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A GIS-based modelling approach to identify natural drivers of coral reef abundance in the Northern Myeik Archipelago, Myanmar

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Cover image: Hard coral structures in the Myeik Archipelago.

Credit: Michelangelo Pignani - FFI (Howard, 2018).

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List of Abbreviations

ANN	Artificial neural networks
Arc GIS Pro	Latest professional desktop GIS application from Esri
BOBLME	Bay of Bengal Large Marine Ecosystem Project
BP	Koenker studentized Breusch Pagan
CART	Classification And Regression Trees
ESRI	Environmental Systems Research Institute
FAO	The Food and Agriculture Organization of the United Nations
FFI	Fauna and Flora International
FNU	Formazin Nephelometric Unit
GAM	Generalized Additive Modeling
GIS	Geographic Information System
GLM	Generalized Linear Models
GWR	Geographically Weighted Regression
LMMA	Locally Managed Marine Area
LMM	Linear Mixed Model
MARS	Multivariate Adaptive Regression Splines
MAXENT	Maximum Entropy
MNP	Marine National Park
MODIS	MODerate Resolution Imaging Spectroradiometer
MPA	Marine Protected Areas
OLS	Ordinary Least Squares
QQ Plots	Quantile-Quantile (q-q) plot
Random Forest	Data-driven forest classification
RSF	Resource Selection Function

SCUBA	Self-Contained Underwater Breathing Apparatus
SDM	Species Distribution Modelling
SeaWiFS	Sea-viewing Wide Field-of-view Sensor
SST	Sea Surface Temperatures
UNESCO	United Nations Educational, Scientific and Cultural Organization
UTM	Universal Transverse Mercator
VIF	Variance Inflation Factor
VME	Vulnerable Marine Ecosystems
WCS	Wildlife Conservation Society

Abstract

To predict the coral abundance of the Northern of Myeik, I compared various progressions of model techniques, including stepwise regression (using OLS), GWR, and Random forest analysis methods, to investigate relationships between coral abundance survey data and environmental variables such as depth, slope, aspect, rugosity, chlorophyll, sea surface temperature, and turbidity. Depth and SST have the most significant effect on predicted coral species abundance. Increased reef abundance was associated with a reduction in sea surface temperature stability and shallower optimum depths. Even then, GWR outperformed the other studied approaches in places with a substantial degree of input-output disagreement. The GWR model production was used to produce a final predicted coral abundance modelling map. The accuracy of the GWR model was determined by using Random forest predict modelling to map and comparing the higher R^2 and predicted and observation graphs to the slope and interest value of each model. This sampling tool for a reef prediction model can be used in preference of potential species abundance modelling (e.g., seagrass, mangrove) in future Myanmar coastal management projects, resulting in more accurate predictions and more educated species management decisions. It can assist the Department of Fisheries in making fisheries management decisions and help to keep fish stocks stable in the long run by fostering a greater understanding of key environmental variables.

1 Introduction

Coral reefs are highly beneficial and rich biodiversity ecosystems found around the globe. They provide shelter for many aquatic organisms up on the food chain, act as a barrier to the coastline, and help to keep sandy beaches stable (Chabanet et al., 2005). Likewise, coral reefs are critical for biodiversity because they provide habitat for 35,000–60,000 plant and animal species (more than a quarter of all aquatic life worldwide)(El-Naggar, 2020). Corals act as nursery grounds and shelters for many natural damages for many marine species (Ko et al., 2019). Coral covering and terrain complexity of the coral habitat have an important good impact on fish abundance. They support more affluent and fishing communities with subsistence, commercial fisheries, and source of medicines (Chabanet et al., 2005). As a result, they provide ecosystem products and services to humans, such as cultural ecosystem services, seafood, touristic opportunities, stability of the coastal, appealing and (Moberg & Folke, 1999a).

Global reefs have been attacked by combined natural and anthropogenic drivers such as global climate change, hurricanes, increased human activities, eutrophication, and coral diseases (Meer et al., 2015). Increased seawater temperature has a detrimental effect on aquatic ecosystems and alters their biological processes. This impact results in the development of harmful algae, creating a layer on the water’s surface and obstructing sunlight's passage (Mansour, 2020). Because of the susceptibility and vulnerability of these ecosystems to stressful conditions, increased sea surface temperatures (SST), ultraviolet radiation, eutrophication, salinity, sedimentation, and thermal emissions in marine habitats cause coral reef habitats to deteriorate (ibid.). High marine water temperatures cause mass bleaching of coral reefs (Brown, 1997), while ocean acidification hinders the calcifying abilities of corals (Hoegh-Guldberg et al., 2007).

Nonetheless, a significant amount of non-climate related threats that harm coral reefs are caused by humans’ activities. Activities such as overuse of reef resources, climate change, illegal fishing, oceanic acidification, global warming, overcrowding from tourism, overfishing, fishing with explosives, and water pollution may damage reefs by encouraging algal overgrowth (Halpern et al., 2008; Sadorus, 2014). Mansour (2020) also recognized anthropogenic activities such as urbanization, increased leisure activity, and overfishing are the significant causes of reef habitat degradation. Terrestrial runoff such as fertilizer and sewage input increases turbidity, leading to increased macroalgal cover (Bell, 1992; Coles SL, 2003;

Halpern et al., 2008; Hoegh-Guldberg et al., 2007). Moreover, increased anthropogenic threats and their interactions with natural stressors are believed to trigger reef diseases and bleaching, resulting in coral cover loss (Mona et al., 2019). Hence, there is a need to assess these threats and seek to eliminate or reduce their effects by using effective methods and different tools to protect coral reef ecosystems.

Coastal and marine ecosystems are essential for the developing economies of the Myanmar people. Myanmar has diverse habitats that support endemism and high species diversity (Mandle et al., 2017). More than 90% of the human populations depends on coral fish. A more significant number of fishing households settlements live within 30 kilometers of coral reefs in Myanmar and depend considerably on them for revenue, tourism, stability of the coastal environment, employment, and cultural significance (Burke et al., 2011a; Howard, 2018).

However, Myanmar reportedly has few measures in place to protect coral reefs (Howard, 2018). Because of historical and political insecurity, proper conservation of the marine environment has been lacking for an extended period (Jones, 2018). Latest surveys on coral reefs and demersal stocks in Myanmar have shown a dramatic reduction in species diversity in Myanmar (Howard, 2018; Jens-Otto Krakstad, Bjørn Krafft, 2016). The range of fishing activities close to islands is extensive (Saw Han Shein, 2013), and evidence of overfishing and destructive fishing is observed underwater (Howard, 2018). Especially near the inner islands of the archipelago, where subsistence fishing is common. Trawling is the dominant fishing activity in the archipelago on the extensive shallow platforms (40-70 m deep) between the islands (Obura et al., 2014). There has been an overall scarcity of fish, a heavy density of sea urchins, and coral entanglement, indicating a high level of fishing pressure (ibid.).

Additionally, coral reefs in the Myeik Archipelago are under pressure from growing unlawful human activity (Anelli et al., 2019; Sarginson, 2019), pollution, and nutrient additions (Howard, 2018). There is an immediate need to minimize these risks while increasing protecting areas of high ecological importance. Coral reefs continue to face threats, and because they are very patchy, it is difficult to identify a point of impact for reef protection (True, 2015). Marine protected areas (MPA) also emerged as an effective management measure for the protection of coral reefs from all human-related threats and from the effects of climate change (Bridge et al., 2012a). Data on the geographic distribution of vulnerable marine species is necessary to establish suitable marine nature reserves (Sundahl et al., 2020). However, there have been very few studies in Myanmar to map and model coral abundance to inform decisions. There has been very little information about coral reef abundance and changing patterns of environmental factors due to the constraints of technical and financial capacities (Rao et al., 2013b). There is a consensus among scholars that relatively little is understood regarding the abundance and distribution of coral reefs in Myanmar since direct observations are difficult and often expensive to reveal the spatial distribution and geographic location of coral reefs (El-Naggar, 2020, Bridge et al., 2012a).

Though preservation efforts have increased over the decades, the usable information is limited, and mapping the spatial abundance of coral is logistically demanding and costly. There are technical and financial challenges to using expensive video-based surveys, a widely used method in developed countries to map the abundance of coral reefs. The species distribution and abundance model has been wildly applied in marine ecology to better of a species' interaction with its biotic and abiotic atmosphere by studies for biogeographical and ecological theories regarding species occurrence (Franklin, 2010). Different methods based on species distribution models have been widely used in many ecosystems (Elith & Graham, 2009). They have been applied to make habitat distribution and biological functional classes (Garza-Pérez et al., 2004) and coral reef community metrics (Harborne, 2006). SDMs are useful instruments for investigating a wide variety of aquatic ecological and biogeographical issues using readily accessible data, to map and generate the knowledge about the distribution of coral reefs, and thus to identify priority sites for management, conserve and prevent many threats (Davies & Guinotte, 2011; Hill et al., 2014; Sundahl et al., 2020).This thesis aims to determine and map the abundance of coral reefs in the Myeik Archipelago, Myanmar, using a simple species abundance model based on readily available data.

Predictive modelling relies on capturing the relationship between explanatory variables and the predicted variables from part occurrence and exploiting this relationship to predict future outcomes (Frees et al., 2014). Environmental and physical drivers of species richness are often used as proxies to predict the future abundance of benthic marine habitats across vast spatial scales and prioritize management sites (Bridge et al., 2012b). Numerous studies have proven that a variety of environmental factors that effect on coral reef species abundance. Some of these factors include, depth (Costa et al., 2015), sea surface temperature (Alexander, 2016; Franklin et al., 2013a; McClanahan et al., 2019; Veazey et al., 2016), slope (Costa et al., 2015; Huff et al., 2013; Miles, 2018), water current (Sundahl et al., 2020), salinity (Guinotte et al., 2003; Huff et al., 2013), chlorophyll (Hill et al., 2014), turbidity (Maina et al., 2008), distance from the shoreline (Costa et al., 2015), substrate, and food availability (Bryan & Metaxas, 2006; Davies & Guinotte, 2011; Sundahl et al., 2020). Similarly, other factors that determine the abundance pattern of coral species are light and water clarity (Holmes & Subedee, 2014).

This study examines both geophysical (depth, slope, aspect, rugosity) and environmental variables (e.g., chlorophyll, turbidity, sea surface temperature) that significantly influence coral reefs abundance to identify and predict coral abundance location. Developing a simple and good predictive model using widely and freely available data might serve as a good place to start learning about processes and spatial patterns and generate knowledge about the abundance of coral habits without expensive field surveys. This study explores, influence of readily available geophysical variables on depth, slope, aspect, rugosity, and environmental variables, such as Chlorophyll, sea surface temperature (SST) and turbidity on coral reefs abundance.

Objectives

The study aims to develop a simple predictive model for coral reef abundance in Myeik Archipelago in Myanmar using openly and readily available remote sensing products and GIS layers. It has been achieved through the following twofold specific objectives:

- To identify environmental and physical factors that determine coral reef abundance in Myeik Archipelago, Myanmar.
- To develop a simple methodology for predicting coral reef abundance in Myanmar and data poor regions using openly available and accessible spatial data.

2 Literature Review and Conceptual Framework

This chapter summarizes relevant literature and establishes the study's methodological and analytical foundations.

2.1 The importance of coral reefs

Coral reefs are home to most of the world's biodiversity (Connell 1978; Moberg & Folke 1999; Odum & Odum 1955). The most diverse collection of marine life is discovered in the coral reefs (Turner et al., 2009). Many organisms would perish if the reef did not exist (Miller 1995, Turner et al. 2009). They produce more living biomass in a tiny region than any other marine ecosystem (Rao et al., 2013a). For example, fishes and most species depend on vital resources from the coral reef habitat, e.g., food, nursery (Moberg & Folke, 1999b) marine shelter (Anelli et al., 2019) and survival and reproductive requirements (Jones & Syms, 1998; Wilson et al., 2006). Similarly, many reef species' pelagic juvenile stages that migrate into these nearby habitats serve as food sources for commercially valuable fish, or they may live and mature until they are harvested (Moberg & Folke, 1999b). Coral reef habitats also provide live resources to humans, e.g., fish, shellfish, and algae (Moberg & Folke, 1999b) and services, e.g., tourism and coastal protection (Bridge et al., 2012a) as well as shore protection against a waves and storms (Moberg & Folke, 1999b; Turner et al., 2009) and supply essential drugs such as anti-cancer and ultraviolet-blocking compounds (Odum & Odum 1955, Turner et al. 2009).

Coral reefs are essential for the food and livelihoods of local human communities in island nations (Burke et al., 2011; Moberg & Folke 1999; Sarginson, 2019). For example, it is reported that overexploitation and deforestation have resulted in the destruction of at least 100,000 local fishermen jobs in the Philippine Islands (Moberg & Folke, 1999b). Coral reefs are valuable ecosystems for a diverse range of organisms and offer critical ecological services to thousands of families (Burke et al., 2011b). Thus, coral reefs are the most important aquatic environment for their tremendous ecological diversity, ecosystem resources, and economic sectors (Bryant,1998).

2.2 Coral reef in Myanmar

The Indian Ocean has the world's second-largest coral reef biodiversity (Siringoringo et al., 2019). The Andaman Sea has the most diverse reef biomass of any Indian Ocean area because of its similarities to the Reef Triangle that are found as fringing reefs, with a proclivity to rise faster on the eastern side islands (Sarginson, 2019). Southeast Asia's coral reefs represent

28% of the world's total active coral reef population that provide various essential ecosystem services to indigenous costal fisher communities (Brander et al., 2015; Burke et al., 2011a).

Coral reefs cover an area of roughly 600,00 square kilometers worldwide; more than 50% are located in the Indian Ocean (Myint, 2003). Since Myanmar is a tropical country situated in the southeastern hemisphere, it is home to a diverse range of coral ecosystems distributed along the country's coast (Myint, 2003). Myanmar's biodiversity is unique due to its varied habitats and ecosystems. (Rao et al., 2013b). The Myeik Archipelago (Figure 3.1) extends from Mali island to Kawthoung's Za Det Gyi island with its vast coral reefs and other differing aquatic resources (BOBLME, 2015). The Myeik Archipelago's southern waters, along the Tanintharyi coast, are densely populated by various coral species, consisting of hard and soft corals (Zöckler et al., 2013).

The FAO recorded that Myanmar's coastal regions annually catch over two million tons of marine fish, according to the CBI Market Intelligence Database (Anelli et al., 2019). More than 500 large numbers commercial fishing vessels are currently working in the Tanintharyi area, using unsustainable fishing gear and techniques, resulting in a dramatic reduction of fish stocks and the loss of coral reefs (BOBLME, 2015). Myanmar's coral reefs are still endangered by blast harvesting, a damaging and straightforward form of fishing that utilizes explosives to stun fish concentrated in coral reefs and, collaterally, blow up reef areas. In addition to killing a few target species, this strategy causes huge by-catches by killing all other creatures in the coral environment and destroying reef structures that could take years to recover, if at all (Holmes & Subedee, 2014). The Myanmar Fisheries Act (1990) legislation and fishing rights of international vessels (1984) expressly forbids explosives, damaging gears, harmful agents, toxic chemicals, and poison. However, difficulties in reaching remote fishing grounds, lack of proper logistical facilities, insufficient qualified human resources in addition to imperfections of governance are significant limitations for law enforcement and the efficient use of resources. More detail is also missing to analyze this environment correctly (Myint, 2003).

2.3 Threats to coral reefs

The total, about 58% of the global coral reefs are under immediate threat (Holmes & Subedee, 2014) and declining globally because of many challenges, including demographic growth in coastal areas, overfishing, soil erosion, climate change, and pollution caused by a watershed, or ocean pollution and destruction (Bridge et al., 2012a). Natural and anthropogenic factors at a broad and regional level endanger reefs worldwide (Turner et al., 2009). In several (not all) regions of the planet, long-term data suggest that the reef cover is declining (Bellwood et al., 2004; Gardner et al. 2003, Wilson et al., 2006). Nowadays, overfishing marine reefs or fish connected with reefs is a primary concern (Moberg & Folke, 1999b).

Coral reefs are affected by both environmental and anthropogenic stresses (Anelli et al., 2019). Sea Surface Temperature, tsunami, and years of El-Nino are the primary triggers of coral bleaching in the Andaman Sea (Sarginson, 2019). Natural hazards include reef bleaching due to rising sea surface temperatures (Bridge et al., 2012a), storms, cyclones, earthquakes, and disease outbreaks (Turner et al., 2009). Globally, the EI-Nino epidemic of 1997-98 resulted in excessively rising sea temperatures, resulting in coral bleaching and death (Turner et al., 2009). Increased temperatures may cause the symbiotic algae to die off (bleaching) and corals to die (Williams et al., 2010). Sea surface temperature effects may include reducing reef cover, a rise in algal cover, a decrease in species richness, and a decrease in fish biomass. Additionally, rising carbon dioxide (CO_2) emissions are gradually acidifying the world's oceans. Coral reefs are becoming more vulnerable to disruption or harm due to hurricanes, infestations, and pathogens resulting from global warming and acidification (Burke et al., 2011b).

Coral bleaching due to thermal stress has been observed on the outer islands and the hazard spread around the islands in Myanmar (Kleypas et al., 1999; Obura et al., 2014). Trawling is a typical fishing operation on shallow water areas (40-70 meters deep) in the archipelago's outer part (Obura et al., 2014). Overfishing and destructive fishing are seen underwater in Myanmar (Howard, 2018), especially in the seascape's inner islands, where subsistence fishing is widespread. Dynamite fishing and anchoring have long-term effects on corals (Sarginson, 2019). The increase of the sediment load correlated with humans from the transition to land or in particular the dredging of tropical and sub-tropical countries, as well as global climate change or the rise of sea surface temperatures, are one of the most urgent problems faced by the current coral reef (Dikou & Van Woesik, 2006). Myanmar's under-resourced government cannot control the threat of illegal and unregulated fishing (Howard, 2018), which is reflected a significant decrease in marine resources over the last three decades (BOBLME, 2015; Sarginson, 2019). Climate change will worsen established biodiversity problems in Myanmar by (a) indirect mechanisms such as human reliance on goods and services provided by marine ecosystems and (b) direct mechanisms such as the reduction of suitable ecosystem for species with reduced ecological resilience (Sarginson, 2019). Therefore, coral reefs need to recover from current damages and threats to be minimized so as to safeguard the abundant ecosystem services they provide (Burke et al., 2011b). The study aims to close this information gap by determining the location and abundance of coral reefs to protect them from threats in the Myeik Archipelago. Efficient knowledge of SDM mapping for coral protection would benefit fisheries managers, regulators, and development partners, who will use these models to recognize resources for reef protection, prioritize strategies, and prepare interventions.

2.4 Status and challenges of coral reef management in Myanmar

Myanmar's long coastline currently has just four marine protected areas, and the country cannot conserve and manage natural resources (Milano, 2011). This is due to insufficient environmental funding to adequately resolve the dangers posed to biodiversity by decades of economic and political sanctions (Rao et al., 2013a). In addition, there are no precise conservation mechanisms for coral reefs in Myanmar (Holmes & Subedee, 2014). Lunn (2015) reported that coral reef threats still remaining and that the reefs are highly patchy. Thus, identifying a target reef position in the face of numerous threats is not easy. Since there is currently a lack of investigative resources in the region to acquire sufficient data, Myanmar has urgently needed several researchers to fill the knowledge gap for coral reef protection and communication on marine priority issues (BOBLME, 2015; Holmes & Subedee, 2014).

In Myanmar marine species are at a hazard of habitat loss and over-exploitation in and outside protected areas (Rao et al., 2013b). While fishing within the limits of protected areas is forbidden, the subsistence and industrial fishermen are using various fishing gears for different target species including illicit activity of dynamite fishing (or blast fishing) prevalent in certain areas. Their devastating effects are evident on corals around Lampi island, the Marine National Park (MNP) in Myanmar and the protected area in the Myeik archipelago (Milano, 2011). Consequently, unregulated and illegal fishing activities and vessel anchoring pose significant challenges to the coral reef environment in the Myeik Archipelago due to relatively limited knowledge accessible on this region and has not been revised since 1995 (Milano, 2011). These challenges call for appropriate responses to deal with them. Mapping and modelling the spatial abundance of coral reefs could be the first step toward this goal.

2.5 Environmental and geophysical factors affecting the abundance of coral

Management priorities for benthic marine ecosystems in specific locations can potentially be identified by predictions of environmental and physical factors of species (Davies &

Guinotte, 2011; Ward et al., 1999). Corals have a substantial temperature range to thrive, but their development is slightly higher in summer than in winter (Miller, 1995). Nevertheless, the highest growth rates were reported under warm weather and high light conditions, which are more typical of tropical waters than temperate waters. (Miller, 1995). Globally, that sea surface temperatures are a significant factor in the loss of coral reefs. (Selig et al., 2012).

Furthermore, Sea surface temperature can forecast coral abundance and development (Hill et al., 2014). Temperature rises may have several adverse effects on corals, including coral bleaching death, slower recovery, and increased disease prevalence (Selig et al., 2012). Corals have symbiotic algae living in their tissues, without these algae, the corals become white and die if the algae are not reabsorbed from the ambient water in the immediate future (Holmes & Subedee, 2014). When corals are subjected to temperatures more than 1 degree Celsius above average mean summertime temperatures, they may lose their symbiotic algae or zooxanthellae, resulting in widespread mortality at regional scales (Selig et al., 2012). Increases in sedimentation, temperature, pollutants, or disease tension corals, forcing them to expel the symbiotic algae residing in their tissues, resulting in coral bleaching (Holmes & Subedee, 2014).

Besides SST, several studies have shown that other environmental variables, such as substrate type, salinity, and winds have an impact on the abundance and distribution of corals. West & Salm (2003) published a list of environmental causes that are likely to be linked to coral bleaching tolerance and resilience, such as turbidity, absorption of light, climate, temperature fluctuations, high-energy waves, cloud cover, upwelling and deep water's proximity. However, SST and radiation variables significantly impact the abundance and distribution of coral reefs (Maina et al., 2008). Maina (2008) concluded that the most critical environmental variables determining coral distribution are SST, currents, calcite/aragonite saturation, and substrate. The distribution of deep water corals was primarily linked to physical factors around the North American continental margins such as depth and slope, besides SST (Miles, 2018).

Costa and Veazey (2016) identified sea surface temperature, depth, euphotic depths, shore distance as major, important environmental variables in their Hawaiian mesophotic reef colonization prediction model (Veazey et al., 2016). Similarly, Kleypas (1999) identified temperature as significant determinant of global scale reef abundance between salinity, nutrients, light supply, and aragonite saturation. Franklin (2013) also identifies different environmental variables as important factors for coral abundance, such as turbidity, benthic geomorphology and wave ability. Other non-thermal factors including light, turbidity, water motion, have a significant effect on coral bleaching and molarity but can differ depending on other stressors and geographically.

Huff (2013) used ocean currents, ocean temperature, sea-floor slope, depth, primary surface abundance, dissolved oxygen and salinity as candidate covariates to assess coral density and height. Turner et al. (2009) mentioned the most physically perceivable surrogates for the depth being dominant. An especially significant indicator of coral density is the depth since it is very well defined and easily calculated, and reliable data sets of coral density may be available (Hill et al., 2014). Depth usually rises, the volume of light decreases, and sensitivity to waves and temperature falls. Coral reefs develop faster in brighter water that helps the symbiotic algae in the coral's tissue grow The algae typically observed populations occur in deeper water (both nearshore and offshore coral reefs), while larger forms can endure powerful waves and swell forces (Hill et al., 2014). Slope and roughness were also necessary to predict Leptoseris (Costa et al., 2015). Higher coral density was associated with more remarkable chlorophyll survival and optimum depths around 400 m, according to Hill (2014), and Christmas tree reef abundance is significantly predicted by the depth and January currents.

2.6 Modelling spatial abundance of a coral reef: data sources

Marine environment management is also hindered by insufficient of detailed geographical information on the distribution and abundance of biodiversity and biophysical processes that structure local ecosystem (Hill et al., 2014). Several approaches are used to model species, but they are sometimes constrained by data availability (Leverette & Metaxas, 2006). The lack of basic and reliable knowledge about biodiversity, environments, and ecosystems is one of the most important challenges that developing countries face when it comes to protecting ecosystems or awarding protected status to particular species (Lopes et al., 2019). Lack of good quality information pose a serious threat to successful ecosystem management and risks failure in the worst case (Hilborn, 2007). However, the acquisition of data on organisms, ecosystems, or fisheries in developing nations is proportionately expensive, not least because support for sciences and exploration is small; as sciences generally ranks inferior in government preferences in such countries (Chao et al., 2015; Pinheiro et al., 2015). Additionally, data collection in deep-water habitats is far more difficult, yet new technological developments provide more sophisticated tools for the mapping of shallow-water marine systems (Selig et al., 2012).

Information from field surveys, satellites, established interaction between coral bleaching and other environmental factors have been used to identify and create a synthetic model that can be used to forecast the exposure of corals to climate change and bleaching (Maina et al. 2008). Data from intensive field surveys is one of the widely used sources of reefs in shallow waters (down to 30 meters in depth). However, the focus taxa, primary aims, and sampling techniques significantly restrict the comparability of data across regions and over time. Intensive field surveys such as scuba diving and remotely operated video-assisted surveys are expensive, time-consuming, and labor-intensive (Downie et al., 2013) for developing countries. Besides this, field surveys sometimes provide details on a species/location basis, but often at a much smaller geographical level (Franklin et al., 2013a). Owing to the special conditions for studying these remote areas and depth structures, the coral reefs of the Myeik Archipelago have received little attention. Specifically, high prices for the purchase of fuel, advanced equipment, and lack of experts and specialists are the significant challenges for coral reef studies in Myanmar (Holmes & Subedee, 2014).

Remote sensing products are important data sources for characterizing coral reef morphology and ecosystem complexities. Several studies have shown that spectral knowledge can be used to map reef cover on a medium to large scale (around hundreds to tens of thousands of square kilometers), using conventional remote sensing technologies such as hyperspectral or multispectral satellite images or aerial photos (Anelli et al., 2019). It has been successfully used in applications such as Mapping, detecting the change in coastal zones, monitoring environmental changes, mapping sea bed topography, habitat mapping, and stock assessment, e.g., estimating marine gastropods biomass (Mumby, 1997). Remote sensing data and products have been widely applied to predict ecological responses to climate change and anthropogenic stresses (Maina et al., 2008).

Satellite image provides cost-effective methods to monitor coral reefs at a regional and global scale than intensive field-based studies. Moreover, satellite data are the primary source of several physical, climatic, and environmental data such as sea surface temperatures, wave height and direction, and other sea properties. Even in very shallow waters, they can also help discriminate between live and dead coral (Bryant et al., 1998). Aerial photography images and data from reef overflights will give a more accurate picture of reef position and bathymetric data down to tens of meters. On the other hand, aerial surveys and the study of their results are much more expensive than those based on satellite data. They are difficult or impractical to perform legally in certain countries due to security considerations (Bryant et al., 1998). Remote sensing technologies enabled the mapping of shallow coral reefs on a global and regional scale. At the same time, the field surveys may often provide details at the species level, and they are usually restricted to a specific geographic area. SDMs may incorporate field observations data into statistical models that predict macroecological scale spatially continuous coral species distribution to combine the capabilities of different approaches to improve the biological characterization of the reefs (Franklin et al., 2013b).

Besides problems of data availability, available environmental and coral reef field survey data (e.g. Fauna & Flora International (FFI) coral field observation data, Nansen Cruise ship survey data, and Wildlife Conservation Society (WCS), data) have also not been widely used in Myanmar. In this study, I aim to use readily available coral data (from the FFI field survey - covering the period 2013–2014) and freely and openly available remote sensing products of environmental factors to model the distribution of corals in Myanmar.

2.7 Spatial abundance modelling: approaches and methods

SDMs are widely being used by conservation scientists, ecologists, and government agencies to map the potential distribution of Vulnerable Marine Ecosystems (VME) at global and regional and supply information about the underlying environmental factors that influence their abundance (Lauria et al., 2017). Several statistical models have been developed to map and model species abundance patterns and trends (Secondi, 2014). SDMs are statistical models that may include primary surveys, mapped ecosystems, or observational models. Those with microclimatic (satellite) observations are especially useful for predicting global coral species abundance (Franklin et al., 2013a).

Zhao (2016) used a semi-parametric geographically weighted regression method that was useful in his research on social and economic variables influencing forest vulnerability. In recent years, classical regression methods such as the Resource Selection Function (RSF), algorithmic modelling, which focuses on machine learning, Classification & Regression Trees (CART), Generalized Linear Models (GLM), and Maximum Entropy (MAXENT) have grown in popularity (Secondi, 2014). Logistic regressions and logit models, random forests, or MAXENT have been widely used in habitat suitability modelling using presence and absence data (Pittman et al., 2007). Shi (2006) reported that GWR models outperformed ordinary least-squares models and offered valuable knowledge about the local ecological change impacting deer spread (Shi et al., 2006). Mart and Spain (2011) have used GWR to investigate involve spatial variance in managing biodiversity and decisions.

The majority of previous GWR implementations in SDM have concentrated on contrasting the GWR model to a global model like OLS, with combinations of model fit, prediction accuracy, or spatial autocorrelation in residuals as reference metrics. Different methods and software have been used to coral reef distribution using several parameters such as sea surface temperature, turbidity, slope (Bridge et al., 2012b; Hill et al., 2014; Huff et al., 2013; Leverette & Metaxas, 2006; Siringoringo et al., 2019; Veazey et al., 2016; Williams et al., 2010). However, most of these researches focused on one or a few combinations of these parameters. In my study, I use a combination of all parameters that can be easily accessed. While all the mentioned methods have their merits, this study combines multiple linear regression, Global Weighted Regression (GWR), and data-driven forest classification (Random forest) methods to find the driving factors and predict coral abundance in the Myeik archipelago. These methods were chosen because they are simple and do not need advanced statistical analysis. Even more, these methods are readily available in software packages like Arc GIS Pro. OLS method was chosen because it is commonly used in regression analysis before a starting point for all spatial regression analysis. GWR was chosen to analyze spatially varying relationships, if any. The random forest, an ensemble learning method, was selected because it is considered to provide higher accuracy and is more robust to deal with noisy data, though I have a very small sample size.

2.8 Research Gaps

The Myeik Archipelago's species abundance and environment health is largely unknown and thus little understood till recently (Anelli et al., 2019; Rao et al., 2013a). The species diversity causing reefs to bleach, and the health of these systems are poorly known (Holmes & Subedee, 2014). Myanmar faces challenges such as lack of adequate infrastructure, insufficient human resources, limited funds, lack of trained personnel to manage the resources effectively, and insufficient ability to analyze and interpret data to support government decision-making (Myint, 2003). Therefore, there is a need to increase research to explore coral reefs in the Myeik archipelago to enable appropriate management and conservation for future generations in Myanmar.

There is also limited information, knowledge, and understanding about the coastal and marine ecosystems. There is no comprehensive marine biological/ ecological survey, and the only available data is old and outdated. This research will aim to fill critical data gaps, increase knowledge and awareness, help Myeik Archipelago's biodiversity, and improve its fisheries and sustainable tourism. Developing potential Marine Protected Areas (MPAs) encouraged as one such strategy for preserving and managing exploited fisheries and marine communities; however, managers lack reliable and relevant data on the archipelago's aquatic ecosystems implement such a tool.

3 Materials and methods

This chapter briefly presents the coral reef abundance data and the biological and environmental datasets used in the study. It describes in details the approaches used to predict reef abundance in the Northern Myeik Archipelago.

3.1 Study areas

The study area (Figure 3.1) is located in the Myeik (formerly Mergui) Archipelago, which is located in the Andaman Sea's northeastern waters off Myanmar's southern coast in the Tanintharyi Region. The Myeik Archipelago, a cluster of approximately 800 islands that spreads from Mali isle to Similand isle and covers about 6,000 km^2 along Myanmar's southern Tanintharyi coast, is Myanmar's most expanded coastal region and is surrounded on the west by the Andaman Sea (Jones, 2018; Myint, 2003; Obura et al., 2014). The Archipelago is dwelled by at least a community of 2000–3000 semi-nomadic people known as the Moken, commonly called Sea Gypsies (Jones et al., 2018). Fishers migrate between islands to fish in coral areas and for invertebrates (Myint, 2003).

The extensive Tanintharyi coastal region operates both inshore and offshore fisheries. Many trawlers and squid light luring fishing boats target various marine resources like fish, rays, squid, shrimp, and crabs within shallow water (Obura et al., 2014; Zöckler et al., 2013). The district of Myeik is wealthy in natural resources and biodiversity, having diverse seagrass meadows, mangroves, mudflats, and coral reefs that provide for many marine species including threatened and rare species of cetaceans and turtle rays, sharks (Rao et al., 2013a; Sarginson, 2019, Zöckler et al., 2013). Myeik Archipelago areas are recognized as a critical Biodiversity area and a UNESCO site. Moreover, it provides many ecosystem services, including food from reef fish, sea urchins, molluscs, fishes, crustaceans, other recreation sites for tourists. In this region, coral reefs are vital for the sustainability of two industries: tourism and fisheries (Myint, 2003).

The region has essential protected areas such as; Lampi National Park (Figure 3.1). It is the only national marine protected area of the country established in 1994 (Giardino et al., 2015; Myint, 2003; Zöckler et al., 2013). There are also two major Shark Protected Areas of 1706 km^2 (Figure 3.1) and 11,734 km^2, albeit without specific management controls (Howard, 2018; Obura et al., 2014). The region has a tropical monsoon climate. The sea surface temperature generally varies with around 27 to 34 (Howard et al., 2014). The sea surface temperature declines of depth, with a thermocline area extending from 50 to 230 meters off the Tanintharyi shore, while salinity rises steadily with depth and remains constant below 130 meters. (Myint, 2003).

Different hard and soft coral types occur in the southern part of the marine area of Tanintharyi, and all kind of coral species can be found near the isles of the Myeik Archipelago and along the Taninthayi Coastline (Holmes & Subedee, 2014; Zöckler et al., 2013). Coral reefs, mangrove flourish, seagrass beds primarily in the Myeik archipelago. Many of the inner islands are covered in mangroves, while the outer islands are surrounded by coral reefs (Myint, 2003). Specifically, coral communities are most abundantly distributed from Tanintharyi coastal areas to the offshore island of Myeik Archipelago. As recent research, a family of Acroporidae, hard coral (Genus- *Montipora)* (dominant overall 33%), is the most complex and distributed species, although several species remain unexplained (Ko, 2019; Obura et al., 2014). Coral reefs that surround the uninhabited islands of the Myeik Archipelago are also plentiful. It is especially strong near islands that are located off the coast, on the offshore islands (Ko, 2019).

Myeik Archipelago contains 1,700 km² of coral formations with about 512 species of hard corals, reef invertebrate fauna 258 specimens (Howard, 2018) are to be found in that area to according to the recent research by the Department of Marine Science at Mawlamyine University (Milano, 2011). However, dragging seagrass beds and reefs, blast fishing, trawlers, and overexploitation a devastating impact on Myanmar's coral reefs both within and outside conservation areas (Anelli et al., 2019; Rao et al., 2013a, Holmes & Subedee, 2014; LWIN, 2009).

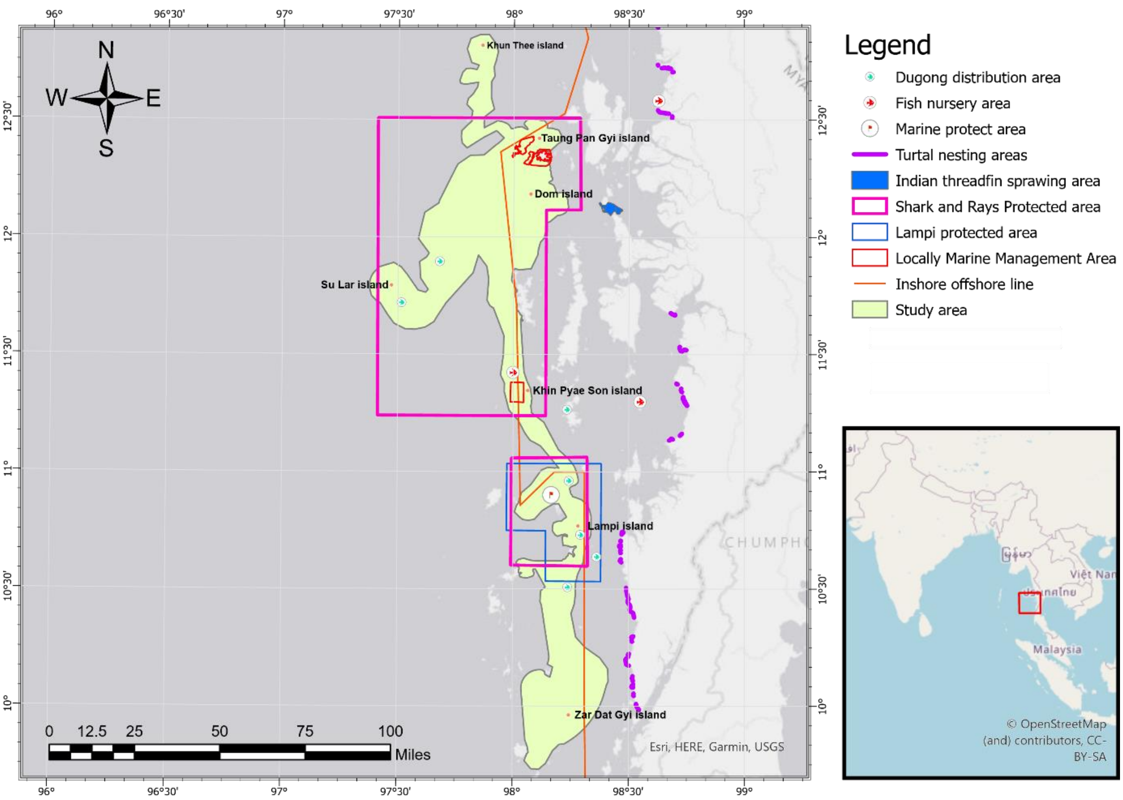


Figure 3.1Location of the study area in the Thintharyi region within the Myeik Archipelago.

3.2 Data and materials

3.2.1 Coral survey data

The present study is using the hard coral survey data from Howard (2018) that included 102 sites surveyed for coral and resilience indicators during January 2013 and May 2014. It was conducted at a depth between 0-30m below sea level around all islands within the Tanintharyi region of Myanmar (Figure 3.2). Most of the datasets were collected by SCUBA divers using the reefs check method and consist of latitude and longitude coordinates of each observation and hard coral parentage cover. This survey data was checked for invalid point location and extreme values, imported into GIS, and cleaned data using visual inspection. Details about the coral reef survey data used in this study are provided in Appendix A.

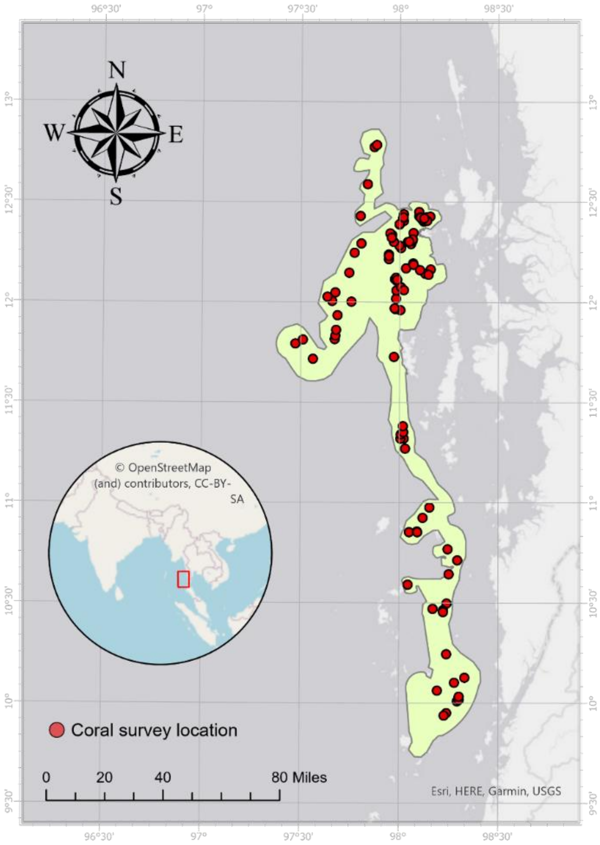


Figure 3.2 Coral reef survey locations by FFI (Howard, 2018) using reefs check survey from 2013 to 2014 within the Northern Myeik Region.

3.2.2 Exploratory variables: environmental and biophysical data

Based on existing literature (see section 2.5), potentially important environmental and biophysical variables-(depth, bathymetric aspect, bathymetric slope, rugosity, sea surface temperature, chlorophyll, and turbidity) were selected as exploratory variables for the study (Table 3.1). Data on the seven predictors were compiled from different sources and were chosen based on their availability. All environmental and biophysical data layers were projected to the Indian 1954 UTM Zone 47N coordinate system. Processing of exploratory variables and further analysis was carried out in ArcGIS Pro. The processing and analysis workflow is provided in Figure 3.3.

Table 3.1 The seven environmental variables that were used as predictor variables in sample coral abundance modeling are mentioned below table.

No.	Variable	Unit	Descriptor	Type of data	Data source
1	Depth	meter	Bathymetry	Continuous digital map	https://allencoralatlas.org/
2	Slope	degrees	Substrata Typology	Derived from bathymetry data	Slope calculated using ArcGIS Pro's Slope tool.
3	Rugosity	no unit		Derived from bathymetry data	Seafloor complexity was calculated with the ArcGIS Pro's focal statistics tools.
4	Aspect	Radians	The substrate's orientation	Derived from bathymetry data	Compass direction of a maximum slope calculated using ArcGIS Pro's Aspect tool.
5	Sea Surface Temperature	°C	Temperature	Derived from model	The temperature of the sea surface during the daytime as measured by the MODIS Aqua sensor. 4x4 km http://oceancolor.gsfc.nasa.gov/
6	Chlorophyll-a concentration	mg/ m^{-3}	Chlorophyll	Derived from model	Chlorophyll-a concentration during the daytime as measured by the MODIS Aqua sensor.

No.	Variable	Unit	Descriptor	Type of data	Data source
					4x4 km http://oceancolor.gsfc.nasa.gov/
7	Turbidity	FNU	Turbidity	Derived from model	https://allencoralatlas.org/

Depth is a major environmental gradient that influences species spatial habits, and in the situation of corals, it is the main determinant of their abundance (Figure 4.2 a). (Davies & Guinotte, 2011; Greathead et al., 2015; Lauria et al., 2017; Murillo et al., 2011). I obtained bathymetry data from the Allen Coral Atlas database (2021) of the Arizona State University. It is mapped in centimeters and at a resolution of 10 m (Knapp et al., 2019). I extracted three measurements of benthic geomorphology (Rugosity, Slope, Aspect) from the bathymetry data. Slope is a morphological indicator of the seabed (Figure 4.2 b)(Franklin et al., 2013a). Low values indicate smooth ocean bottoms or sand accumulation areas, and higher values indicating possible rugged ledges (Lauria et al., 2017).

Aspect (Figure 4.2 c) determines the direction of the seabed at a specific position and offers detail on the area's sensitivity to local and regional currents (Wilson et al., 2007). This seabed topographic feature is critical in affecting benthic population structure because it can influence current regimes and the flux of suspended food material (Guinan et al., 2009; Tong et al., 2012).

Rugosity is also a critical indicator of intertidal biodiversity since it offers a range of microhabitats that facilitate species coexistence. Thus, increased rugosity can help intertidal marine biodiversity (Mazzuco et al., 2020). This parameter is primarily used to predict species abundance when specific knowledge about the sediment type is unavailable (Pittman et al., 2007; Pittman & Brown, 2011). The standard deviation of depth was used to measure the rugosity of the seabed using the neighborhood function of three × three windows in the manner described by Bridge et al (2012a).

Concentrations of chlorophyll can be connected with the export flow of organic particulate carbon (Jung & Kunstmann, 2007) and are the available nutrient on the seabed (Knudby et al., 2013). With a precision of 35 percent, the SeaWiFS sensor measures chlorophyll on a scale of 0.01–64 mg/m3 (Barbini et al., 2005; Hooker & McClain, 2000). 4 km resolution monthly average sea surface temperature data and Chlorophyll-a surface concentration from January 2013 to December 2013 were obtained from Aqua-MODIS and SeaWiFS (http://ocean color.gsfc.nasa.gov/). The extraction of data, subsetting to the studied area, and coordinate transformations were all included in the data processing. I worked out a mean monthly SST and chlorophyll concentration to get an average of all the results.

Turbidity information (for the year 2020) was collected from the Allen coral atlas database team at Arizona State University (Carlson et al., 2020). Changes in turbidity (or water clarity, transparency) are used to examine estuarine and coastal waters (Fabricius et al., 2013). Increased turbidity or decreased water visibility will inhibit coral growth by reducing the amount of available light for photosynthesis (Fabricius et al., 2013).

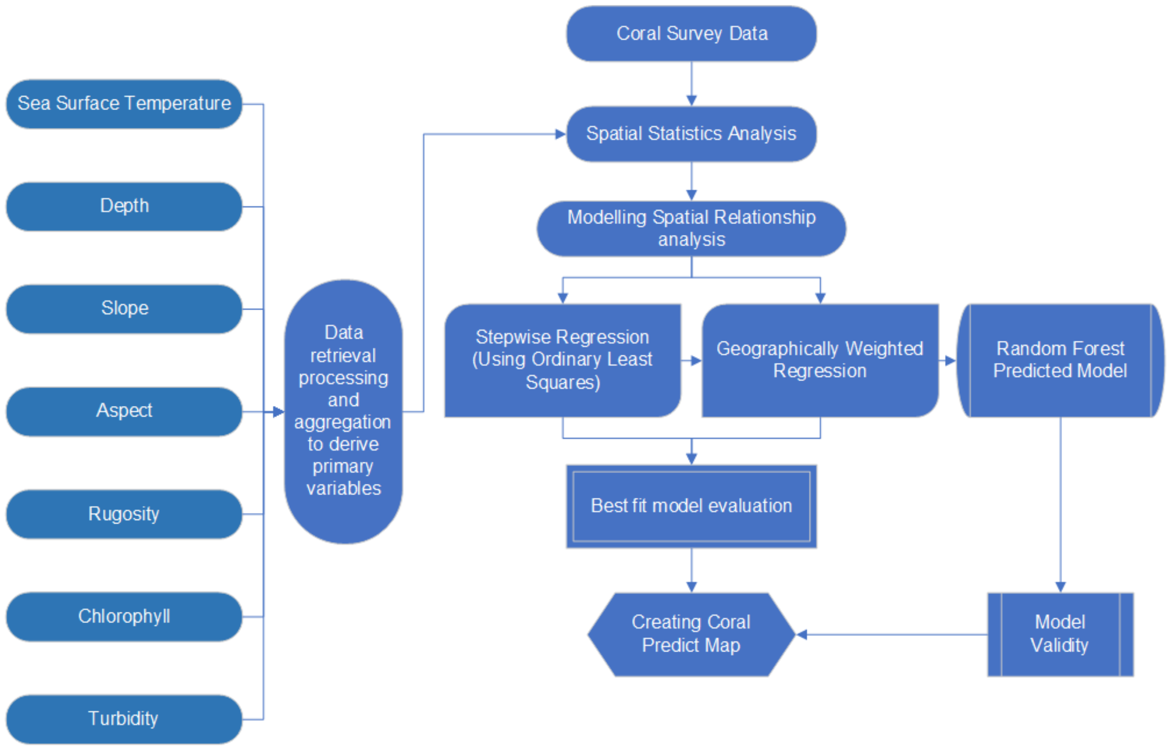


Figure 3.3 summary flow diagram for creating GWR method approach to predict coral abundance model

3.3 Data exploration

I explored the data using simple descriptive statistics and exploratory spatial data analysis tools in ArcGIS. Histogram and normal QQ Plots were used to explore distribution patterns. The association between hard coral and various environmental variables was investigated using scatter plots and correlation matrices. Additionally, I examined for multicollinearity in the selection of predictors.

3.4 Modelling the environmental drivers and abundance of coral reef

This research began with traditional linear regression models, assessing and exploring spatial statistical relationships between environmental variables and coral reef abundance using basic GWR and random forest classification and regression. Under the principle of spatial stationarity, global regression models (e.g., generalized linear regression models) can only compute one relationship between species and environmental variables beyond broad spatial scales (Li et al., 2018; Tseng et al., 2013; Windle et al., 2010). I examined the spatial non-stationarity of ecological processes using the geographically weighted regression (GWR) method. Additionally, previous research indicates that geographically weighted regression (GWR) produces more reliable predictions and fewer spatial pattern in the residuals than generalized additive modeling (GAM) and global logistic regression (Li et al., 2018).

GWR's straightforward local modeling methodology will sometimes provide a more reliable predictive spatial distribution map for the answer variable than techniques such as ordinary least squares (OLS), GAM, Linear mixed model (LMM), Classification and regression tree (CART), GLM, multivariate adaptive regression splines (MARS), and Artificial neural networks (ANN) (Zhang et al., 2005). Local models can help illustrate spatially distinct relationships between environmental and abundance variables given the fact that the importance of environmental variables on species' abundance and distribution can vary significantly across its range (Brunsdon et al., 1998a; Fotheringham & Brunsdon, 1999; J. Franklin, 2010; Li et al., 2018; Runge et al., 2014; Tseng et al., 2013; Windle et al., 2010). GWR is a powerful method for analyzing spatial data relationships that exhibit spatial non-stationarity (Brunsdon et al., 1998b).

Global (OLS) and local (GWR) methods were employed in this analysis to predict the abundance of hard coral in the research area. Notably, the GWR model discloses the coefficients and intercepts within each predictor parameter for each observation point. (Fotheringham & Brunsdon, 1999). These coefficient surface maps are instrumental methods for examining the relationship between each environmental variable and coral abundance and other variables around the study area. I have used a data-driven forest-based classification and regression approach to predict coral reef abundance using environmental variables, an adaptation of Leo Breiman's random forest algorithm (Breiman, 2001). I compared the random forest and GWR models to each other to see how the results differed.

3.4.1 Model selection

First, I used the ordinary least squares (OLS) linear regression method to investigate and validate relationships between and among species complexes and environmental variables (Fotheringham et al., 2003). The backward stepwise regression model was used to describe the variables or factors that impact coral abundance, the interaction between coral and significant factors, and exploration. The VIF (variance inflation factor), Jarque Bera model biases, adjusted R^2 value, Koenker studentized Breusch Pagan (BP), Akaike Information Criterion (AIC), and spatial autocorrelation (SA) were used to test multiple linear regression models. The standardized residuals of the OLS model were examined using histograms and normal QQ plots. Diagnostics like Joint Wald, Joint F, and the Koenker statistic were used to ensure the model's validity. In addition, I examined spatial autocorrelation in residuals using Moran's (Ciotoli et al., 2017).

Geographically Weighted Regression (GWR) was used to address the issue of non-stationarity in the results. Identified environmental variables from backward elimination regression in OLS were chosen to create the GWR model. The suitable GWR model was chosen based on Adjusted R^2 and Akaike's Information Criterion (AIC) values. The model with the highest Adjusted R^2 and lowest AIC was considered the most accurate in predicting the validated data. We plotted the coefficient values for each explanatory variable to analyze how the association among each explanatory variable and the dependent variable differs around the study area.

3.4.2 Comparison of model outputs and model validation

The GWR model was evaluated by comparing the score of AIC and adjusted R^2 with OLS results. To determine the validity of the prediction models, I used regression analysis of predicted versus observed coral abundance values as a model goodness of fit analysis (Smith & Rose, 1995). I compared coefficient of determinant, and coefficients (slope and intercept parameters) (Piñeiro et al., 2008). Numerous studies demonstrate the serious importance of comparing predicted and observable values while evaluating the significance of regression analysis (Smith & Rose, 1995).Additionally, the random forest model was evaluated by comparing the predicted and observed coral abundance graphs using the model performance report based on the training data (10%).

4 Result

4.1 Observed environmental characteristics of coral habitats

Coral was found at a various depth; the maximum depth in the study area was 22.7 m. Figure 4.2a shows that its depth distribution pattern in the study area. High coral abundance was observed in the north-east, with deeper levels ranging from 0 to 5 m. Depth has a negative correlation with coral abundance (Figure 4.1). Warmer waters were identified in the study area's northern and northwestern regions. However, water temperature in the study area was relatively warmer in the southern than in the north east and below the Lampi sites (Figure 4.2f). . For minimum temperature (in 2013), the Northern region distribution displayed a strong peak and round 28.97 ˚C, whereas Taung Pan Gyi region existence generally extended between 28.24 ˚C and 28.56 ˚C (Figure 4.2 f). The southern part peaked at moderately warmer temperatures and Lampi regions peaked at slightly cooler temperatures (28.78–28.95˚C). The middle of the North- Eastern region had a higher minimum temperature of 28.24 ˚C, compared to less than 0.1 ˚C for reef abundance. SST was negatively correlated with reef abundance (Figure 4.1).

Table 4.1 Summary statistics of environmental characteristic at the coral reef survey location points coral

STATISTIC	MEAN	SD	MINIMUM	MEDIAN	MAXIMIN
Depth(m)	4.1	2.7	0.000065	3.2	12.56
Sea Surface temperature (C)	28.65	0.17	28.23	28.63	29.05
Chlorophyll	1.10	0.52	0.34	0.95	2.41
Turbidity	48.60	14.53	2.77	44.38	139.52
Rugosity	0.54	0.07	0.29	0.53	0.92
Slope	1.07	0.44	0.04	1.02	4.31
Aspect	178.71	44.15	0.59	176.57	354.80

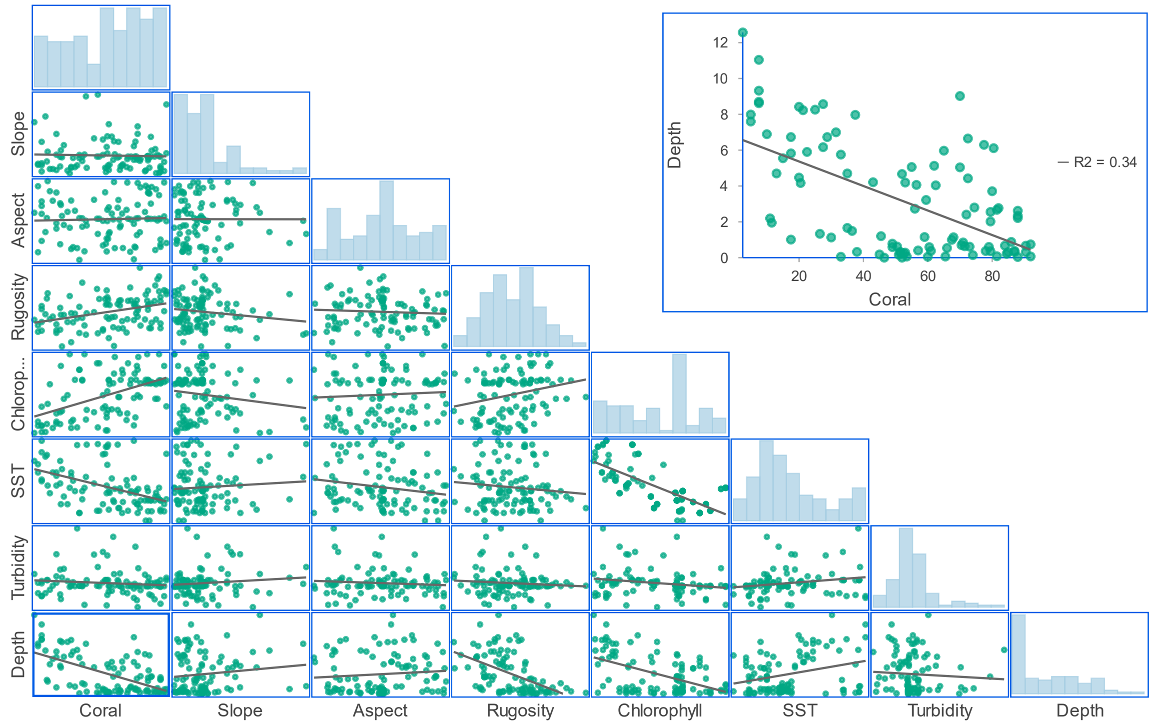
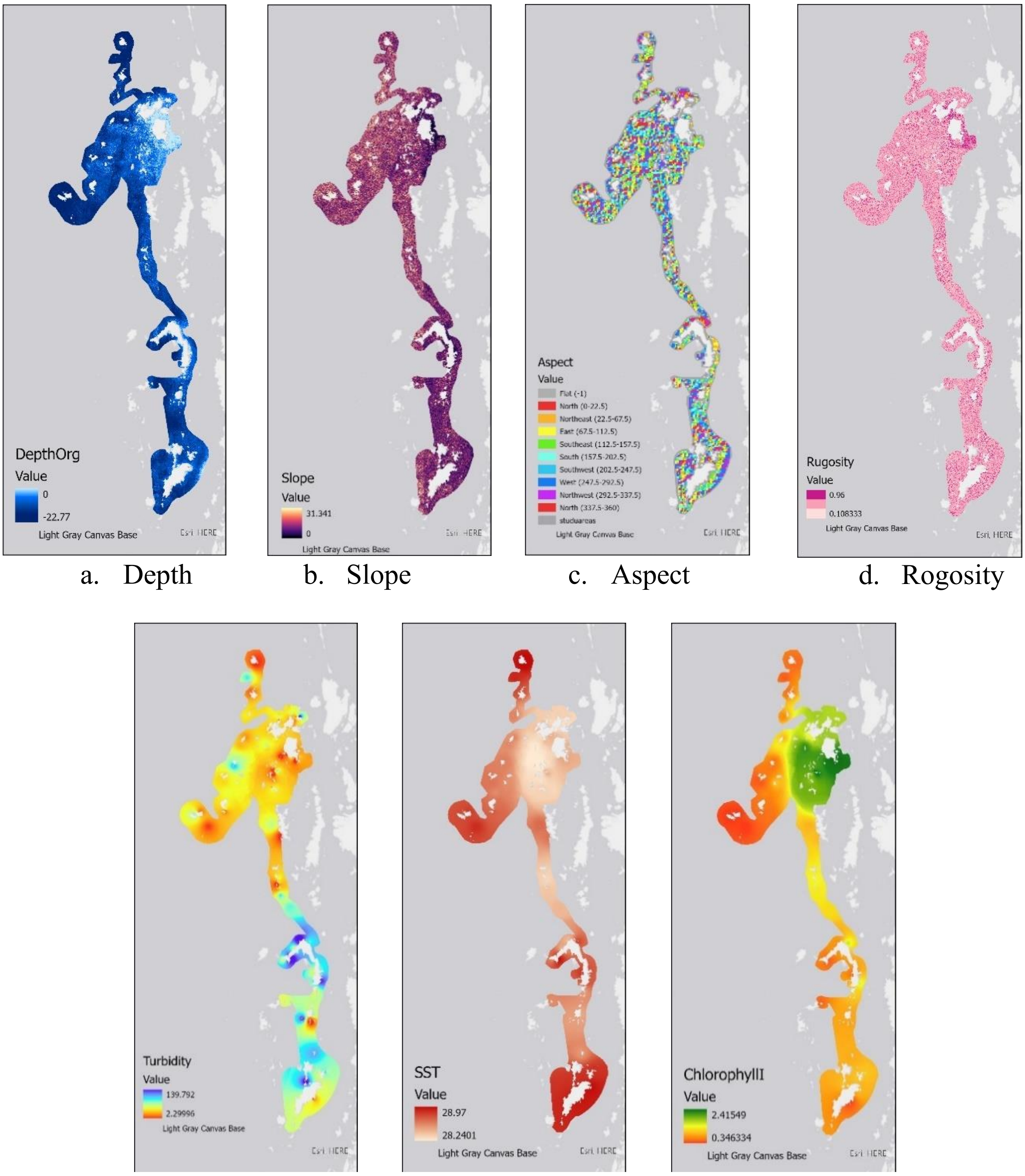


Figure 4.1 The relationship between coral abundance and environmental variables

Figure 4.1present the relationship between coral reef abundance and environmental variables. This graph indicated that the exploratory variables (independent) are not correlated among the other environmental variables at each observation location, meaning there was no multicollinearity (Statistika, 2015; Ciotoli et al., 2017). (). The moderate negative correlation was observed between coral abundance and depth (r^2 = 0.34) and SST and coral abundance (r^2 = 0.26), while there was weak relationship between rugosity and coral abundance (r^2= 0.13).



a. Depth b. Slope c. Aspect d. Rogosity

e. Turbidity f. SST g. Chlorophyll A

Figure 4.2 The seven environmental variables used to analyze in the predicted coral abundance models. These include (a) depth(m), (b) slope (degrees), (c) aspect, (d) rugosity, (e) Turbidity (f) Sea Surface Temperature (°C),(g) Chlorophyll A.

4.2 Significant environmental and physical factors for coral abundance

The multiple regression using OLS shows that only depth ($p < 0.001$) and sea surface temperature ($p = 0.0406$) were significant variables out of seven variables. There was not enough evidences about the influence (linear relationship) of slope, aspect, chlorophyll, turbidity, and rugosity or coral reef abundance. The coefficients have a negative correlation with both depth and sea surface temperature. Though the model with SST and depth passes all other assumptions, except spatial autocorrelation, linear regression, including the model, seems free from bias. However, spatial autocorrelation testing (Moran's I = 0.2, p = 0.005) revealed spatial autocorrelation in the model residuals. This suggest that the dependent variables' effects are non-stationary (spatially varying) around the study area. There was also an indication of the presence of heteroscedasticity. As a result, local regression (GWR) would provide a more accurate description of the procedure than a global regression model (OLS). Appendix 1 contains a description of the OLS results table and spatial autocorrelation graph.

Table 4.2 Result of OLS model diagnostics

VARIABLES	DEPTH	SST	NOTES
Coefficient	-3.61	-31.04	negative
Probability*	0.000013	0.040601	significant p-value (p < 0.05).
VIF	1.87	2.18	<7.5
Akaike's Information Criterion		915.81	model fit/performance value
Adjusted R squared		0.40	model fit/performance value
Multiple R square		0.44	model fit/performance value
Koenker (BP)		6.16	>0.05
Joint Wald		0.00	<0.05
Jarque Bera(JB)		0.69	>0.05

Table 4.3 shows the essential variables on coral abundance based on forest-based classification and regression model. According to a Random forest statistical model, the three most important variables to explain coral abundance in the study area were depth, SST, chlorophyll (having 22% of the total sum of Gini coefficients) whereas rugosity (12%) and slope (8%) have also higher impact on coral reef abundance prediction.

Table 4.3 Importance of variables based on classification and regression

VARIABLES	%
Depth	22
SST	22
Chlorophyll A	22
Rugosity	12
Slope	8
Turbidity	7
Aspect	7

4.3 Predicted abundance and niches

Linear regression models show that slope, aspect, turbidity, chlorophyll, and rugosity did not contribute significantly to the abundance of coral reefs. GWR model was fitted with all seven variables as well as only with depth and sea surface temperature to predict coral abundance. The GWR model with SST and depth explains 70 percent variances in the coral abundance ($R^2 = 0.70$, AIC = 913). However, the GWR model with all seven predictor variables has lower was R^2 and higher AIC ($R^2 = 0.49$, AIC = 920) than the GWR model with depth and SST. The GWR model (with depth and SST as predictors) performed better than OLS model ($R^2 = 0.44$, AIC = 915) as expected.

Spatial non-stationarity of the influence of environmental variables on the distribution of coral abundance were visually examined. The local coefficient estimates of each significant predictor parameter, local R^2, and model standard residuals were used to evaluate the model performance. The predicted surface maps show the abundance of coral abundance vary spatially across the study areas, with both depth and SST having a negative relationship. The coefficient between depth and coral abundance ranged from 1.8 to - 4.6, while the coefficient of SST was from 14.4 to -80.6. The negative relationship between coral and water depth was significant in the north-east Taung Pan Gyi and North west of Dom island, while the south-east areas showed no significance (Figure 4.3).

The effect of SST on coral abundance was influential in the northeast of Taung Pan Gyi island, around Dom island, Southern of Zar Dat Gyi island, and in the middle of Khin Pyae Son island (Figure 4.4). However, relatively higher temperatures were observed at the edge of North and south and far from Dom island. Figure 4.4 show that the model worked very well in the region edge of Khun Thee island at the northern and southern sections, with a local R^2

greater or equivalent to 0.84. In contrast, GWR model fit was relatively weaker in Taung Pan Gyi area, and between Dom island and Mee seine island, explaining only around 34 % of the variance of coral abundance. The standard residuals from GWR show that the residual distribution was random throughout the study area, showing the importance of the GWR model (Figure 7.3).

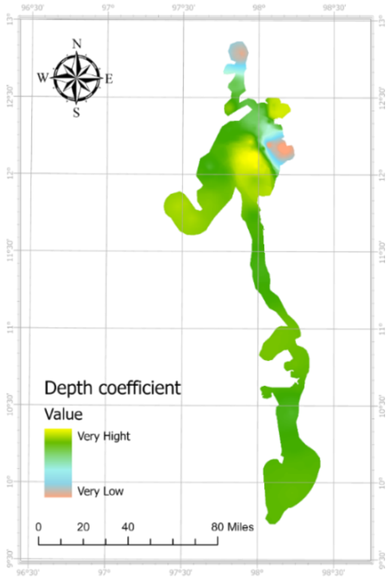


Figure 4.3 Depth coefficient surface maps obtained from the GWR analysis.

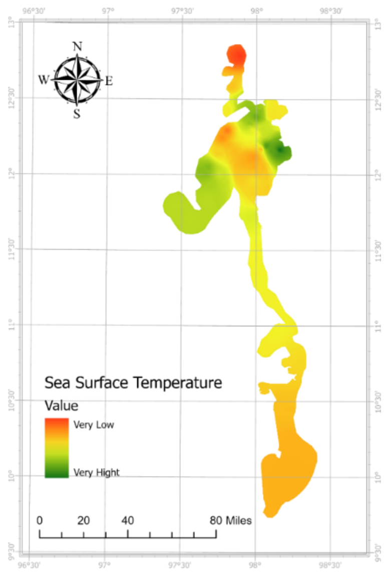


Figure 4.4 SST coefficient surface maps obtained from the GWR analysis.

4.3.1 Predicted coral abundance surface maps

The predicted surface map of coral abundance using the GWR model is presented in Figure 4.5. The figure shows that the predicted coral abundance varied from up to 77.8, with several areas having notably high abundance: in the Taung Pan Gyi island (TPG) places of the northeastern part, Lampi island off south-east part and Khin Pyae Son island. Other areas had a moderate to a high abundance of hard coral abundance. However, the edge of the western region at Su lar island and the northern part at Khun Thee island have relatively lower abundance. The finding indicate that coral abundance is higher in the lowest water of the continental shelf areas in the northern part, as expected (Figure 4.5). The results also suggest that high coral abundance is associated with low sea surface water temperature.

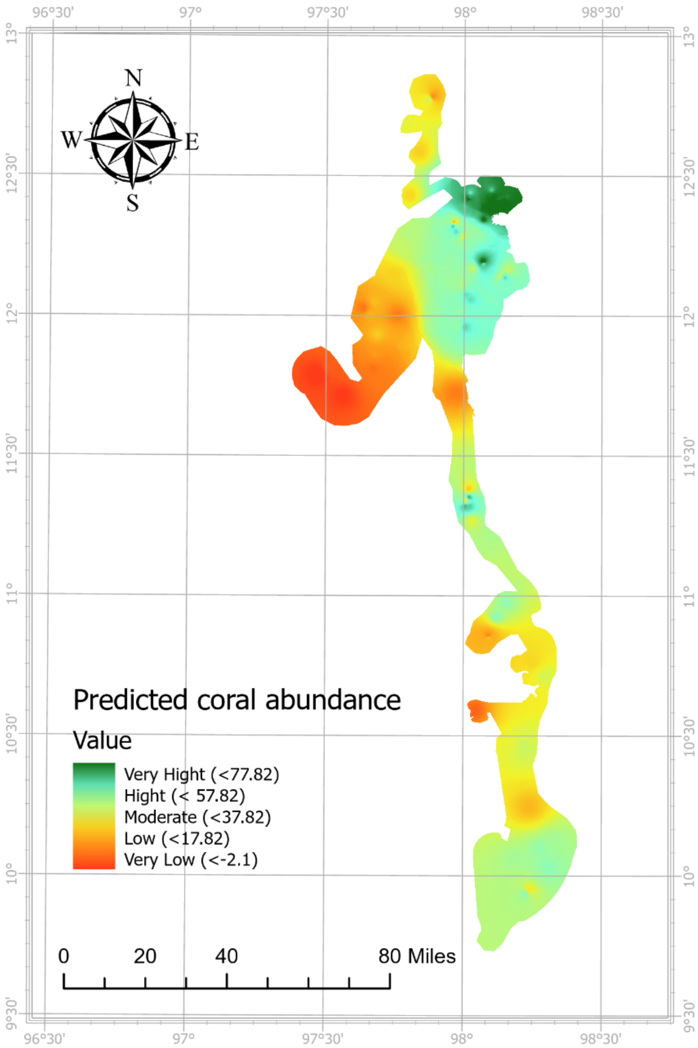


Figure 4.5 Predicted coral abundance in the Myeik areas based on GWR model, SST, and depth as the predictor variables

Figure 4.6 shows coral abundance predicts maps produced by random forest method using all seven explanatory variables. The predicted abundance map shows a similar spatial pattern as the GWR model prediction. Though the percentage of variance explained for training data with this model was 91%, the variance rate for validation data was only 11%. It shows the impact of overfitting on training data by random forest. The out-of-bag validation R squared indicates that the variation explains about 11 % of the model in the response. In this comparison, the GWR model looks better (i.e., explaining 70% of variance) than random forest. It clearly shows the importance of spatial clustering patterns, which can be better explained by the spatial model such as GWR.

The largest coral abundance areas were located on the Taung Pan Gyi island area in the northern part. Both predicted maps at the Taung Pan Gyi island areas showed high abundance, with larger areas occurring off Khin Pyae son island. However, not many corals were observed off the southern part, with few abundances of coral.

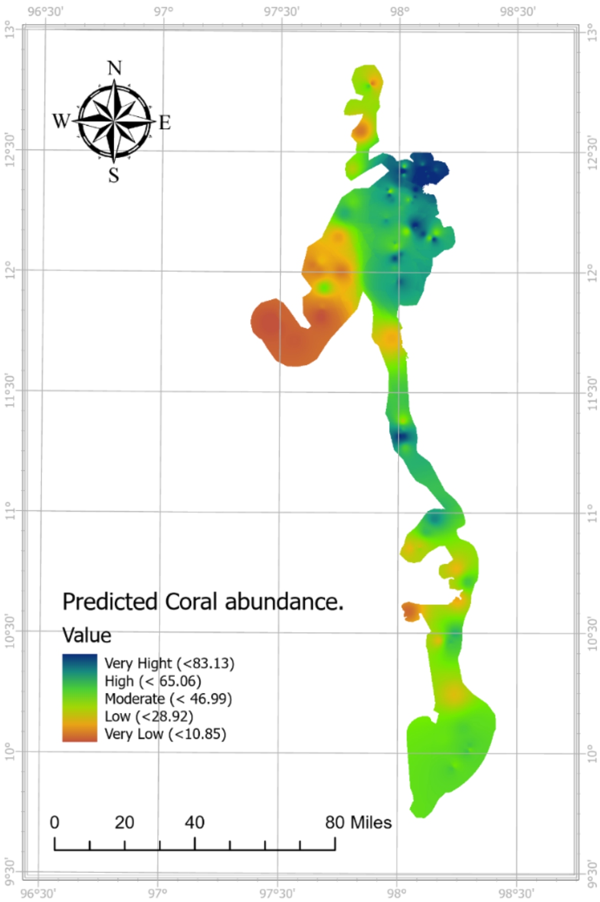


Figure 4.6 Predicted coral abundance in the Myeik areas using forest-based classification and regression model

4.4 Validation of the models

The findings indicated that the GWR model performs better than the OLS model in terms of parameter equilibrium and variance described (Ortiz-Yusty et al., 2013). The relationship between predicted and observed value showed the model is relatively good (Figure 4.7). The relationship showed how good the model is (as an R^2 value near one is considered a perfect model). The GWR result showed that the relationship between predicted coral abundance and survey hard coral have $R^2 = 0.71$ (Figure 4.7) with a normal distribution of residuals around the least square line. The regression analysis of observed vs. predicted values is conceptually simple; the slope should equal one, and the intercept variable should equal zero. (Smith & Rose, 2008). A graphical analysis of observed and predicted values for the model revealed a slope of 1.05, which was close to 1, and an interest of -2.4, explaining about 71% variance (Figure 4.7).

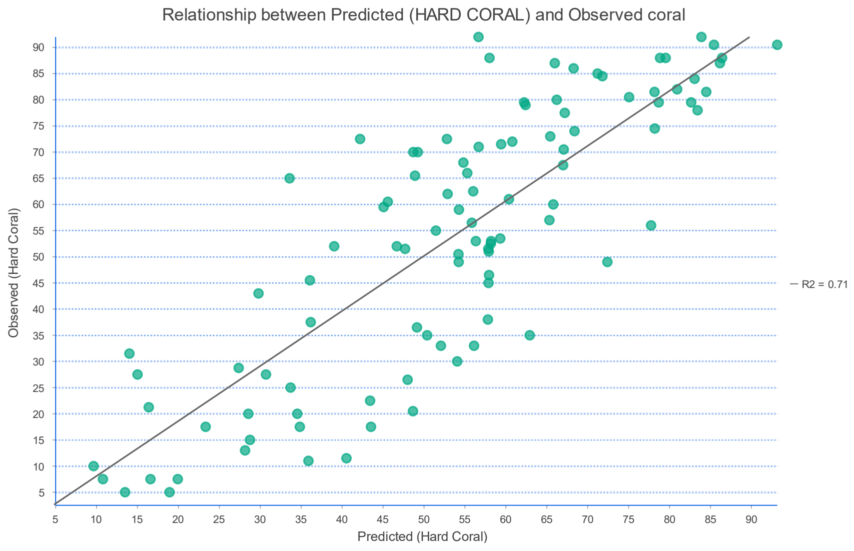


Figure 4.7 relationship between predicted (hard coral) and observed coral abundance based on GWR model

The regression between the random forest model prediction and observed coral abundance shows that about 83% of total linear variance explained by the regression model (Figure 4.7), which is slightly higher than the GWR model. Nonetheless, the GWR model performance was slightly better, as indicated by the slope and intersect of the line (Figure 4.7 and 4.8). On the other hand, both GWR and random forest models predicted a similar pattern of abundance.

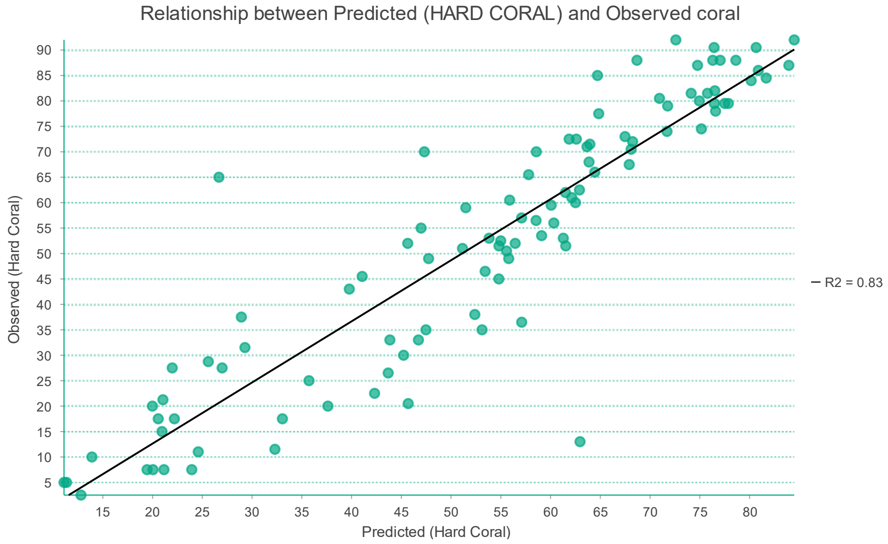


Figure 4.8 relationship between predicted (hard coral) and observed coral base on Random forest model

5 Discussion

5.1 Environmental and physical factors in determining coral reef abundance

Regression analysis can help us understand which factors contribute to a phenomenon and determine how each factor contributes to that phenomenon. These methods are used when relationships between the target species and environmental variables are not entirely understood (Alexander, 2016) and predict unknown values and model spatial relationships.

This study showed that depth was the most influential variable on coral abundance across the Northern Myeik. Random forest showed that all variables have an important contribution. There was a very high spatial dependency of coral reef abundance. Depth and SST were the important factors of coral abundance showing a spatial variance. The finding is consistent with what Costa et al. (2015) observed. Depth is more readily measurable, more reliable, and more widely available than in other model habitats features (Huff et al., 2013). GWR predicted model of coral abundance was highest in a shallow depth and, moderate sea surface temperature environments along the northern Taung Pan Gyi island around depth 2-6 m (Giardino et al., 2015). This is similar to Ko (2019), who expressed that Taung Pan Gyi areas had the highest coral common species at water transparency at 5 m depth.

The result also showed that turbidity has no significant effect on coral abundance because the water was transparent at 5 meters depths, according to previous research (Ko, 2019) allowing for photosynthesis. The trend of highest coral abundance was found in shallower depth with distribution in the eastern and southern part were lower than the northern part of Taunf pan Gyi island Coral abundance. These corals were concentrated in shallow depth because it’s growth potential is higher due to light availability for photosynthesis (Hill et al., 2014). Deeper water, however, had lower coral abundance due to unavailability of light to support photosynthetic systems for coral growths (Miller, 1995).

Sea surface temperature was an important factor of coral abundance and distribution (Huff et al., 2013; Leverette & Metaxas, 2006). In this study, sea surface temperature negatively affected hard coral, similar to Selig et al. (2012). GWR model indicated larger coral clusters in moderate warmer water. Other research has found that temperature might not be a limiting factor for coral growth and abundance around the Myeik archipelago (Howard et al., 2014, Dullo et al., 2008, Lauria et al. 2017, Obura et al. 2014). Since SST is thought to affect coral calcification rates, physiology, and biochemistry, this study shows that sea surface temperature can play a critical role in coral habitat selection (Guinotte et al., 2006). Other research has found that corals that have already been subjected to moderate degrees of thermal stress have a larger capacity for adaptation and are more resilient to future thermal stress events (Selig et al., 2012). This may be one reason for the study's findings.

Coral bleaching is the most obvious impact of climate change on coral reefs, when unusually warm water temperatures disrupt the coral-algal symbiosis, potentially resulting in mass coral mortality (Coles SL, 2003). Additionally, sea surface temperatures greater than one degree Celsius above normal summertime maximums may kill their symbiotic algae or zooxanthellae, of corals, resulting in widespread mortality on local levels (Selig et al., 2012). It is essential for coral colonies since a slight rise in temperature of 0.1°C can increase the geographic extent of coral bleaching (McWilliams et al., 2005). The example of the temperature effect on coral bleaching shows how climate change may, in the long run, affect biodiversity and ecosystem services that are supported by coral reefs. However, this study does not include the effect of temporal changes and SST changes on the abundance of corals in the region.

Other environmental variables (slope, aspect, rugosity, Chlorophyll, turbidity) were not found significant for coral abundance in the GWR model. In contrast, the random forest model demonstrated that all seven variables were important for coral abundance. One of the reasons could be that GWR is a local linear model (assuming linear relationship between dependent and independent variables), so linear GWR model could not capture the nonlinear relationship between environmental variables and coral abundance., For example, as seen in the correlation matrix, the relationship between coral abundance and other factors, e.g., slope, aspect was not linear; that’s why the GWR model with all variables was not better. On the other hand, random forests capture both linear and non-linear relationships, as shown by importance – all variables having higher than 7% importance. This may highlight the need for nonlinear spatial modelling, the alternative to GWR, which can capture both non- liner relationship and spatial heterogeneity of a relationship.

5.2 Spatial autocorrelation and importance of GWR

I compared the performance of multiple regression analysis, GWR, and random forest in this analysis. The results showed that the best modelling method for predicting coral abundance was the GWR model, compared to multiple linear regression and data-driven random forest classification and regression methods. OLS model was included in this study first to explore if there were linear relationships. GWR model provided realistic estimates of predictive performance, explaining 70 % of the variance in coral abundance. In comparison, the best OLS model (with a combination of different environmental and physical variables) explained only 44 % of variances, while the random forest can explain about 11 % of variances.

The results showed the presence of spatial autocorrelation in coral reef abundance. The GWR model is a spatial statistical technique used to investigate spatial non stationarity as environmental factors vary by location. GWR's major benefit over OLS regression is its capacity to handle spatial non stationarity (Propastin et al., 2008). The findings show that the GWR model fits differently than traditional the OLS result and offers comprehensive knowledge about the spatial heterogeneity of depth and SST caused by geographical and ecological influences (Propastin et al., 2008). Figure 4.5 illustrates a map of the GWR predicted value of the coral abundance based on the FFI observations data (2013-2014). GWR model showed a high concentration of predicted coral abundance in the Northeast Taung Pan Gyi island, with moderate abundance found around the Dom island.

Regressing expected vs. observed values, where slope, intercept, and the coefficient of determination (R^2) value represent the accuracy, model bias, and overall model fit, is a sample and straightforward approach to analyzing the model goodness-of-fit (Piñeiro et al., 2008). These parameters provide elements for assessing model success and gaining trust in it (ibid). Both observed and predicted coral abundance results from GWR, there was a linear relationship (Figure 4.7). While R^2 shows the proportion of the total variance explained by the regression model (and also how much of the linear variation in the observed values is explained by the variation in the predicted values), the slope and intercept that describe the consistency and model bias, respectively (Piñeiro et al., 2008). The results (R^2 = 0.71, and intercept = -2.41 and slope= 1.0) clearly show that the GWR model, though not the best, was good enough to predict coral reef abundance. While the random forest predicted result (R^2 = 0.82, and interest = -11.4 and slope=1.2) (Figure 4.8). Based on Piñeiro et al. (2008), GWR was selected as the best model than Random forest as it has a slope near to1.0 and intercept near to 0.

GWR is a spatial statistical tool used to analyze spatially non stationary or spatial autocorrelation at a local level (Mennis, 2006). Although spatial nonstationary can mean that a global model was mis specified, the searching for appropriate explanatory variables may be more accurately guided by examining the spatial patterns in parameter estimates obtained using a local technique such as GWR. Alternatively, the influence of unknown variables may be expressed using locational data.

Indeed, environmental factors and their interactions are scale-dependent in their spatial non-stationarity (Foody, 2004). Global regression models such as ordinary least squares (OLS) are unable to capture the effect of spatial scale heterogenity on the relationships between a dependent variable and independent variables where there is such scale dependence (Propastin et al., 2008). If the bandwidth becomes coarser, the GWR effects grow more global, showing more generalized regional patterns, and the relationship's spatial non-stationarity tends to decrease. GWR model was helpful in estimating the abundance of corals in the Myeik archipelago due to the spatial non stationarity of the variables. Finally, the GWR model can be an sample and best solution to spatial problems in geography and ecology that are non-stationary and scale-dependent (Propastin et al., 2008).

5.3 MPA and coral reef abundance

Myanmar's marine areas include protected areas for conservation purpose such as marine protected areas, that are mostly, locally managed. However, the habitats and ecosystems inside and outside protected areas in Myanmar are threatened by continuing habitat destruction and overexploitation, and their potential to preserve biodiversity effectively is restricted by a number of additional factors, including their scale, regional representation, insufficient management capability, and a lack of policy and regulatory structure (Rao et al., 2013c). MPAs are essential for managing coral reef ecosystems, but they must be supplemented by direct actions to reduce anthropogenic activities that lead to climate change (Selig et al., 2012). The relationship between predicted coral reef abundance and marine management area in Myanmar depicts that the highest coral abundance areas are notably located near the two LMMA areas than other protected areas (Figure 5.1). It shows that the local fishing community participating in the local marine management project is essential in implementing a sustainable ecosystem and marine conservation management project. The objectives of the protected areas can be achieved if local communities are included in management plans and discussions (Dearden, 2018).

Environmental factors that can affect the geographical abundance of biodiversity are used in marine spatial planning and ecosystem-based strategies (Crowder & Norse, 2008). Coral reefs abundance map can inform marine conservation planning (Leathwick et al., 2008). The results have demonstrated that a simple GWR model using openly and readily available datasets can be used to predict coral abundance, despite the uncertainties inherent in the findings. Predicted maps like this can be very useful for coral reef conservation and management in Myanmar. The method and data used in this study can be helpful for further assessment and analysis of coral distribution and abundance in other data- poor areas. This will also serve as a foundation for spatially explicit ecosystem modelling and coral reef marine spatial planning and the implementation of large-scale species distribution modelling projects at Myanmar's Department of Fisheries. Furthermore, resource managers, policymakers, and development agencies can use these models to identify resources for coral reef conservation, set priorities, and prepare strategies using the accurate information of projected coral abundance chart.

Knowing the best modelling method to use in a particular situation should lead to better predictions and more informed species management decisions (Alexander, 2016). The proper use of predicted coral abundance mapping and multiple methods to support fisheries management decision-making for the Department of Fisheries could help sustain a stable fish population by promoting a better understanding of the key environmental variables. Thus, MPAs found in the Myeik region where corals exist need to be regulated and managed to protect and conserve the corals.

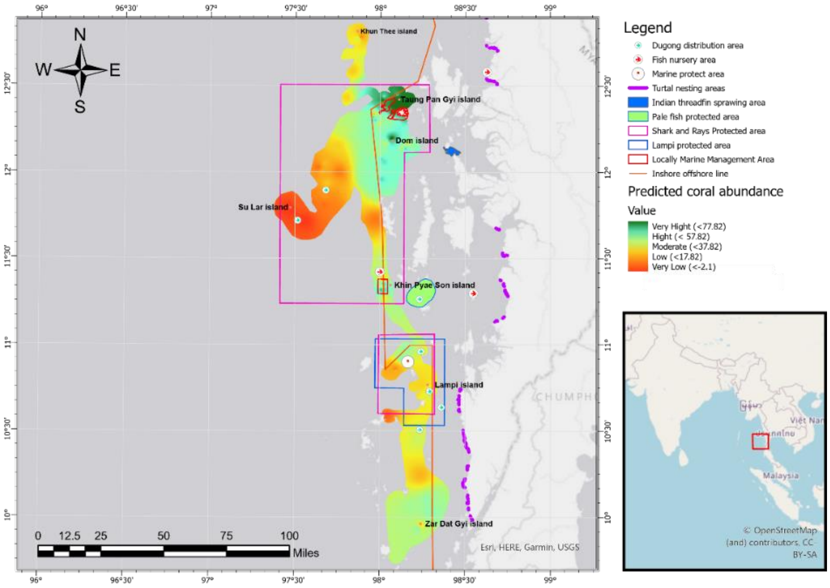


Figure 5.1 compare with marine management areas in Northern Myeik

5.4 Limitation

Due to the limitation of surveying large sea areas, it was hard to fully understand the ecological niche and coral reef distribution and abundance pattern. GWR enables us to make prediction surface map based on the current environmental and physical circumstances.

This study is based on only a very few surveyed coral abundance location data (102 sample points), which is the major limitation of this study. Importantly, random forest classification and regression model requires enormous sample size. However, I tried to use random forest model with small sample size, , which could be the main reason for poor model performance. This study chooses several environmental factors, including depth, slope, aspect, rugosity, turbidity, sea surface temperature, chlorophyll which were included in the study because they could be significant in assessing the prediction coral abundance map. Salinity was not included as an environmental variable in the analysis because the high-resolution sea surface salinity data was not available for the entire study area. One other major limitation of this study is that it does not consider critical anthropogenic drivers/factors in the modelling. Considering the time constraints, lack of readily available human activity data was the only reason for no to anthropogenic factors in the prediction models. However, this research is an important first step toward creating potential spatial predictions of species abundance for coral reef habitats in Myanmar water that can.

6 Conclusion

This research uses a simple GIS-based approach to identify environmental and physical factors that influence coral reef abundance in Myeik Archipelago in Myanmar. The model considers seven exploratory environmental variables relevant to the coral abundance: depth, slope, aspect, chlorophyll, SST, turbidity and rugosity. According to the OLS findings, the relationship between any or possibly all explanatory variables and the dependent variable is non-stationary throughout the study area. This study, a relatively simple analysis, indicates that GWR revealed significant local variation in the coral abundance and environment relationships and illustrates the potential for capturing the spatial non-stationarity of the influencing factors. The GWR model results show that depth and Sea Surface temperature were the most important factors for spatial variation of the coral abundance in the Myeik. However, the random forests model shows that all seven variables – depth, slope, aspect, rugosity, chlorophyll, SST, and turbidity were important factors for coral abundance and indicated a non-linear relationship between some environmental variables and coral abundance. Based on the model prediction, high coral abundance areas were found around the Taung Pan GYi island and Khin Pyae Sone island. Simple prediction models like GWR, as used in this study, can be used to identify priority areas for coral management plan and to create functional marine protection areas. They also provide beneficial information for marine conservation. Thus, such prediction models and predicted maps could help DOF managers and decision-makers to identify spatially potential coral abundance locations, providing cost effective solution to expensive coral surveys.

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Appendix A. Supplementary Material on the Preparation of Input Datasets

Table 7.1 Summary statistics *for OLS (significant at the α = 0.05 level) Significant variables are indicated with an asterisk (*).*

Variables	Coefficient values	Robust_Pr [b]	VIF
Depth	-3.241727	0.000073*	1.878527
Slope	-0.276382	0.909747	1.026319
Aspect	0.016285	0.428305	1.069873
Rugosity	23.594969	0.183289	1.425434
Chlorophyll	1.573359	0.743431	2.601162
SST	-34.104549	0.016199*	2.152849
Turbidity	-0.011159	0.898731	1.115527

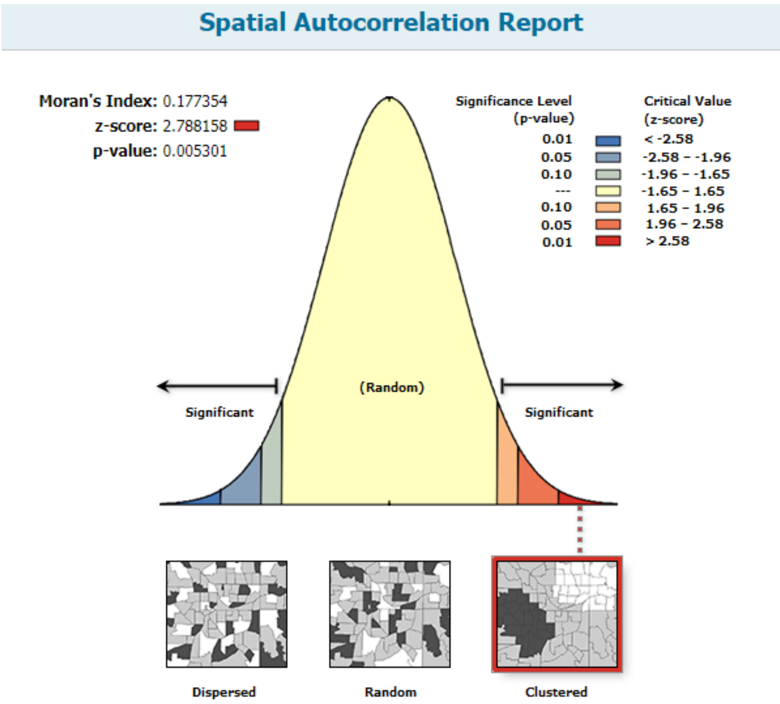

Figure 7.1 OLS Result of nearest neighbor analysis showing the coral abundance.

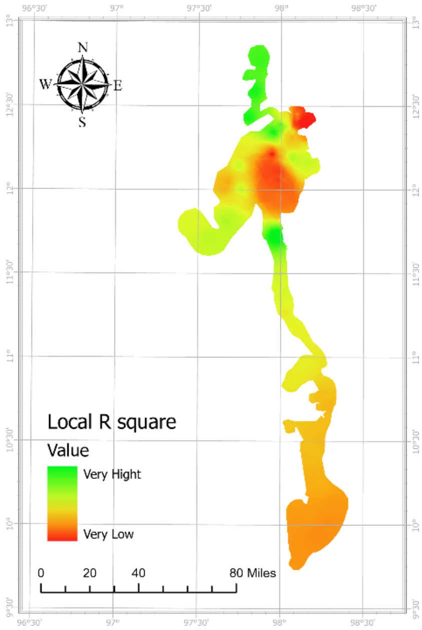

Figure 7.2 GWR result of local R^2

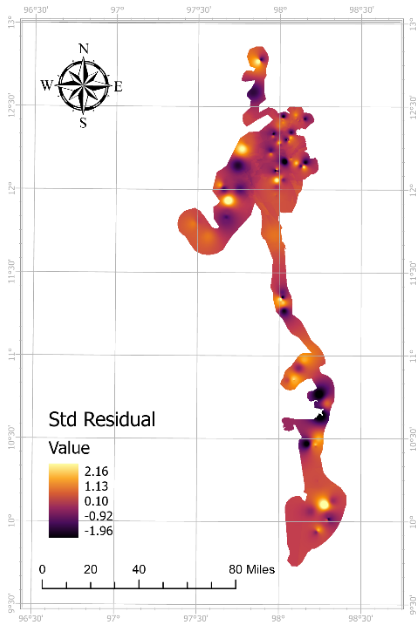

Figure 7.3 GWR result of Std. Residual

Table 7.2 FFI coral reefs survey data

SITE	AREA	LATDD Y	LONGDD X	SITE NAME	HARD CORAL
1	TYT	12.44203	98.01769	Thawaythadangyi Kyun	35
2	TYT	12.339	97.95778	Thawaythadangyi Kyun	13
3	TYT	12.30397	98.03683	Ba Gyee Kyunn Southwest	30
4	TYT	12.16753	98.15206	Wadi Kyunn Southeast	26.5
5	TYT	12.14542	98.12672	Daung Kyunn Southwest Tip	36.5
6	TYT	12.17211	98.02803	Ao Lei Kyunn Southwest Tip	20.5
7	TYT	12.01889	97.97922	Kyet Paun Kyunn Northeast Bay	53
8	LMP	10.85931	98.08764	Wa Ale Kyunn East	31.5
9	LMP	10.76942	98.24247	Lampi	11
10	LMP	10.47208	98.16825	Nyaung Whee	17.5
11	ZDG	10.24697	98.23747	Shwe Kyun Gyi	43
12	ZDG	10.24703	98.237	Pa Law Ka Kyan	20
13	ZDG	10.12939	98.32811	Thay Yae Kyunn	50.5
14	TYT	12.30578	98.04544	Za Latt	35
15	TYT	12.27286	98.00242	Pearl farm	53
16	TYT	12.34608	97.94833	Phalar Aw	53.5
17	TYT	12.28439	97.99325	Palu Palal Hill	59.5
18	TYT	12.30308	97.96714	Thit Lat Tan Aw	60
19	TYT	12.32369	97.95511	Thawaythadangyi Kyun	74
20	TYT	12.41425	98.11039	Tit Ti Tu Aw	90.5
21	TYT	12.421	98.10864	Shar Aw	88
22	TYT	12.43067	98.09583	Palu Palal Aw	88
23	TYT	12.40447	98.11822	Sas Tit Aw	82
24	TYT	12.45219	98.09483	Palu Palal Hill	77.5
25	TYT	12.42639	98.10069	Shar Aw	81.5
26	TYT	12.40758	98.01611	Zat Latt East	80.5
27	TYT	12.42589	98.13167	Taung Pan Gyi	81.5
28	TYT	12.42003	98.11914	Taung Pan Gyi	74.5
29	TYT	12.42939	98.15019	Taung Pan Gyi	56
30	TYT	12.40922	98.1353	Taung Pan Gyi	88
31	TYT	12.29306	98.05336	Mee Kway Island	68
32	TYT	12.34708	98.06619	Zalwal	78
33	TYT	12.30769	98.06	Dahaw	71.5
34	TYT	12.31569	98.06314	Dahaw	79.5
35	TYT	12.42342	98.01253	That Pan Nyo	92
36	TYT	12.1955	98.06517	Nyaung Hmine	90.5
37	TYT	12.18942	98.0675	Nyaung Hmine	72
38	TYT	12.06053	97.9805	Mee Kway Island	88
39	TYT	12.16294	98.09864	Dahaw	79
40	TYT	12.13997	98.14372	Dahaw	87
41	TYT	12.3905	97.99528	Taung Pan Gyi	85
42	TYT	12.41453	98.11167	Tit Ti Tu Aw	79.5
43	TYT	12.425	98.10142	Shar aw	84

SITE	AREA	LATDD Y	LONGDD X	SITE NAME	HARD CORAL
44	TYT	12.42083	98.12031	Taung Pan Gyi	79.5
45	TYT	12.42167	98.0125	That Pan Nyo	87
46	TYT	12.30447	98.04375	Bar Ge Mountain	61
47	TYT	12.39114	97.99583	Aw Wine	67.5
48	TYT	12.10911	97.98183	Kyun Pone	62
49	TYT	12.07728	98.00383	Salin Taung	73
50	TYT	12.06211	98.01906	Salin Taung	57
51	TYT	11.96306	97.99986	Mee Sein Is.	70.5
52	TYT	11.96758	97.97442	Mee Sein Is.	56.5
53	TYT	12.11789	97.97258	Kyun Pone	33
54	TYT	12.12456	97.97864	Kyun Pone	72.5
55	LMP	10.64517	98.24794	Lampi	11.5
56	PSB	11.32242	98.01889	La Ngan	86
57	PSB	11.32239	98.00253	La Ngan	84.5
58	PSB	11.34342	98.00536	La Ngan	72.5
59	PSB	11.35439	98.01664	La Ngan	49
60	LMP	10.71556	98.2905	Lampi	52
61	LMP	10.9785	98.15028	Lampi	71
62	LMP	10.92739	98.11636	Lampi	51.5
63	LMP	10.49978	98.23775	Nyaung Whee	60.5
64	LMP	10.46631	98.22008	Nyaung Whee	65.5
65	LMP	10.45567	98.22061	Nyaung Whee	51.5
66	PSB	11.27269	98.02614	Kyat Mi Thar Su Is.	22.5
67	PSB	11.38333	98.01581	Saw Pu Is.	25
68	TOR	11.71831	97.55844	Sular Nge Is.	7.5
69	TOR	11.79461	97.46953	West Sular Is.	2.5
70	TOR	11.81414	97.50667	West Sular, North Is.	10
71	TOR	11.81719	97.66856	Kon Thee Is.	5
72	TOR	11.83575	97.67144	East Sular Is.	5
73	TOR	11.86275	97.67511	East Sular	17.5
74	TOR	11.93703	97.68253	West Islet	65
75	TOR	12.00519	97.75297	Dana Theik Di Is.	7.5
76	TOR	12.00694	97.65561	South to Sular Kha Mouk Islet	15
77	TOR	12.02892	97.63161	Double Is.	27.5
78	TOR	12.05125	97.67125	Sular Kha Mout	27.5
79	TOR	12.14792	97.74086	Bailey Is. (Jer Bout Is.)	17.5
80	TOR	12.24808	97.76731	West Spur	70
81	TOR	12.29519	97.80114	Metcalfe Is.	55
82	TOR	12.43278	97.79856	Chevalier Rock	37.5
83	TOR	12.59025	97.83269	Tanintharyi Is.	20
84	TOR	12.77703	97.8665	Kabuzya Is.	70
85	TOR	12.78606	97.88033	Kun Thee Is.	7.5
86	TYT	12.42508	98.01425	Sack Is.	80
87	TYT	11.97078	97.97094	Mee Sein Is.	62.5

SITE	AREA	LATDD Y	LONGDD X	SITE NAME	HARD CORAL
88	PSB	11.72864	97.96819	Hlwa Sar Gyi Is.	21.25
89	LMP	10.85514	98.04733	Wa Ale Is.	28.75
90	LMP	10.59272	98.04103	Bo Ywe Is	7.5
91	ZDG	10.01153	98.29047	Zar Dat Gyi	59
92	ZDG	9.95294	98.23811	Zar Dat Gyi	52
93	ZDG	9.93917	98.22444	Zar Dat Gyi	51
94	ZDG	10.01822	98.30078	Zar Dat Gyi	38
95	ZDG	10.03528	98.30075	Zar Dat Gyi	52.5
96	ZDG	10.06394	98.18992	Zar Dat Gyi	49
97	ZDG	10.10372	98.27603	Zar Dat Ngal	92
98	TYT	12.11367	97.98428	Kyun Pone	33
99	TYT	12.21793	97.94239	Kyun Gedway	66
100	TYT	12.24042	97.94181	Kyun Gedway	45
101	TYT	12.23269	97.94233	Kyun Gedway	46.5
102	LMP	10.85503	98.08842	Lampi	45.5