature (SST), cloud fraction, wind speed, and turbidity showed distinct patterns of variability across the four islands (Figure 3.2 to Figure 3.5). SST values ranged between 24°C and 32°C from 1985 to 2022 (Figure 3.2). The long-term SST warming trends were also quantified, with Pantai Pasir Cina showing the highest increase at 0.0193°C per year, followed closely by Pulau Lang Tengah at 0.0189°C per year, Mantanani Reef at 0.0183°C per year, and Tekek Reef with the lowest trend of 0.0158°C per year. Throughout this period, Tekek Reef consistently demonstrated a narrower range of SST (28.74 ± 0.92°C), represented by the shorter vertical range in the time series graph (Figure 3.2 (C)), while Mantanani Reef exhibited the greatest SST variability, with the highest standard deviation of 1.37°C (28.82 ± 1.37°C), as shown as longer in Figure 3.2 (D). These long-term standard deviation values help quantify interannual SST variability at each site, complementing the seasonal trends illustrated in Figure 3.6. Pantai Pasir Cina and Pulau Lang Tengah experienced the highest average SSTs, with 28.95 ± 1.00°C and 29.06 ± 0.99°C, respectively. The historical monthly mean SST for these four sites was consistently highest in mid-year and lowest at the beginning of the year (Figure 3.6 (A)). Mantanani Reef exhibited a consistent one-month delay compared to other study sites – while other study sites had the lowest SST in January, Mantanani Reef had the lowest SST in February. Similarly, while other places had the highest SST in May, Mantanani Reef experienced the highest SST in June (Table 3.2). In all locations, a rapid transition occurred over ~4 months from the coolest to the warmest month.

The cloud fractions at Pantai Pasir Cina and Pulau Lang Tengah exhibit very similar patterns; while montly values may vary slightly between the two sites, their overall mean and standard deviation (0.44 ± 0.15) are identical (Figure 3.3 (A) and (B)). Throughout this period, Mantanani Reef consistently demonstrated the highest cloud fraction, although it had a narrower range (0.47 ± 0.13) (Figure 3.3 (D)). The historical monthly mean cloud fraction was consistently highest during the third quarter of the year, while the lowest cloud coverage was observed in April and May (Figure 3.6 (B)). Tekek Reef displayed a different pattern compared to the other sites, as it experienced the widest range of cloud fractions. In contrast, Mantanani Reef showed the lowest variability in cloud cover throughout the year, peaking in July and reaching its lowest values in April and May. Historical monthly mean cloud fraction was highest for all sites in October and lowest in April, except for Mantanani, which had the highest in July and the lowest in May (Table 3.2).

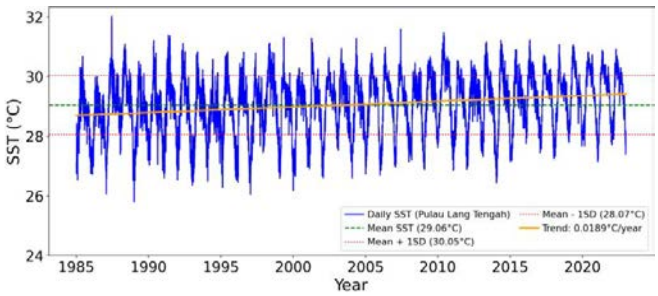
The satellite-derived wind speeds generally remained below 20 m/s across all study sites, with standard deviations ranging from 2.11 m/s to 2.35 m/s (Figure 3.4). Pulau Lang Tengah recorded the lowest wind speed (4.33 m/s) (Figure 3.4 (B)), while Mantanani Reef experienced the highest average wind speed (5.42 m/s) (Figure 3.4 (D)). A period of higher winds was consistently apparent from November to February, in contrast to lower winds through the middle of the year (March to June) (Figure 3.6 (C)). However, a smaller mid-year increase in winds, peaking around July/August, was apparent for Tekek Reef and of lesser magnitude for Pantai Pasir Cina and Pulau Lang Tengah. Historical monthly mean wind speed was highest at the start and end of the calendar year (January and December), with the lowest wind speed in April/May (Table 3.2).

The satellite-derived turbidity represented by kd_490 values is generally below 0.15 m^{-1} for each study site (Figure 3.5). Pantai Pasir Cina and Pulau Lang Tengah had the lowest turbidity levels, with 0.07 ± 0.02 m^{-1} and 0.07 ± 0.05 m^{-1}(Figure 3.5 (A) and (B)), respectively, while Mantanani Reef exhibited the highest turbidity at 0.10 ± 0.06 m^{-1} (Figure 3.5 (D)). Tekek Reef had the highest standard deviation, with values ranging from 0.08 ± 0.17 m^{-1} (Figure 3.5 (C)). A period of higher turbidity was consistently observed from November to February, contrasting with lower turbidity during the middle of the year (March to June) (Figure 3.5 (D)). Pantai Pasir Cina and Pulau Lang Tengah demonstrated a consistent turbidity pattern throughout each other. Historical monthly mean turbidity was highest at the start and end of the calendar year (January and December), with the lowest turbidity in April/May (Table 3.2).

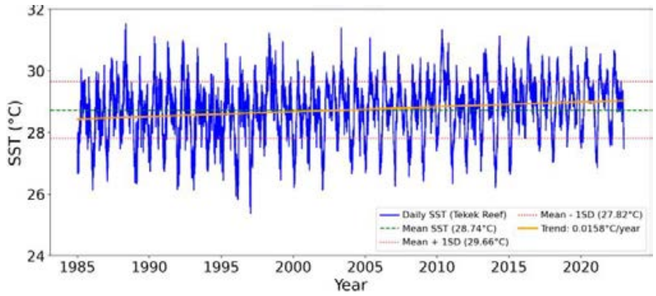
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

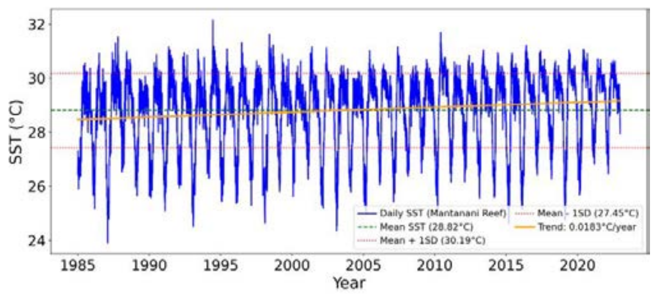
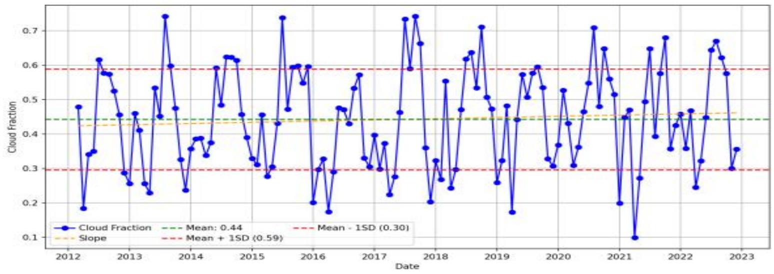
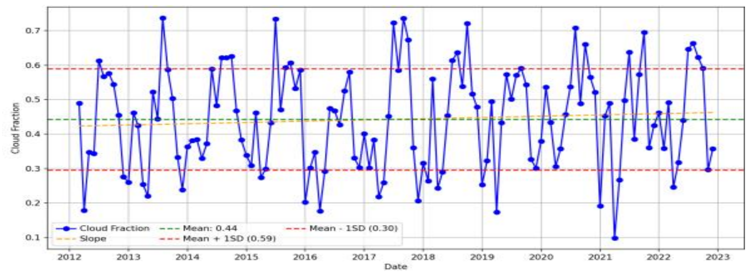


Figure 3.2. Satellite-derived SST from 1985 to 2022 at four islands in Malaysia.(A) Pantai Pasir Cina, PM; (B) Pulau Lang Tengah, PM; (C) Tekek Reef, PM; (D) Mantanani Reef, EM. The blue line represents the satellite-derived SST, the green line is the mean satellite-derived SST, the red line is the mean ± SD, and the orange line shows the trend.

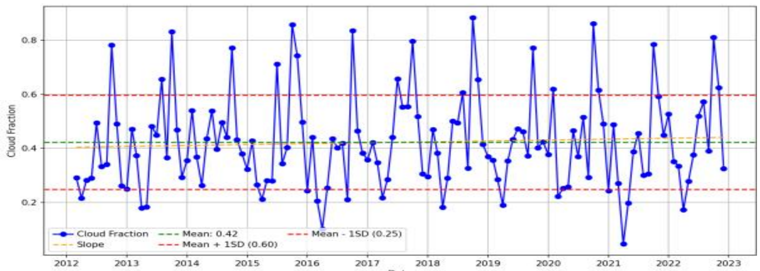
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

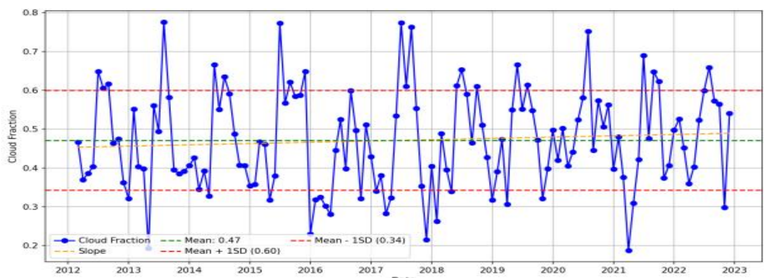
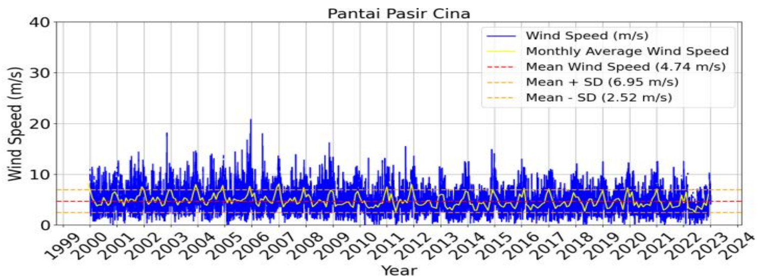


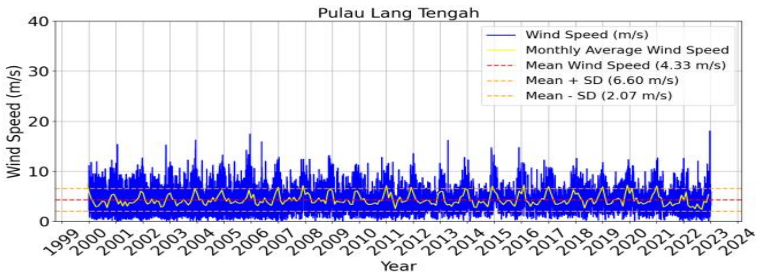
Figure 3.3. Satellite-derived cloud fraction from 2012 to 2022 at four islands in Malaysia.Pantai Pasir Cina, PM; (B) Pulau Lang Tengah, PM; (C) Tekek Reef, PM; (D) Mantanani Reef,

EM.The blue line represents the satellite-derived cloud fraction, the green line is the mean satellite-derived cloud fraction, the red line is the mean ± SD, and the orange line shows the trend.

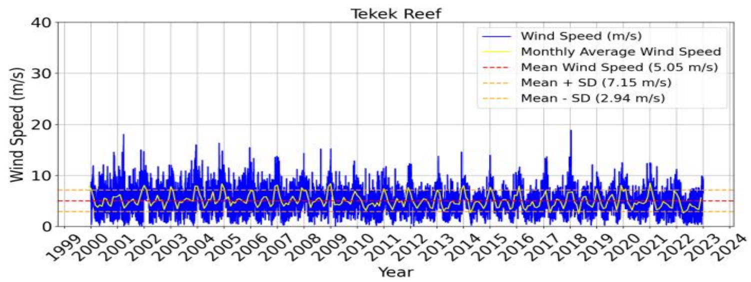
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

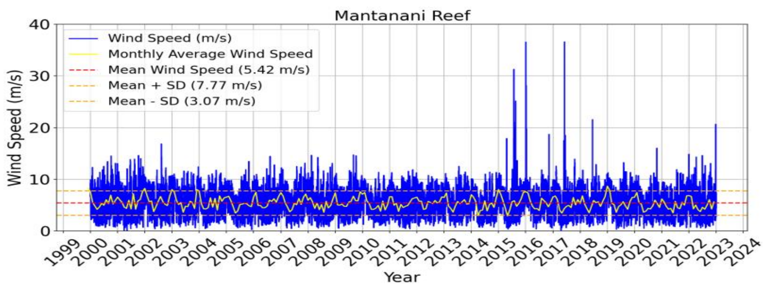
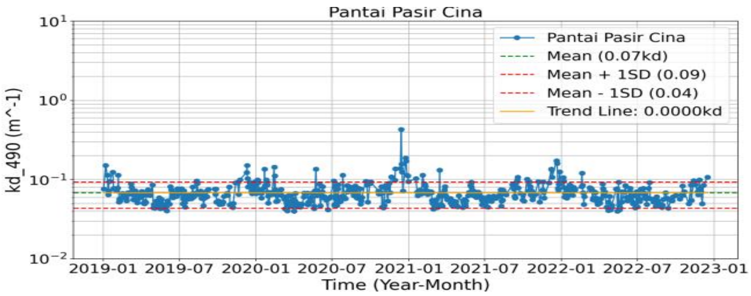


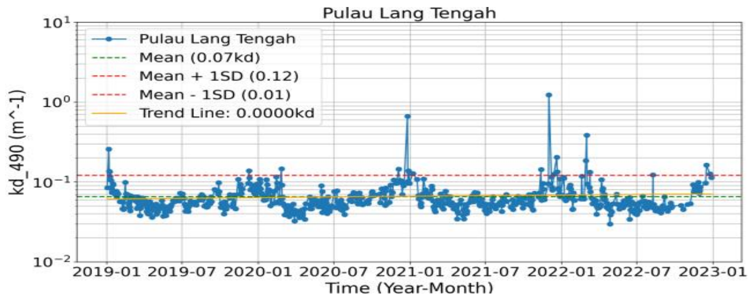
Figure 3.4. Satellite-derived wind speed from 2000 to 2022 at four islands in Malaysia.Pantai Pasir Cina, PM; (B) Pulau Lang Tengah, PM; (C) Tekek Reef, PM; (D) Mantanani Reef, EM.

The blue line represents the satellite-derived wind speed, the yellow line represents the monthly average wind speed, the red line is the mean satellite-derived wind speed and, the orange line is the mean ± SD.

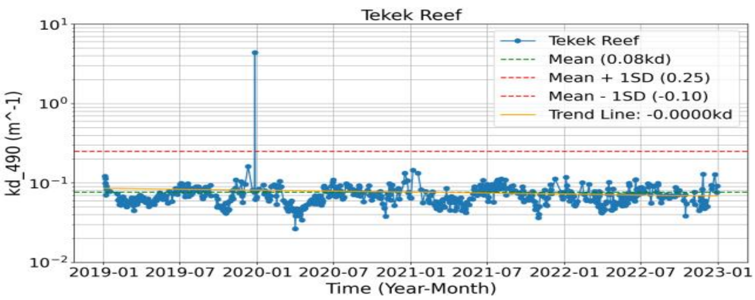
(A) Pantai Pasir Cina, PM



(B) Pulau Lang Tengah, PM



(C) Tekek Reef, PM



(D) Mantanani Reef, EM

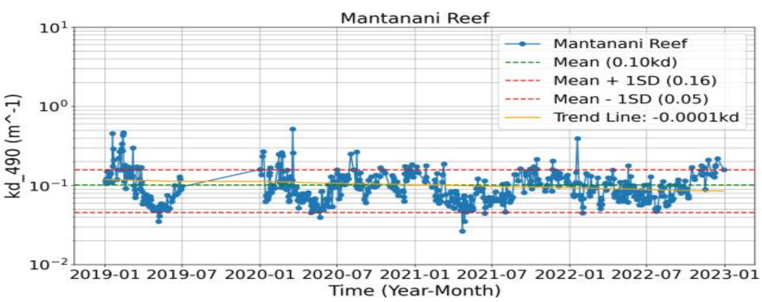


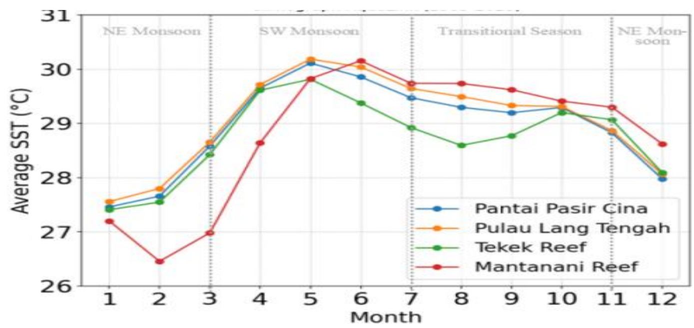
Figure 3.5. Satellite-derived turbidity from 2000 to 2022 at four islands in Malaysia.(A) Pantai Pasir Cina, PM; (B) Pulau Lang Tengah, PM; (C) Tekek Reef, PM; (D) Mantanani Reef, EM. The blue line represents the satellite-derived turbidity, the green line is the mean satellite-derived turbidity, the red line is the mean ± SD, and the orange line shows the trend.

Table 3.2:

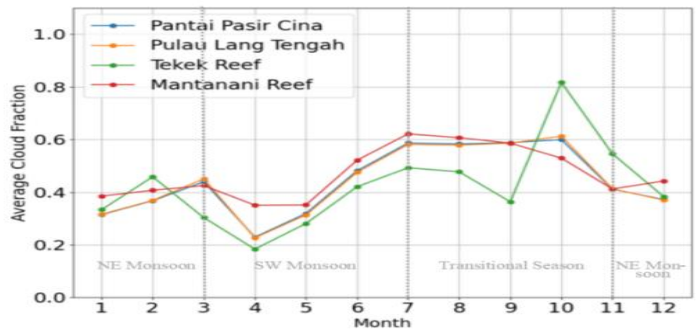
Temporal Variation in Physical Properties at Four Malaysian Islands

Study sites	**Physical Properties**	**Month with Lowest Value**	**Month with Highest Value**
Pantai Pasir Cina, PM	**SST**	January	May
	Cloud Fraction	April	October
	Wind Speed	April	December
	Turbidity	May	December
Pulau Lang Tengah, PM	**SST**	January	May
	Cloud Fraction	April	October
	Wind Speed	May	December
	Turbidity	April	December
Tekek Reef, PM	**SST**	January	May
	Cloud Fraction	April	October
	Wind Speed	April	January
	Turbidity	April	January
Mantanani Reef, EM	**SST**	February	June
	Cloud Fraction	May	July
	Wind Speed	May	January
	Turbidity	May	December

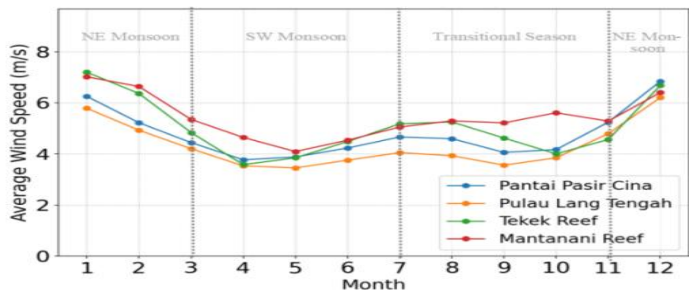
(A) SST (1985-2022)



(B) Cloud Fraction (2012-2022)



(C) Wind Speed (2000-2022)



(D) Turbidity (2000-2022)

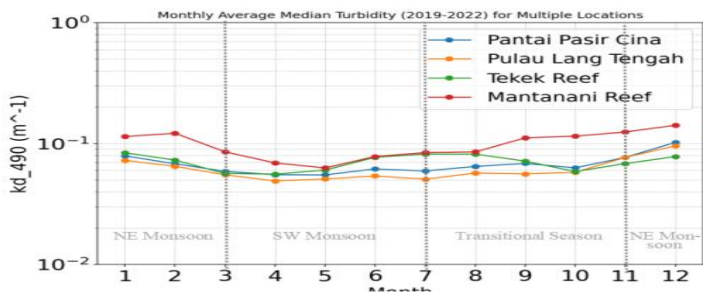


Figure 3.6. Historical monthly mean of satellite-derived physical variables at four islands.(A) SST (1985-2022); (B) Cloud Fraction (2012-2022); (C) Wind Speed (2000-2022); and (D) Turbidity (2000-2022).

The relationships between environmental variables across the study sites are shown in Table 3.3. At all four sites, higher wind speeds corresponded to increased turbidity levels. The analysis revealed a significant positive correlation between wind speed and turbidity at all four study sites in Malaysia. Pantai Pasir Cina and Pulau Lang Tengah exhibited the strongest correlations, with Pearson correlation coefficients exceeding 0.90, indicating a strong positive linear relationship. Tekek Reef and Mantanani Reef also showed positive correlations, although slightly weaker.

Additionally, a negative correlation was observed between SST and wind speed across the sites, suggesting that higher SSTs were associated with lower wind speeds (Table 3.3). This relationship was particularly strong at Tekek Reef, where the Pearson coefficient was -0.93, indicating a clear inverse relationship. Similarly, a negative correlation was found between SST and turbidity across the sites, suggesting that higher SSTs were linked to lower turbidity levels, and vice versa. Cloud fraction exhibited both weak negative and weak positive correlations with turbidity and SST at most sites, suggesting limited interaction between cloud fraction and these variables.

Table 3.3:

Correlation Matrix of Physical Properties Across Four Malaysian Sites

PPC PLT TR MR	SST		Cloud fraction		Wind speed		Turbidity	
SST	1		0.2792	0.2549	-0.8328	-0.8697	-0.6911	-0.7021
			0.0069	0.5218	-0.9310	-0.7037	-0.5203	-0.3321
Cloud fraction			1		-0.2390	-0.3123	-0.1322	-0.2233
					-0.0443	-0.1174	0.0882	0.0102
Wind speed					1		0.9087	0.9085
							0.7114	0.7855
Turbidity							1	

Summarising the timing of annual maximum and minimum values, three distinct seasonal patterns of physical properties are evident in Malaysia (Table 3.4). Averaging the physical variables across each of these three periods reveals typical seasonal patterns for Malaysia. From November to February, all sites recorded the lowest SST and highest wind speed and turbidity. The highest monthly-mean wind speed and turbidity values for all sites occurred during the March to June period, in which the lowest monthly-mean SST in PM. Cloud fraction had the highest monthly-mean values in the July to October period. The November-February period coincides with the NE monsoon and the following period (March-June) with the SW monsoon, while the third period is a transitional season (July-October).

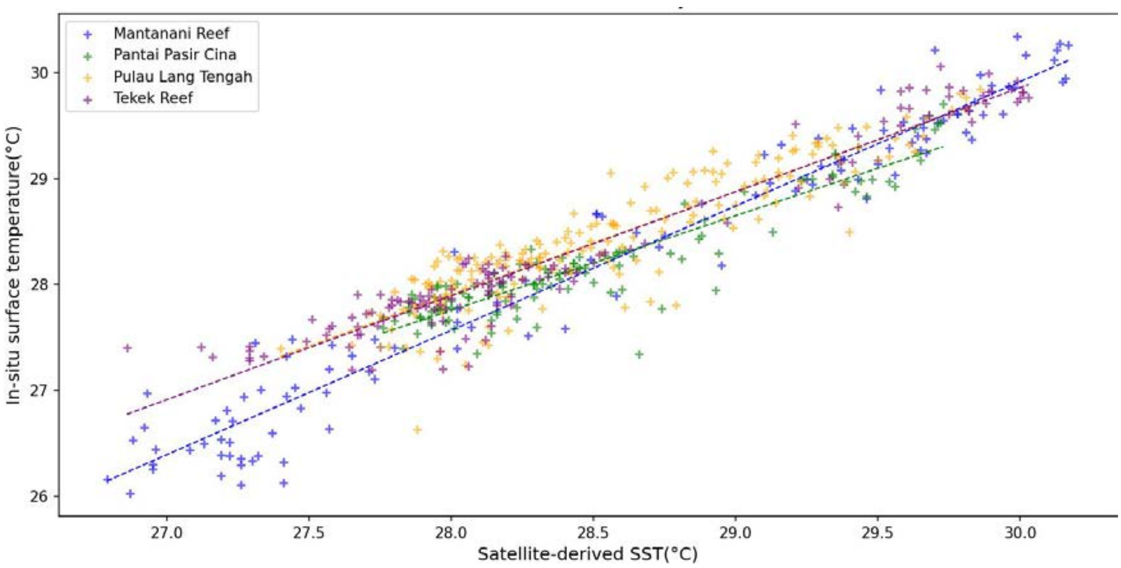
Table 3.4:

Seasonal Variations in Study Sites and Environmental Parameters in Malaysia

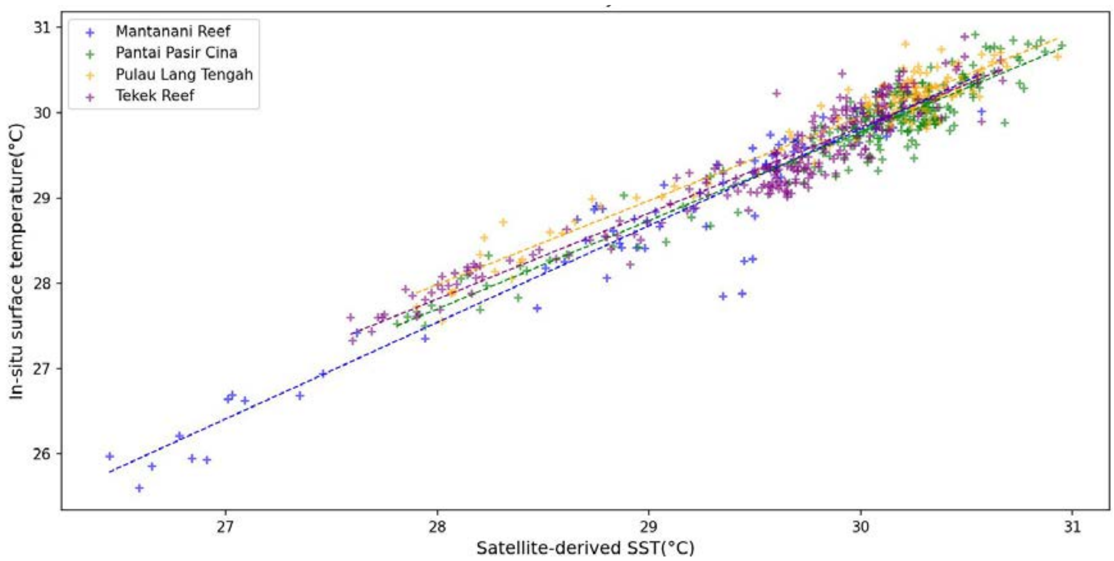
Study sites	**Physical Properties**	**Nov to Feb (NE monsoon)**	**Mar to Jun (SW monsoon)**	**Jul to Oct**
Pantai Pasir Cina (PM)	**SST**	28.10 ± 0.57	29.87 ± 0.25	29.33 ± 0.13
	Cloud Fraction	0.38 ± 0.05	0.34 ± 0.13	0.59 ± 0.01
	Wind Speed	5.60 ± 0.95	3.96 ± 0.24	4.37 ± 0.30
	Turbidity	0.08 ± 0.02	0.06 ± 0.00	0.06 ± 0.00
Pulau Lang Tengah (PM)	**SST**	28.22 ± 0.56	29.97 ± 0.25	29.43 ± 0.15
	Cloud Fraction	0.38 ± 0.05	0.34 ± 0.13	0.59 ± 0.02
	Wind Speed	5.18 ± 0.81	3.58 ± 0.16	3.85 ± 0.21
	Turbidity	0.07 ± 0.02	0.05 ± 0.00	0.06 ± 0.00
Tekek Reef (PM)	**SST**	28.10 ± 0.70	29.60 ± 0.20	28.88 ± 0.25
	Cloud Fraction	0.41 ± 0.10	0.30 ± 0.12	0.54 ± 0.19
	Wind Speed	5.93 ± 1.17	3.97 ± 0.46	4.76 ± 0.58
	Turbidity	0.07 ± 0.01	0.06 ± 0.01	0.07 ± 0.01
Mantanani Reef (EM)	**SST**	27.72 ± 1.18	29.53 ± 0.83	29.60 ± 0.14
	Cloud Fraction	0.41 ± 0.02	0.41 ± 0.10	0.59 ± 0.04
	Wind Speed	6.14 ± 0.78	4.43 ± 0.30	5.29 ± 0.24
	Turbidity	0.12 ± 0.02	0.07 ± 0.01	0.10 ± 0.02

Seasonal comparisons between satellite-derived and *in-situ* SST revealed mostly strong correlations, with R-squared values ranging from 0.43 to 0.95 (Figure 3.7 and Table 3.5). The period from November to February (NE monsoon), all four islands exhibited strong correlations, with temperature ranges exceeding 2.5ºC. Tekek and Mantanani Reef showed the highest correlations among all seasons. From March to June, coinciding with the SW monsoon, the correlations remained strong across all sites, with Pantai Pasir Cina and Pulau Lang Tengah showing their highest correlations. The third period, July to October, showed comparable correlations to the prior period for Pantai Pasir Cina and Pulau Lang Tengah; however, Pantai Pasir Cina exhibited the lowest correlation ($R^2 = 0.41$) among the values. Mantananni Reef had no data available during this period because the *in-situ* temperature logger collected data only from November 2021 to May 2022 (as described in Chapter 2.3.2.1, Table 2.1).

(A) November to February



(B) March to June



(C) July to October

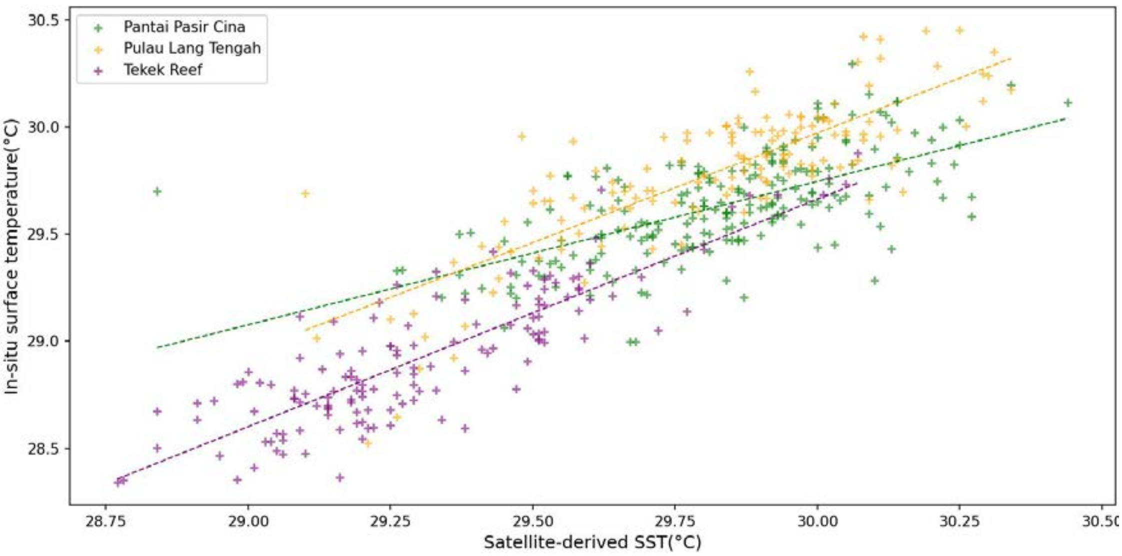


Figure 3.7. Comparisons of satellite-derived SST and *in-situ* SST on (A) November to February; (B) March to June; (C) July to October.

Table 3.5:

Correlation and R-squared Between Satellite-Derived SST and In-Situ SST for Four Islands by Season

Season	**Site**	**R²**	**p-value**
November to February	**Pantai Pasir Cina**	0.8531	<0.0001
	Pulau Lang Tengah	0.8101	<0.0001
	Tekek Reef	0.9361	<0.0001
	Mantanani Reef	0.9546	<0.0001
March to June	**Pantai Pasir Cina**	0.8967	<0.0001
	Pulau Lang Tengah	0.9296	<0.0001
	Tekek Reef	0.9053	<0.0001
	Mantanani Reef	0.9193	<0.0001
July to October	**Pantai Pasir Cina**	0.4055	<0.0001
	Pulau Lang Tengah	0.6632	<0.0001
	Tekek Reef	0.7311	<0.0001
	Mantanani Reef	No data available	

3.4.2 Incorporating Reef Resilience Score on Coral Bleaching Prediction

A limited number (n=33) of the 2015 to 2017 study sites (Figure 2.5) overlapped with the locations of the 2011 reef resilience dataset(refer Appendix 3). Some of these 33 points may appear overlapped in figures due to identical or closely bleaching percentage and DHW values. The calculated average total reef resilience score was 44.84, with a standard deviation of 12.89. Using the threshold classification method, the resilience categories were determined as follows: high (≥ 57.73; AVG + 1 SD), medium-high (44.84 to < 57.73), medium-low (31.95 to < 44.84), and low (< 31.95; AVG - 1 SD). None of the overlapping study sites in 2021 were classified as high resilience. Most coral bleaching observations showed less than 10% of colonies affected, with only five surveys reporting bleaching levels above 10% (Figure 3.8). DHW values ranged from 0°C-weeks to 5.5°C-weeks. Approximately 11% of the variance in field coral bleaching observations was explained by satellite-derived predictions (R^2 = 0.1122). Notably, low resilience study sites (red, orange) exhibited higher coral bleaching percentages than the regression line, including when DHW values were low. At one low resilience study site, 80% coral bleaching was corresponded with a DHW value of 0°C-weeks. Conversely, most bleaching events with less than 20% bleaching occurred at Medium-High resilient sites (yellow), even when DHW exceeded 4°C-weeks.

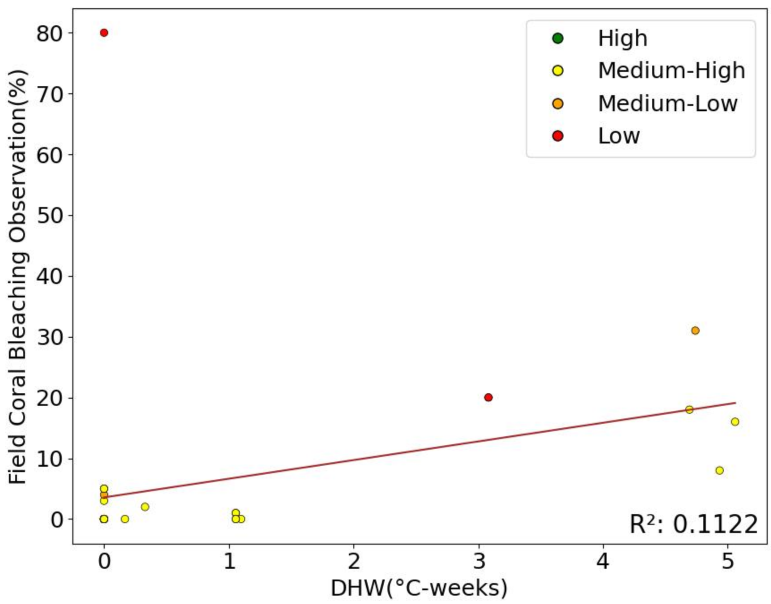


Figure 3.8. Scatter plot for satellite-derived DHW and field coral bleaching observations by incorporating 2011 reef resilience score. Data presented are a subset of those shown in Figure 2.5 for which 2011 resilience data were available.

3.4.3 The Update of Reef Resilience from 2011 to 2021

Of the 18 study sites assessed in Pulau Tioman in 2011, 12 were revisited in 2021 to re-evaluate 16 resilience factors. The calculated average total reef resilience score was 46.21, with a standard deviation of 6.59 in 2011, and 48.50 average with a standard deviation of 6.37 in 2021. The thresholds between the four resilience categories were 52.80, 46.21, and 39.92 in 2011 and 54.87, 48.50 and 42.13 in 2021. Among the 12 revisited sites (Table 3.6), six sites maintained their relative resilience category between the two time periods (Asah, Lighthouse, North Point, Pirate, Renggis North, and Soyak North). Five sites displayed improvements in their resilience categories - Chebeh, Malang Rock, Sepoi, and Teluk Dalam shifted from the Medium-high category in 2011 (yellow) to High in 2021 (green), while Labas improved from Medium-low (orange) to Medium-high (yellow). Previously classified as High, Renggis South was the only site in Tioman that experienced a decline in resilience category (to Medium-high). Spatially, the western and southern regions of Tioman exhibited lower resilience status, while the northern, northwest, and northeast areas showed higher reef resilience status (Figure 3.9). Resilience scores improved at eight sites (by as much as +10 at Sepoi), whilst scores declined at four sites (changes ranged from -3 to -4.5).

Table 3.6:

Reef Resilience Scores for Tioman Marine Park: 2011 and 2021: High (Green), Medium-high (Yellow), Medium-low (Orange), and low (Red). Asterisks (**) indicate study sites assessed only in 2011.

	Study Sites	Resilience Score 2011	Resilience Score 2021
1	Air Batang **	14.5	
2	Asah	33.5	34.5
3	Batu Nipah **	31	
4	Chebeh	49	54
5	Genting **	21	
6	Labas	37.5	43
7	Lighthouse	48	43.5
8	Malang Rock	45.5	51.5
9	North Point	42.5	49

10	Paya **	27	
11	Pirate	46	43
12	Renggis North	56.5	52.5
13	Renggis South	53	48.5
14	Sepoi	42	52
15	Soyak North	52.5	53.5
16	Tekek **	23	
17	Teluk Dalam	48.5	57
18	Tumuk **	33	

(A) 2011 (B) 2021

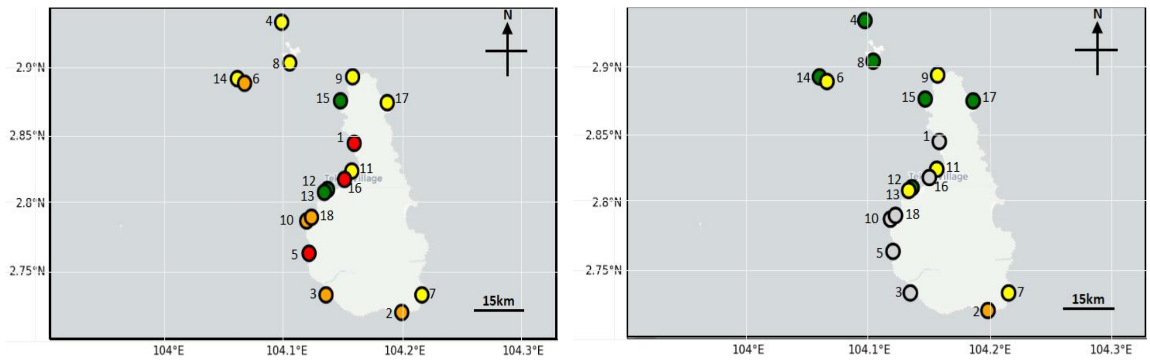


Figure 3.9. Reef resilience status comparison between (A) 2011 and (B) 2021 for selected study sites that were revisited in both years in Tioman Marine Park. Colors of the circles represent the reef resilience score (Table 3.6); grey in panel B indicates the score was not updated based on 2021 data.

Out of the 15 study sites assessed in Pulau Redang in 2011, 10 were revisited in 2021 to re-evaluate 16 resilience factors.The calculated average total reef resilience score was 56.95, with a standard deviation of 6.15 in 2011, and 53.15 average with a standard deviation of 6.06 in 2021. The thresholds between the four resilience categories were 50.80, 56.95, and 63.10 in 2011 and 47.09, 53.15 and 59.21 in 2021. Among the 10 revisited sites (Table 3.7), eight sites —maintained their resilience category between the two time periods (Chagar Hutang, Gua Kawah, P. Kerengga Besar, P. Ling, P. Paku Besar, Tanjung Lang, Teluk Mat Delah, and Terumbu Kili). No sites displayed improvements in their resilience categories. However, P. Lima and P. Paku Kecil, both located in the eastern region of Redang experienced a decline in resilience category from Medium-high (yellow) to Medium-low (orange). Overall, the reef resilience status in Pulau Redang remained relatively stable, with most sites maintaining their classification between the two studies (Figure 3.10). However, resilience scores for the two improved sites increased by on 0.5, whilst for the eight sites whose values declined the change in score ranged from -1 to -8.

Table 3.7:

Reef Resilience Scores for Redang Marine Park: 2011 and 2021: High (Green), Medium-high (Yellow), Medium-low (Orange), and low (Red). Asterisks (**) indicate study sites assessed only in 2011.

	Study Sites	**Resilience Score 2011**	**Resilience Score 2021**
1	Chagar Hutang	62	62.5
2	Gua Kawah	62.5	57.5
3	P. Ekor Lembu **	36.5	
4	P. Kerengga Besar	55.5	56
5	P. Lima	57	52
6	P. Ling	60.5	57
7	P. Paku Besar	47	43
8	P. Paku Kecil	60.5	52
9	Pasir Akar **	47	
10	Pasir Mak Kepit **	22	
11	Tanjung Gutong **	64	
12	Tanjung Lang	51.5	46.5
13	Teluk Mat Delah	64.5	57.5
14	Teluk Pandam **	58.5	
15	Terumbu Kili	48.5	47.5

(A) 2011 (B) 2021

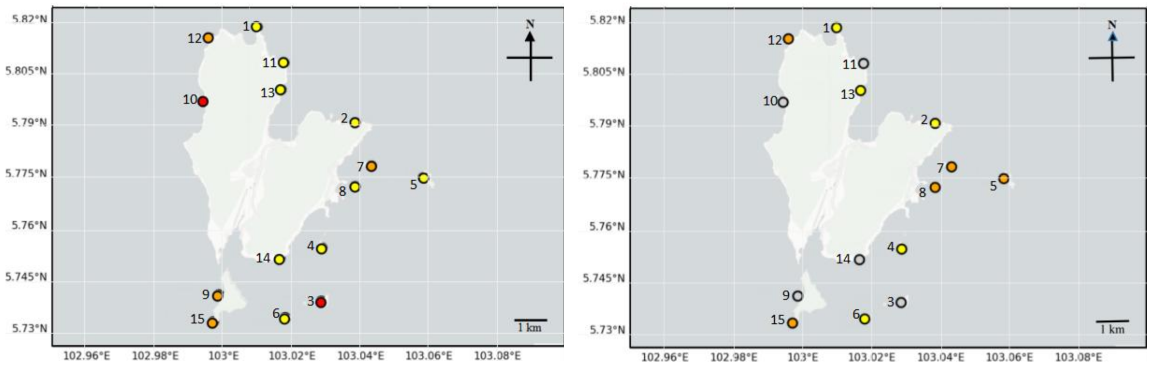


Figure 3.10. Reef resilience status comparison between (A) 2011 and (B) 2021 for selected study sites that were revisited in both years in Redang Marine Park. Colors of the circles represent the reef resilience score (Table 3.7); grey in panel B indicates the score was not updated based on 2021 data.

Of the 10 study sites assessed in the Sibu-Tinggi Marine Park cluster in 2011, five were revisited in 2021 to update the resilience scores (Table 3.8). The calculated average total reef resilience score was 48.70, with a standard deviation of 3.51 in 2011, and 45.40 average with a standard deviation of 6.43 in 2021. The thresholds between the four resilience categories were 45.19, 48.70, and 52.21 in 2011 and 38.97, 45.40 and 51.83 in 2021. Among these five sites, three sites maintained their relative resilience category between the two time periods (Nanga, One Tree Rock, and Siam Knoll). No sites displayed improvements in their resilience categories. Two sites experienced a decline in their resilience category: Ibol Besar moved from the High to Medium-high, and Pulau Lima Kecil from Medium-High to Medium-Low. The western regions of Sibu-Tinggi exhibited higher resilience status (Figure 3.11). The greatest decline in resilience score occurred at Pulau Lima Kecil (by -9.5).

Table 3.8:

Reef Resilience Scores for Sibu-Tinggi Marine Park: 2011 and 2021: High (Green), Medium-high (Yellow), Medium-low (Orange), and low (Red).

	Study Sites	**Resilience Score 2011**	**Resilience Score 2021**
1	Ibol Besar	53	48.5
2	Mentinggi **	42	
3	Nanga	50.5	49.5
4	One tree rock	48	47.5
5	P. Ambong **	35.5	
6	P. Lima Kecil	43.5	34
7	P. Sibu Hujung **	28.5	
8	Siam Knoll	48.5	47.5
9	Sibu SW **	25.5	
10	Tanjung Mariam **	51.5	

(A) 2011 (B) 2021

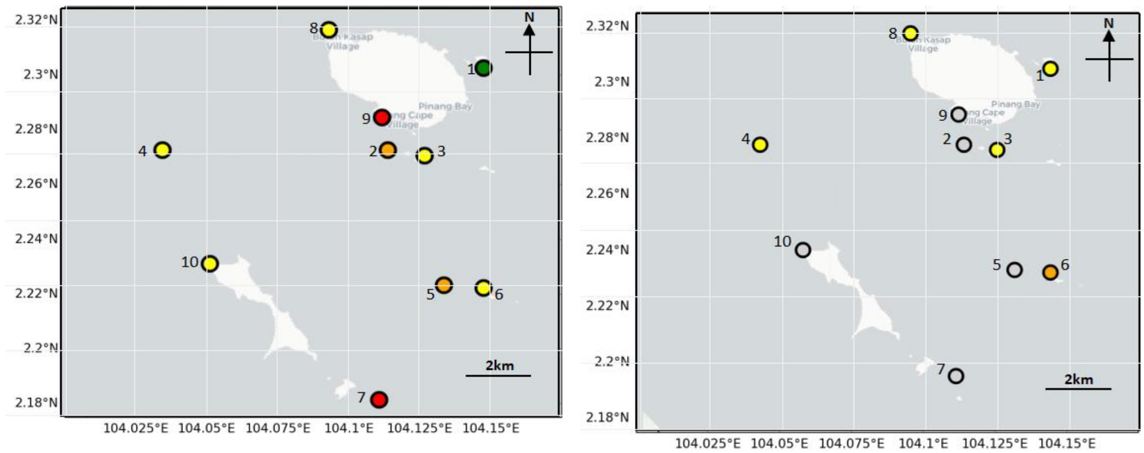


Figure 3.11. Reef resilience status comparison between (A) 2011 and (B) 2021 for selected study sites that were revisited in both years in Sibu-Tinggi Marine Park.Colors of the circles represent the reef resilience score (Table 3.8); grey in panel B indicates the score was not updated based on 2021 data.

3.4.4 Temperature Variations among Islands

The average MM SST and standard deviation (SD) for each of the 31 islands showed the range of temperatures observed across the study area (Table 3.9). The mean SST across the islands ranged from 28.46°C to 29.27°C. Payar (island located in WCPM) exhibited the highest mean temperature of 29.27°C ± 0.69°C, while Tenggol (island located in ECPM) recorded the lowest at 28.45°C ± 0.82°C. Several islands (island located in ECPM), such as Perhentian, Redang, and Lang Tengah, demonstrated relatively high mean temperatures, each around 28.8°C, with standard deviations ranging from 0.84°C to 0.85°C, indicating moderate variability. On the other hand, islands (island located in WCEM) like Mantanani, Usukan, and Kota Belud exhibited higher standard deviations (1.31°C, 1.28°C and 1.28°C, respectively). Kapalai and Mataking (island located in ECEM) had some of the lowest mean SST values with relatively low variability, both around 28.5°C with their standard deviations of 0.53°C and 0.56°C, respectively.

The calculated F-statistic of 0.5901 indicated the ratio between variations in mean temperatures among the islands and the variations within island groups. The associated p-value of 0.9592 suggested that there is no statistically significant difference in temperature variations among the islands at 95% significance level.

Table 3.9:

Average MM SST and SD for 31 islands in Malaysia

Island Name (No of Satellite Pixel)	Located	Mean ± SD Temperature (°C)	Island Name (No of Satellite Pixel)	Located	Mean ± SD Temperature (°C)
Payar (1)	WCPM	29.27 ± 0.69	Mataking (2)	ECEM	28.46 ± 0.56
Sembilan (4)	WCPM	29.16 ± 0.37	Lahad Datu (5)	ECEM	28.83 ± 0.62
Tioman (8)	ECPM	28.53 ± 0.75	Mantabuan (1)	ECEM	28.53 ± 0.56
Perhentian (4)	ECPM	28.84 ± 0.85	Pom Pom (1)	ECEM	28.48 ± 0.56
Kapas (1)	ECPM	28.55 ± 0.77	Sibuan (1)	ECEM	28.60 ± 0.56
Tenggol (1)	ECPM	28.45 ± 0.82	Semporna (12)	ECEM	28.60 ± 0.49
Lang Tengah (1)	ECPM	28.78 ± 0.84	Mabul (1)	ECEM	28.53 ± 0.52
Yu (1)	ECPM	28.68 ± 0.83	Kapalai (2)	ECEM	28.50 ± 0.53
Redang (2)	ECPM	28.76 ± 0.85	Mantanani (2)	WCEM	28.55 ± 1.31
Tinggi (2)	ECPM	28.60 ± 0.72	Usukan (1)	WCEM	28.67 ± 1.28
Pemanggil (1)	ECPM	28.55 ± 0.75	Kota Belud (1)	WCEM	28.67 ± 1.28
Tengah (1)	ECPM	28.60 ± 0.72	Gaya (1)	WCEM	28.79 ± 1.09
P. Sibu (2)	ECPM	28.61 ± 0.72	Manukan (1)	WCEM	28.81 ± 1.07
Banggi (1)	WCEM	28.69 ± 0.93	Sapi (1)	WCEM	28.79 ± 1.09
Labuan (2)	WCEM	28.83 ± 0.90	Tiga (2)	WCEM	28.84 ± 0.98
Miri (2)	WCEM	28.65 ± 1.09			

3.4.5 Clustering Malaysian Islands

The K-means clustering analysis grouped the 31 Malaysian islands into distinct clusters based on their MM SST. The temperature variations in Table 3.10 correspond to different cluster numbers, ranging from 1.61°C for two clusters to 0.24°C for fifteen clusters. After considering temperature variations and geographic proximity, twelve clusters were selected as the most appropriate grouping for these islands (Figure 3.12), with the average temperature variation of 0.33°C per cluster.

Table 3.11 presents the clustered islands with their locations, minimum and maximum MM SST values, and distinction order. Cluster 0, comprising Payar Island, recorded the highest range of SST, with temperatures fluctuating between 28.3°C and 30.37°C. In contrast, Cluster 8, which included Mantanani, Usukan Cove, and Kota Belud, exhibited a slightly lower temperature range of 26.24°C to 30.06°C. Islands such as those in Cluster 11 (Semporna, Mabul, Kapalai, Mataking, Mantabuan, Sibuan, Pom Pom) displayed a relatively narrow temperature range, from 27.47°C to 29.39°C. The clustering approach highlights distinct regional differences in SST trends. WCPM islands like Payar and Sembilan showed higher SST values, while the islands in WCEM, such as Mantanani and Sapi showed lower SST values. Islands in the ECEM like Lahad Datu and Semporna showed narrow temperature range between the minimum and maximum MM SST within the island.

Table 3.10:

Temperature Variation Across Clusters in K-means Analysis

# of Clusters	Temperature Variation (°C)
2	1.61
3	1.01
4	1.01
5	1.01
6	0.73
7	0.73
8	0.55
9	0.55
10	0.42
11	0.34
12	0.33
13	0.27
14	0.26
15	0.24

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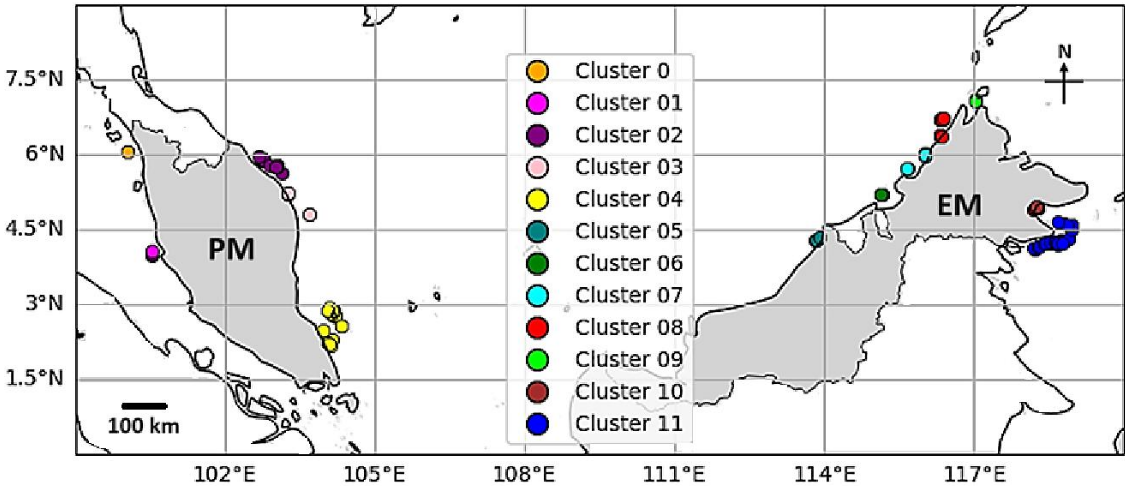

Figure 3.12. Clustering of Malaysian islands based on temperature variations.

Table 3.11:

Islands (Pulau) within Each Cluster Classified Based on K-means Cluster Analysis

Clusters	Located	Islands	Minimum MM (°C)	Maximum MM (°C)	Distinction Order
0	WCPM	Payar	28.3	30.37	5
1	WCPM	Sembilan	28.66	29.76	5
2	ECPM	Perhentian	27.44	29.96	1
		Lang Tengah	27.37	29.93	
		Yu	27.3	29.85	
		Redang	27.34	29.92	
3	ECPM	Kapas	27.30	29.66	7
		Tenggol	27.08	29.6	
4	ECPM	Tioman	27.26	29.59	7
	ECPM	Tinggi	27.31	29.60	
		Pemanggil	27.25	29.60	
		Tengah	27.35	29.61	
		Pulau Sibu	27.31	29.61	
5	WCEM	Miri	26.61	29.86	10
6	WCEM	Labuan	27.11	29.75	10
7	WCEM	Gaya	26.73	30.07	10
		Manukan	26.78	30.07	
		Sapi	26.73	30.07	
		Tiga	26.96	29.99	
8	WCEM	Mantanani	26.24	29.98	2
		Usukan Cove	26.3	30.06	
		Kota Belud	26.3	30.06	
9	WCEM	Banggi	27.04	29.76	9
10	ECEM	Lahad Datu	27.76	29.75	3
11	ECEM	Semporna	27.71	29.27	3
		Mabul	27.6	29.23	
		Kapalai	27.55	29.22	
		Mataking	27.47	29.23	
		Mantabuan	27.56	29.30	
		Sibuan	27.63	29.39	
		PomPom	27.49	29.24	

3.5 Discussion

3.5.1 Seasonal Patterns and the Relationship between Physical Properties in Malaysia

Previous research on *in-situ* measurements or satellite-derived physical properties for Malaysian reefs mainly focuses on specific regions and short-term periods, with a general emphasis on the ECPM over EM and WCPM (Misman et al., 2023). Here, historical satellite data on physical properties from a longer time span for four islands—three located in the East Coast of Peninsular Malaysia (ECPM) and one in West Coast of East Malaysia (WCPM)—

provide a broader understanding of these properties. The results indicate that the reefs in EM experienced greater variability in SST, evidenced by a higher standard deviation, alongside stronger winds and higher turbidity levels in average compared to reefs in ECPM. These environmental differences influence coral morphology, with branching corals—known for their fast growth—being more susceptible to damage from wave, while massive corals grow slower growth rates but greater resilience to environmental stress (Fisher, 2022; Hanapiah et al., 2019; Thomson et al., 2020). Accordingly, EM has a higher abundance of massive corals (Akmal et al., 2024; Montagne et al., 2013), while ECPM is predominated by branching corals (Kamarumtham et al., 2016; Toda et al., 2007). Additionally, given the differences in coral species compositions and the varying threats between ECPM and EM (as described in Chapter 1.5), ECPM faces threats from reef development and tourism (Burke et al., 2002; Lachs et al., 2021; Leem et al., 2022), whereas EM is threatened by overfishing (Burke et al., 2011; Zakariah et al., 2007). Future research should further explore how these factors interact with physical properties to influence coral resilience and health.

The positive correlation between wind speed and turbidity is consistent with findings from prior research (Bever et al., 2018; Lou et al., 2016) that wind speeds exceeding 4 m/s have a significant effect on turbidity levels (Lou et al., 2016; Wenhao et al., 2021). The average wind speed consistently remained below 4 m/s during the period from March to June, with associated lower turbidity levels.

Distinct patterns in key physical properties across Malaysia characterize three distinct seasons throughout the year. The Northeast Monsoon season from November to February (Chuan, 2005; Makaremi et al., 2012; Rind, 1998) experiences the lowest SST and highest wind speeds and highest turbidity. Rainfall patterns in the ECPM and ECEM exhibit similarities with peak rainfall occurring in December, while WCEM experiences maximum rainfall in January during the NE monsoon (Fakaruddin et al., 2020; Thia-Eng et al., 2000). The study confirms the influence of monsoon surges on the ECPM and ECEM which leads to heavy rainfall and strong winds during the monsoon season (Fakaruddin et al., 2020; Goh et al., 2016; Jayakrishnan et al., 2021; Roseli & Akhir, 2014; Saleh et al., 2010; Thia-Eng et al., 2000), resulting in lower SST levels during this period. Conversely, high SST levels and low wind speeds and turbidity predominate SW monsoon season (March to June). These seasonal variations highlight periods of increased environmental stress, particularly through changes in temperature and wind speed.

During the NE monsoon, coral reefs become more vulnerable to stressors such as nutrient runoff from land due to heavy rainfall, while strong currents increase the risk of physical damage to fragile coral types like branching corals (Fabricius et al., 2008; Hernández-Delgado et al., 2024; Safuan et al., 2020); however, the high turbidity and lower temperatures during this season also help reduce the risk of coral bleaching (Lucas et al., 2023; Rosedy et al., 2023; Sully & Woesik, 2020). In contrast, the SW monsoon poses potential bleaching risks due to elevated SST and reduced turbidity levels (Carlson et al., 2022; Lucas et al., 2023; Szereday & Affendi Yang, 2022). To support coral health and resilience, management efforts should therefore adapt to these seasonal shifts and focusing on specific threats and impacts for both the NE and SW monsoon periods. During the NE monsoon, reef management can implement specific actions, such as the construction of artificial wetland systems—similar to those used in the Buccoo Reef—to treat wastewater before it reaches coral ecosystems, preventing pollution and improving water quality (Mallela et al., 2011). Additionally, addressing local threats such as blast fishing, as seen in case studies like the Vanuaso Tikina initiative, can enhance reef resilience by enforcing no-take zones and promoting sustainable fishing practices (Veitayaki et al., 2011).

3.5.2 Understanding Seasonal Variations in Satellite Accuracy for SST Monitoring

Satellite SST accuracy is influenced by both satellite functionality and environmental factors (Gentemann et al., 2009; Kumar et al., 2021; Li et al., 2021). In this study, issues related to satellite functionality can be excluded, as the same *CoralTemp* product was used consistently throughout all seasons. Previous research (Gomez et al., 2020; Szereday & Affendi Yang, 2022), as well as results from Chapter 2.4.2, confirm the reliability and accuracy of CoralTemp for Malaysian waters. While the satellite accuracy remained high during the NE and SW monsoon seasons—with R^2 values exceeding 0.81—the transitional season from July to October showed much lower accuracy, R^2 ranging from 0.41 to 0.73. This seasonal decline in accuracy is likely due to environmental factors, such as increased sea surface roughness (during periods of high wind) and cloud cover during the transitional season, which can interfere with satellite readings (Benas et al., 2020; Zhang et al., 2018). A cool temperature bias in satellite measurements has been noted when wind speeds exceed 12 m/s (Gentemann & Wentz, 2001; Meissner & Wentz, 2009). However, since wind speeds at all sites in this study remained below 8 m/s, wind speed may not be the primary factor affecting satellite accuracy in this study.

The presence of higher cloud fractions during the transitional season likely contributed to the reduced accuracy of SST measurements. The period of July to October exhibited the highest cloud fraction across all sites. Conversely, the November to February (NE monsoon) exhibited the lowest cloud fraction in the ECPM, while the March to June (SW monsoon) had the lowest in the WCEM. A successful, long-term strategy for coral reef conservation relies on the continuous monitoring of global reefs and changes in oceanic conditions, with satellites playing a important role in this monitoring. During the transitional season which has the less reliable satellite-derived measurements, management strategies should prioritize *in-situ* monitoring to complement satellite data. Future studies should explore the combined effects of these factors to develop greater understanding of temporal variability in satellite accuracy under different environmental conditions, hence enhancing environmental monitoring and management practices.

3.5.3 Reef Resilience Scores

The change in R^2 from 0.14 to 0.11 when reducing the number of data points from 139 bleaching observations selected based on their proximity to peak DHW to surveys overlapping with 2011 Resilience Report locations suggests that the overall relationship between satellite-derived DHW and observed coral bleaching is weak. However, the consistent trend in both cases indicates that temperature alone does not account for the severity of coral bleaching observed in Malaysian coral reefs and that resilience factors influence bleaching across a range of heat stress levels. Reefs with lower resilience exhibited higher percentage of bleached coral colonies even under low heat stress conditions, whereas medium-high resilient sites demonstrated lower coral bleaching percentage even when exposed to higher levels of heat stress (Figure 3.8). Reefs with lower resilience were associated with higher levels of development; e.g., in Pulau Tioman, the western reefs, which experience higher levels of development and tourism (Omar et al., 2016; Zeighami, 2019), showed a decline in resilience from 2011 to 2021. Consequently, the less-visited eastern and northern reefs, which are characterized by minimal diving and snorkeling activities (Omar et al., 2016; Salleh et al., 2012; Zeighami, 2019), exhibited higher resilience scores in the results. Similarly, western reefs in Pulau Redang where development and tourist activities are concentrated on the west coast, also exhibit low resilience (Razak et al., 2024).

The incorporation of resilience scores for coral reef sites explains, at least in part, the weak positive correlation of satellite predictions with observed bleaching, particularly in sites with lower resilience scores. Coral resilience has been linked to 61 resilience variables (Obura & Grimsditch, 2009), 11 of which were identified as particularly significant for effective coral reef management (McClanahan et al., 2012). Increased environmental stressor levels, such as tourism and pollutants, result in lower coral resilience scores, rendering corals more susceptible to bleaching (Carilli et al., 2009; Montefalcone et al., 2020; Page et al., 2023; Raj et al., 2021). Consequently, in this study higher bleaching percentage of bleached coral colonies were observed in reefs with lower resilience scores despite the low heat stress conditions. These findings are consistent with previous studies in which tourist activities contributed to increased coral disease and coral competitors such as algae and sponges (Akmal & Shahbudin, 2020; El-Naggar, 2020; Lamb et al., 2014).

An additional factor contributing to low bleaching percentages despite high DHW values could be prior severe bleaching events that significantly reduced coral cover, leaving fewer susceptible corals with different morphologies. Coral morphology influences their susceptibility to environmental stress, with fast-growing branching corals being more vulnerable to wave action and heat stress, whereas slower-growing massive corals exhibit greater resilience (Fisher, 2022; Hanapiah et al., 2019; Thomson et al., 2020). Field observations and further investigations would be needed to confirm this.

3.5.4 Clustering Malaysian Islands

The clustering approach used in this study organized 31 islands into 12 distinct clusters, proves effective when compared with existing research. This consistency reinforces the presence of closely related physical properties among islands within the same cluster, highlighting the unique environmental conditions that each cluster experiences. As discussed in Chapter 1.5, Malaysia's four coastlines, each with distinct local threats, exhibit diverse coral reef compositions and varying ocean physical properties. These coastlines are also exposed to different developmental levels. For instance, sedimentation has emerged as a major issue impacting the WCPM corals (Mubin et al., 2023; Thia-Eng et al., 2000), while theNE monsoon season and tourism affect corals in the ECPM. Overfishing and fishing methods are major issues in the northern part of WCEM and ECEM corals (Asian Development Bank, 2014;

Burke et al., 2011; Praveena et al., 2012; Safuan et al., 2020; Thia-Eng et al., 2000; Zakariah et al., 2007), and high sedimentation rates in southern part of WCEM (Burke et al., 2011). These clusters provide a clearer understanding of how different group of islands may respond to environmental stressors, which caninform and guided targeted conservation strategies tailored to the unique conditions and threats faced by each cluster.

Previous studies have also described variable thermocline patterns across the northern, central, and southern regions of ECPM, with thermocline depth increasing from north to south (Akhir et al., 2011; Akhir et al., 2014; Saadon et al., 1999). This spatial pattern coincides with decreasing temperatures southwards along the coast (Daryabor et al., 2015; Roseli & Akhir, 2014). Wind patterns differ between the west and east coasts of East Malaysia, with WCEM experiencing higher wind speeds and, consequently, higher wave heights than ECEM (Saleh et al., 2010).

3.5.5 Enhancing Coral Management through Cluster-based Approaches

The cluster-based approach used in this study provides a new perspective on coral reef management in Malaysia by recognizing the interconnectedness of islands that share similar physical properties. By grouping islands with similar physical conditions, this approach enables a more targeted and adaptive management strategy at both the cluster and intra-cluster levels. Within each cluster, islands share key environmental characteristics, suggesting that management strategies can be adapted to regional oceanographic conditions rather than treating each island independently. However, despite these shared properties, resilience scores vary among reefs within the same cluster, indicating that local factors further influence reef vulnerability. This suggests that while general management strategies can be applied at the cluster level, localized approaches within each cluster remain essential. The application of a cluster-based approach can also enhance the accuracy of coral bleaching predictions by incorporating SST trends and resilience scores, allowing for more precise early-warning systems and preparedness measures for impending thermal stress events.

Existing marine spatial planning (MSP) initiatives in Malaysia have already emphasized the need for systematic management, particularly in the zoning of marine protected areas (MPAs) (Islam et al., 2017; Safuan et al., 2021; Safuan et al., 2022). For instance, research at Tioman

Island Marine Park proposed conservation zones based on reef health assessments (Lau et al., 2019), while the Tun Mustapha Park in Sabah used systematic planning tools to establish conservation and fishing zones aligned with socio-economic objectives (Jumin et al., 2018). These studies demonstrate the feasibility of spatially structured conservation planning, yet they have not explicitly incorporated environmental clustering in their frameworks. Integrating the findings of this study with MSP approaches could refine zoning strategies by accounting for environmental similarities and variations across different reef areas.

Moreover, co-management frameworks, involving government agencies, local communities, and private entities, have been emphasized for effective coral conservation in Malaysia (Bailey et al., 2023; Ban et al., 2011; Bang et al., 2021; Cinner et al., 2012; Rahman et al., 2019). By applying the cluster-based approach, conservation initiatives can be customized to the specific environmental conditions of each region while ensuring stakeholder engagement in the decision-making process.

3.6 Conclusion

Effective coral reef management in Malaysia requires a multi-faceted approach that considers physical and biological factors. This study has analyzed seasonal patterns of sea surface temperature (SST), cloud fraction, wind speed, and turbidity across four focal islands, revealing that the ocean physical properties of Malaysia's coral reefs can be categorized into three distinct seasons. The reliability of satellite data during NE and SW monsoon seasons is higher than the transitional season, while incorporating reef resilience scores into coral bleaching predictions provides insights into the vulnerability of coral sites, emphasizing factors beyond heat stress alone. The three distinct seasons of physical variations, and the clustering of islands based on temperature patterns offers a systematic framework for understanding regional variations and guiding conservation efforts. By recognizing the environmental dynamics affecting each cluster, management strategies can be adjusted to enhance coral resilience.

Overall, this study contributes to advancing coral reef management in Malaysia through analysis of satellite data, reef resilience, and physical properties. Through future efforts to connect scientific insights with practical management strategies, Malaysia can enhance the resilience of its coral reefs in the face of ongoing environmental pressures and protect these ecosystems for future generations.

Chapter 4: General Discussion

4.1 Summary Outcomes

The strong correlation (R-squared ranging from 0.92 to 0.94) between satellite-derived SST and *in-situ* temperature measurements, with differences within 1°C across diverse survey sites, demonstrates the reliability of satellite observations in capturing SST data over Malaysian coral reef sites. This provides a dependable tool for monitoring thermal stress over extended periods. Despite minor biases in specific locations, the overall alignment between satellite and *in-situ* data validates the use of satellite SST for long-term studies, supporting its role in predicting environmental conditions that may lead to coral stress events.

The moderate accuracy of satellite-derived Degree Heating Week (DHW) predictions in Malaysia included some observations of high coral bleaching prevalence at lower DHW levels and low coral bleaching at higher DHW levels (2015 to 2017). This suggests the utility of incorporating benthic characteristics and other factors (beyond heat exposure) into effective coral reef management.

Malaysian SST seasonal patterns are characterized by temperature variations between monsoon periods, which are highlighted by patterns in rainfall, wind speed, and cloud cover (Chenoli et al., 2018; Mubarak et al., 2022; Sun et al., 2020; Wong et al., 2016). The three distinct seasons—Northeast (NE) Monsoon, Southwest Monsoon (SW), and Transitional Season—affect coral resilience in different ways. During the NE monsoon, high winds and turbidity from nutrient runoff and strong currents increase stress on coral reefs (Fabricius et al., 2008; Hernández-Delgado et al., 2024; Safuan et al., 2020) but help reduce bleaching risks due to lower temperatures (Lucas et al., 2023; Rosedy et al., 2023; Sully & Woesik, 2020), while the SW monsoon brings elevated SSTs and reduced turbidity and raising bleaching risks (Carlson et al., 2022; Lucas et al., 2023; Szereday & Affendi Yang, 2022). Meanwhile, the Transitional Season presents difficulties for satellite-derived measurements due to high cloud cover, suggesting a greater reliance on *in-situ* monitoring to support effective reef management.

Integrating reef resilience scores into predictive models – or into the interpretation of existing monitoring tools – form potential strategies to improve the sensitivity and accuracy of coral bleaching predictions. Sites with low resilience scores demonstrated high coral bleaching percentage even under lower DHW thresholds, highlighting the influence of resilience on how Malaysian corals respond to thermal stress. Updated assessments found improvements in resilience scores at Marine Park Pulau Tioman, while scores remained stable or declined at Marine Park Pulau Redang and Marine Park Pulau Sibu-Tinggi.

The cluster analysis grouped 31 Malaysian islands into distinct clusters based on temperature variability, clarifying on the SST, cloud fraction, wind speed, and turbidity across seasons. The analysis revealed that different clusters experience varying conditions. Some clusters have wider SST fluctuations, suggesting they may face higher risks of thermal stress, while others, with weaker wind speed and turbidity compared to other clusters, may have a higher potential for supporting coral growth. These clusters offer a foundation for future research into physical and environmental factors affecting coral reef health, and will inform more localized and effective reef management strategies.

4.2 Recommendations and Future Research

Further research is needed to explore the depth of the thermocline in East Malaysia (EM) during both monsoon and transitional seasons. While previous studies, including this study, have confirmed the shallower thermocline in the upper ECPM compared to the lower ECPM, there remains a gap in understanding thermocline dynamics in EM. Temperature sensors used in this study, deployed at 6 m depth, provide limited insight into thermocline behaviour, thus necessitating research extending to at least 35m depths in EM to better understand thermocline patterns in the region.

Expanding the scope of resilience surveys beyond the four islands of ECPM in this study is recommended to better understand and evaluate coral reef resilience scores across Malaysia. By conducting more resilience surveys, coral reef management efforts can be tailored to focus on areas with lower resilience scores, such as through facilitating the establishment of protected zones based on resilience assessments. Future research should also emphasize long-term monitoring of reef resilience over multiple periods, allowing for a deeper understanding of how coral ecosystems recover from bleaching events and the factors that affect long-term resilience.

High-risk areas with low resilience scores, in particular, should be monitored more intensively, as they are more prone to severe bleaching during environmental stress events.

Expanding the cluster analysis to other Malaysian reefs, or even reefs across Southeast Asia, could provide valuable insights for region-wide coral reef management. By comparing resilience scores and environmental conditions across a broader geographic area, reef managers can better coordinate conservation efforts and share effective strategies for mitigating bleaching risks.

The calculation of DHW thresholds in this study presents an opportunity for future research to refine predictive models for coral bleaching events in Malaysia. While the employed HotSpot threshold of MMM + 1°C and an accumulation window of 12 weeks showed moderate accuracy rates, alternative DHW thresholds (e.g., MMM + 0°C, noting the small annual temperature range and past usage of this threshold (Guest et al., 2012) and accumulation windows (e.g., 8-weeks or less (Lachs et al., 2021) warrant investigation. Such adjustments may enhance the accuracy of satellite predictions of coral bleaching events, thereby informing more effective coral management strategies in Malaysia. Incorporating frequent field observations will provide more accurate, real-time data that can enhance satellite predictions and inform targeted management strategies. Additionally, future research should consider incorporating environmental factors specific to Malaysia (such as wind speed and turbidity level) to further improve predictive models. Some of these factors varies dramatically between seasons and could provide a more comprehensive understanding of the factors leading to bleaching events.

Given the findings on seasonal variability and environmental factors, future management strategies should account for these patterns. Different management interventions should be applied during different seasons. For example, during the transitional season with high cloud cover—when satellite data is less reliable—*in-situ* monitoring should be prioritized to compensate for reduced satellite accuracy. Continuous monitoring of SST, turbidity, and other environmental factors is also recommended.

In addition to monitoring, stronger regulations on human activities, particularly tourism, should be considered in areas with low reef resilience. These sites have shown higher susceptibility to bleaching and may benefit from limiting tourist access during vulnerable periods, such as peak seasons. Limiting tourist activities, particularly during peak tourist seasons, could help reduce stress on already vulnerable ecosystems.

4.3 Conclusion

This thesis set out to address the need for improving the accuracy of coral bleaching predictions in Malaysia by integrating satellite-derived sea surface temperature (SST) data, resilience assessments, and an understanding of seasonal variability. The overarching goal was to provide more accurate tools for predicting bleaching events and supporting reef management. Through the analysis of satellite-derived dataset reliability, the incorporation of coral resilience factors, and the identification of seasonal patterns, this research provides a clearer understanding of the factors affecting the health of Malaysian coral reefs.

The findings confirm the reliability of satellite-derived SST data over extended periods, yet highlight the limitations of such data during the transitional season, when high cloud cover interferes with satellite measurements. Furthermore, the research demonstrates that while satellite-based Degree Heating Week (DHW) thresholds can predict bleaching with moderate accuracy, integrating additional factors such as reef resilience and local environmental factors enhances predictive accuracy. By combining physical properties by season with site-specific resilience scores, the study provides a more detailed understanding of bleaching risks across different reef systems in Malaysia.

Overall, this thesis contributes to both scientific knowledge and conservation practice. It underscores the value of combining satellite data with local resilience assessments to improve predictions of coral bleaching. While recognizing the limitations of satellite predictions, the research shows that the inclusion of resilience scores and seasonal variability helps to create more accurate, region-specific forecasts. For practical conservation efforts, the outcomes of this study provides useful recommendations for focusing management interventions on vulnerable sites, especially those with low resilience or exposure to stressors like tourism and pollution.

Looking forward, it is essential that continued research builds upon these findings, incorporating even more detailed local data and exploring new technologies for real-time monitoring of reef health. Equally important is the need for adaptive management strategies that can respond to the dynamic nature of reef ecosystems. As climate change progresses, proactive, evidence-based management of reefs becomes increasingly important. By addressing both the scientific and practical aspects of coral conservation, this research provides a foundation for more effective protection of Malaysia’s reefs and coral ecosystems worldwide.

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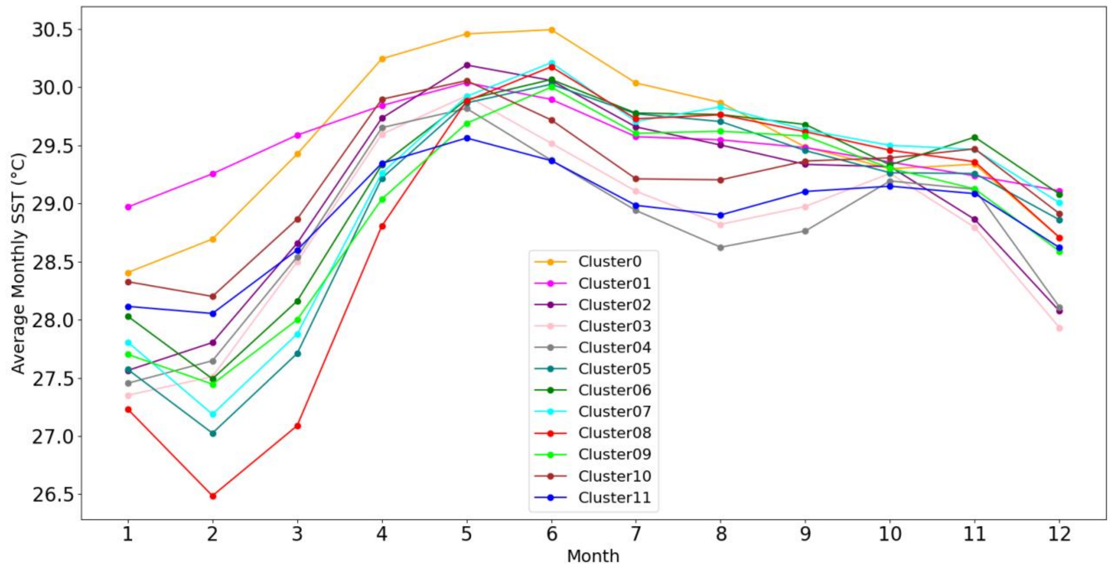
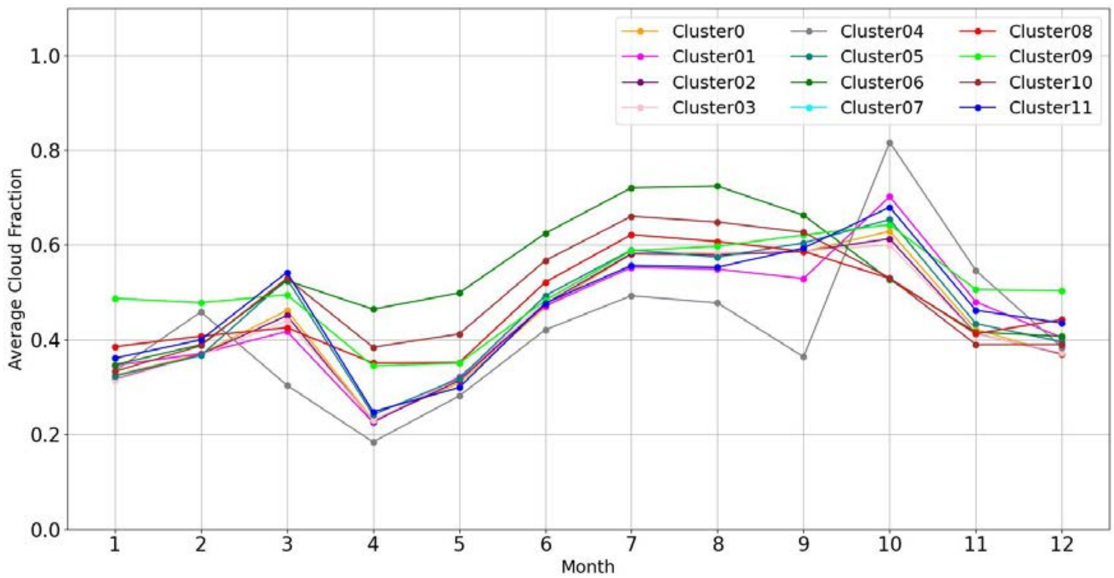
Appendix

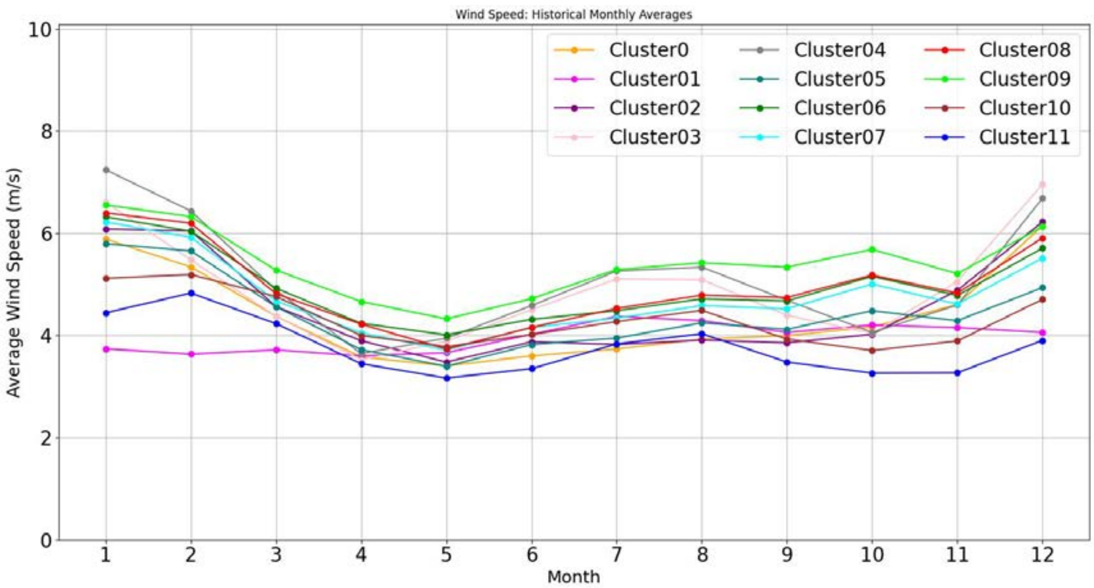
(A) SST



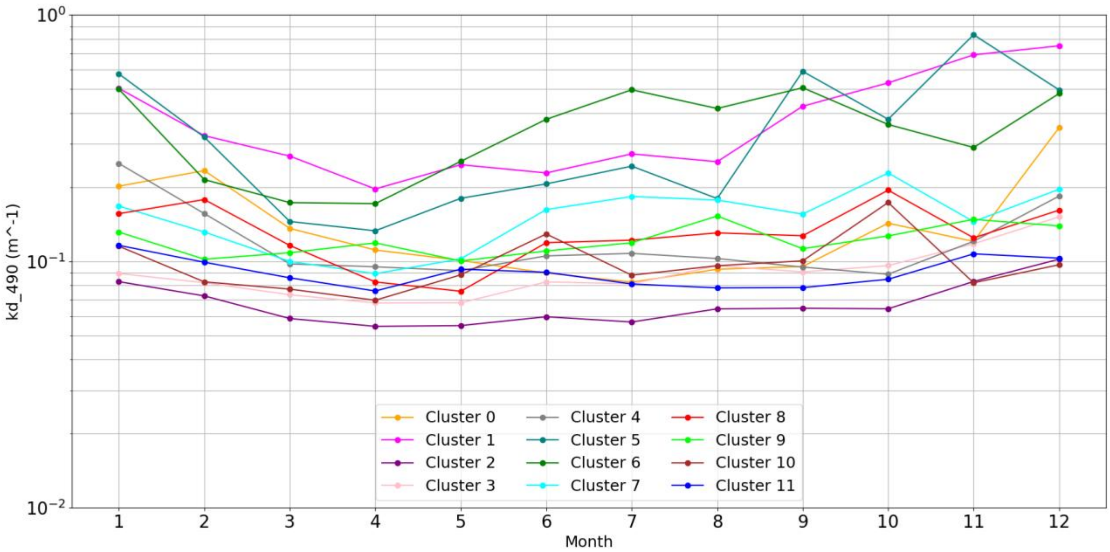
(B) Cloud Fraction



(C) Wind Speed



(A) Turbidity Level



Appendix 1. Seasonal time series of Monthly Mean (MM) satellite-derived physical properties across 12 clusters. (A) SST; (B) Cloud Fraction; (C) Wind Speed; (D) Turbidity Level.

Appendix 2:.

Seasonal Patterns of Satellite-Derived Physical Properties (Cloud Cover, Wind Speed, Turbidity, and SST) Across 12 Clusters.

Cluster	Nov to Mar				Mar to Jul				July to Nov			
	SST	Cloud Fraction	Wind Speed	Turbidity	SST	Cloud Fraction	Wind Speed	Turbidity	SST	Cloud Fraction	Wind Speed	Turbidity
0	28.91 ± 0.44	0.39 ± 0.05	5.27 ± 0.77	0.21 ± 0.09	30.13 ± 0.44	0.41 ± 0.14	3.74 ± 0.38	0.10 ± 0.02	29.61 ± 0.33	0.56 ± 0.08	4.09 ± 0.33	0.11 ± 0.02
1	29.23 ± 0.23	0.40 ± 0.05	3.86 ± 0.23	0.51 ± 0.21	29.79 ± 0.20	0.40 ± 0.13	3.87 ± 0.32	0.24 ± 0.03	29.44 ± 0.14	0.56 ± 0.08	4.21 ± 0.12	0.43 ± 0.18
2	28.19 ± 0.55	0.41 ± 0.10	5.56 ± 0.78	0.08 ± 0.02	29.66 ± 0.60	0.41 ± 0.14	3.93 ± 0.39	0.06 ± 0.00	29.34 ± 0.30	0.55 ± 0.08	4.10 ± 0.44	0.07 ± 0.01
3	28.02 ± 0.62	0.38 ± 0.05	5.70 ± 1.07	0.10 ± 0.03	29.33 ± 0.55	0.41 ± 0.14	4.28 ± 0.60	0.07 ± 0.01	28.99 ± 0.20	0.55 ± 0.08	4.74 ± 0.49	0.10 ± 0.01
4	28.17 ± 0.68	0.41 ± 0.10	5.97 ± 1.16	0.16 ± 0.06	29.26 ± 0.52	0.34 ± 0.12	4.46 ± 0.67	0.10 ± 0.01	28.93 ± 0.24	0.54 ± 0.17	4.79 ± 0.52	0.10 ± 0.01
5	28.09 ± 0.94	0.41 ± 0.08	5.05 ± 0.66	0.47 ± 0.26	29.32 ± 0.95	0.43 ± 0.15	3.89 ± 0.43	0.18 ± 0.05	29.49 ± 0.24	0.57 ± 0.08	4.22 ± 0.20	0.44 ± 0.27
6	28.47 ± 0.84	0.42 ± 0.07	5.55 ± 0.68	0.33 ± 0.15	29.45 ± 0.77	0.57 ± 0.10	4.39 ± 0.34	0.29 ± 0.14	29.63 ± 0.18	0.61 ± 0.13	4.76 ± 0.24	0.41 ± 0.09
7	28.27 ± 0.94	0.41 ± 0.02	5.39 ± 0.73	0.15 ± 0.04	29.40 ± 0.92	0.45 ± 0.12	4.18 ± 0.36	0.13 ± 0.04	29.63 ± 0.15	0.55 ± 0.09	4.61 ± 0.24	0.18 ± 0.03
8	27.77 ± 1.21	0.41 ± 0.02	5.63 ± 0.76	0.15 ± 0.03	29.14 ± 1.25	0.45 ± 0.12	4.29 ± 0.41	0.10 ± 0.02	29.59 ± 0.17	0.55 ± 0.09	4.81 ± 0.24	0.14 ± 0.03
9	28.17 ± 0.68	0.49 ± 0.01	5.90 ± 0.61	0.13 ± 0.02	29.27 ± 0.79	0.45 ± 0.10	4.85 ± 0.42	0.11 ± 0.01	29.45 ± 0.22	0.59 ± 0.05	5.39 ± 0.18	0.13 ± 0.02
10	28.76 ± 0.51	0.41 ± 0.07	4.73 ± 0.52	0.09 ± 0.02	29.55 ± 0.50	0.51 ± 0.11	4.17 ± 0.37	0.09 ± 0.02	29.33 ± 0.12	0.57 ± 0.11	4.06 ± 0.32	0.11 ± 0.04
11	28.50 ± 0.42	0.44 ± 0.07	4.13 ± 0.59	0.10 ± 0.01	29.17 ± 0.38	0.42 ± 0.14	3.61 ± 0.42	0.09 ± 0.01	29.04 ± 0.10	0.57 ± 0.08	3.57 ± 0.34	0.09 ± 0.01

Appendix 3:

Coral Bleaching Observations and Resilience Scores at Study Sites (2015-2017)

Island	Survey Sites	Bleaching Colony Percentage (%)	DHW Value	Resillience Score
Redang	Terumbu Kili	0.00	1.06	48.5
	Terumbu Kili	0.00	1.06	48.5
	Pasir Akar	0.99	1.06	47
	Pasir Akar	0.99	1.06	47
	Pulau Kerangga Besar	4.99	0.00	55.5
	Paku Besar	0.00	0.17	47
	Paku Besar	0.00	1.10	47
Tioman	Labas	0.00	0.00	37.5
Tioman	Chebeh	0.00	0.00	49
	Chebeh	0.00	0.00	49

	Pulau Renggis	0.00	0.00	56.5
	Pulau Renggis	0.00	0.00	56.5
	Pulau Renggis	0.00	0.00	56.5
	Pulau Renggis	16.00	5.06	56.5
	Pulau Soyak	0.00	0.00	52.5
	Pulau Soyak	8.00	4.93	52.5
	Tekek House Reef	0.00	0.00	23
	Tekek House Reef	0.00	0.00	23
	Tekek House Reef	20.00	3.08	23
	Tekek House Reef	20.00	3.08	23
	Pirate Reef	0.00	0.00	46
	Pirate Reef	2.00	0.33	46
	Pirate Reef	5.00	0.00	46
	Pirate Reef	18.00	4.69	46
Tinggi	Sibu Kukus	80.00	0.00	25.5
	Mentinggi	0.00	0.00	42
	Mentinggi	4.00	0.00	42
	Mentinggi	31.00	4.74	42
	Nanga Besar	3.00	0.00	50.5
	Ibol	0.00	0.00	53
	Ibol	0.00	0.00	53
	Ibol	0.00	0.00	53
	Ibol	0.00	0.00	53