GEOSPATIAL MODELING OF THE BIOPHYSICAL ENVIRONMENTS AND MANGROVE BIOMASS OF THE SUNDA BANDA SEASCAPE, INDONESIA

by

MINGSHU WANG

(Under the Direction of Marguerite Madden)

ABSTRACT

Due to its marine biodiversity, the Sunda Banda Seascape (SBS) is one of the largest marine ecoregions of Indonesia requiring conservation management. However, the SBS is under severe threat due to unsustainable development and climate change. There is neither comprehensive regional spatial data nor peer-review research of the SBS available. This study is the first-ever work using satellite remote sensing, machine learning and dynamic model-assimilated data to delineate biophysical environments of the SBS, and classifies it into eight biophysically meaningful regions. The SBS also contains mangrove forests with some of the highest mangrove diversity and biomass of the world. Mangroves are critical for their ecological functions and services to human welfare. Based on the biophysical regions, this study uses bioclimatic models derived from the fifth report of the Intergovernmental Panel on Climate Change (IPCC) to estimate mangrove biomass through 2070. This study will inform conservation practices of the SBS.

INDEX WORDS: Sunda Banda Seascape, biophysical environments, remote sensing, machine learning, classification, mangrove biomass, climate change, IPCC

GEOSPATIAL MODELING OF THE BIOPHYSICAL ENVIRONMENTS AND MANGROVE BIOMASS OF THE SUNDA BANDA SEASCAPE, INDONESIA

by

MINGSHU WANG

B.S., Nanjing University, P.R. China, 2012

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2014

GEOSPATIAL MODELING OF THE BIOPHYSICAL ENVIRONMENTS AND MANGROVE BIOMASS OF THE SUNDA BANDA SEASCAPE, INDONESIA

by

MINGSHU WANG

Major Professor:	Marguerite Madden
Committee:	Lan Mu
	Gabby N. Ahmadia

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
May 2014

ACKNOWLEDGEMENTS

Two years' experience in Master's study in the Center for Geospatial Research, Department of Geography at the University of Georgia has been rewarding to me. I appreciate my colleagues and external collaborators who helped me finish my thesis research. First and foremost, I want to express my deep appreciation to my major professor—Dr. Marguerite Madden. Since I met Dr. Madden three years ago at the ISPRS LiDAR Summer School in Fayetteville, NC, I knew coming here for graduate study is the right choice. She coached my scientific rigor, supported my exploration for opportunities, and broadened my horizon by encouraging my involvement in the American Society of Photogrammetry and Remote Sensing (ASPRS). Without her endless input, timely feedbacks, I would not be able to deliver my thesis today.

I want to thank Dr. Lan Mu, who trained my incisiveness in research, exactness in details and cartography. Without experiencing academic writing with her by expanding my GEOG 8570 (Seminar in Geographic Information Science) term paper into a peer-review manuscript (in press by *Annals of GIS*), I would not be able to finish this manuscript-style thesis work smoothly.

I would like to thank Dr. Gabby N. Ahmadia and Charles Huang from the World Wildlife Fund—United States (WWF-US) for accepting me as an intern in the Conservation Science Program last summer. They brought to me the exciting field of coastal and marine planning and resource management, as well as the hotspot geographic area—Coral Triangle. My thesis could not be shaped without my three month involvement at WWF. I also want to thank Dr. Helen Fox from WWF-US, who provided scientific and environmental policy guidance to me through the development of my thesis.

I would acknowledge Dr. Iliana Chollett from the University of Queensland, Australia, who patiently provided guidance in techniques and witnessed my progress step by step. Her quick response expedited the development of my thesis. I would also acknowledge Anton Wijonarno, and Estradivari Estradivari from World Wildlife Fund—Indonesia (WWF-ID) for providing expert knowledge as local experts. I want to thank James Hutchison from the University of Cambridge, United Kingdom for providing me with key literature on mangrove forests.

I want to acknowledge all my colleagues at the Center for Geospatial Research for their constant support. They are Dr. Thomas R. Jordan, Dr. Sergio Bernardes, Dr. Allison Howard, Dr. Andrea Presotto, Nancy O'Hare, Jiaying He, Caren Remillard and Chris Strother.

I want to also acknowledge Dr. Tom Purucker, my supervisor at the Office of Research and Development, U.S. Environmental Protection Agency and Dr. Tao Hong from Oak Ridge Institute for Science and Education (ORISE) of U.S. Department of Energy for their constant support.

Finally, I would like thank my parents, Kesong Wang and Yan Zhao, for their unconditional love and unswerving support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Background

The Coral Triangle (CT, Figure 1.1) geographically refers to a roughly 5.7 million km^2 triangular area of the tropical marine waters of Indonesia, Malaysia, Papua New Guinea, Philippines, Solomon Islands and East Timor (aka Timor-Leste) (Veron 1995). It has been long recognized as the global apogee of marine biodiversity and called the "Amazon of the seas" because it has 605 zooxanthellate coral species of which 66% are common to all eco-regions (Hoeksema 2007, Veron et al. 2009), as well as 52% of Indo-Pacific reef fishes (Allen 2008). The Indo-Malaysian region of CT has 48 mangrove species (Duke, Ball and Ellison 1998), which is the highest species diversity of mangrove anywhere in the world. Indonesia itself covers 22.6% of the world's mangrove forests (Giri et al. 2011), which is two times larger than Australia— the second largest area of mangrove cover. The CT covers 5.7 million km^2 of ocean waters and sustains the lives of over 138 million people with its biological resources. Located in the center of CT, the Sunda Banda Seascape (SBS) is second largest marine ecoregion in Indonesia, and is home to 76% of known coral species, more than 3,000 fish species, and is among the highest mangrove biomass regions of the world (Hutchison et al. 2013).

However, marine ecosystems, such as coral reefs and mangroves, are currently threatened by local stressors such as overfishing, destructive fishing, coastal development and pollution worldwide. Globally, about 35% of mangrove were lost from 1980 to 2000

(MA 2005), which have been declining faster than coral reefs or tropical rainforests (Duke et al. 2007). An estimated 95% of coral reefs in CT are considered to be at medium or higher threat by human activities, especially related to overfishing (Burke et al. 2011). When the influence of climate change is combined with local threats, the health of coral reefs and mangroves are even more worrisome. In order to address these urgent threats, the Coral Triangle Initiative on Coral Reefs, Fisheries and Food Security (CTI-CFF), a multilateral partnership including six countries, was formed in 2007. The CTI-CFF has become one of the largest conservation initiatives in the marine world.

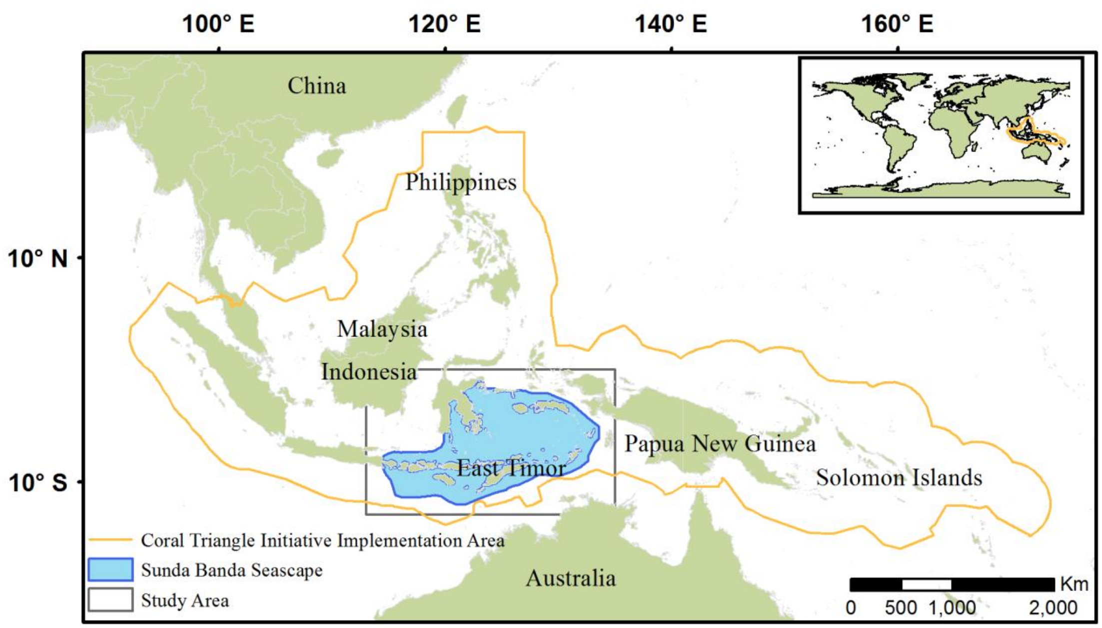

Figure 1.1. The Coral Triangle and the Sunda Banda Seascape, Indonesia.

Recently, the governments of the region and international nature conservation organizations increased allocation of conservation resources to the SBS. However, SBS is an information-poor region, where no comprehensive regional data and peer-review journal articles documenting critical research are available. Existing studies are either: 1) global in scale with coarse resolution, imagery and data that are not sufficient to set up a baseline and inform regional conservation practices; or 2) studies have been very local with focus on individual marine protected areas (MPA). Unfortunately, those MPA may not be representative or suitable to inform marine conservation activities at the regional scale. The SBS is large in size, compared to the MPA field measurement-based research areas (150 million km^2 compared to several km^2, respectively). Importantly, SBS is remote in location and relatively inaccessible. Geospatial modeling and analysis including remote sensing and spatiotemporal modeling offers an ideal set of technical approaches to delineate the biophysical marine and coastal environments of this region. Biophysical environments refer to physical (such as salinity, sea surface temperature and ocean currents) and biochemical (such as chlorophyll a) environmental conditions. Understanding biophysical environments are essential for conservation and management because they are essential for shaping marine biodiversity.

Meanwhile, deforestation is the second largest source of anthropogenic CO_2 emissions, contributing12-20% of the total (IPCC 2007, Hutchison et al. 2013). Biomass is carbon-based biological material derived from living, or recently living organisms. As an energy source, biomass can either be used directly via combustion to produce heat, or indirectly after converting it to various forms of biofuel. Due to the declining status of mangrove forests, geospatial modeling and predicting spatial patterns of mangrove biomass in the context of climate change can help improve mangrove management practices, formulate conservation activities, refine climate models, and update mitigation and adaptation policies.

Based on the unique location of SBS, the alarming threats to coral reefs and mangroves in marine and coastal environments, and the impact of climate change, there is great room for using geospatial modeling and analysis to assess the marine and coastal environments and then inform conservation activities.

1.2 Research Objectives

The overarching research question of this thesis asks how geospatial modeling and analysis can be used to facilitate marine and coastal environment studies and inform conservation practices for information-poor regions in the context of climate change. Developing a methodology for understanding the biophysical environments of an information-poor area permits the establishment of a baseline for any further research and conservation practices - often the first step of ecological assessment and marine spatial planning. Therefore, the first article of this manuscript-style thesis uses machine learning to delineate the biophysical environments of the SBS through satellite remote sensing and dynamic model-assimilated data. Geospatial modeling and predicting mangrove biomass in the context of climate change facilitates monitoring of extent, health and ecological functions of mangroves. This methodology also assists effective and efficient mangrove management. Hence, the second article of this manuscript-style thesis uses bioclimatic models to estimate spatial distribution of mangrove biomass in 2070 (the latest forecasting scenario) based on the fifth report of the Intergovernmental Panel on Climate Change (IPCC).

This thesis includes two main objectives, each of which addresses an important abovementioned problem of marine and coastal environmental studies by applying cutting-edge machine learning algorithms or models that are implemented with geospatial analysis. More specifically, these two objects are:

(1) To identify variables which directly influence marine biodiversity and classify the SBS into biophysically meaningful and practically manageable regions using the machine-learning method, self-organizing map (SOM);

(2) To predict spatial patterns of mangrove biomass in 2070 using bioclimatic models derived from the fifth report of IPCC.

This thesis research is the first-ever study of this kind in the SBS. It provides a baseline for multiple interdisciplinary research. It also potentially informs conservation practices and investments for both international nature conservation organizations and local authorities.

1.3 Literature Review

1.3.1 Marine Ecosystems, Coral Reefs and Mangroves

Marine waters cover two-thirds of the surface of the Earth and marine ecosystems are among the largest of Earth's aquatic ecosystems. They usually include oceans, salt marsh and intertidal habitats, estuaries and lagoons, mangroves and coral reefs, the deep sea and the sea floor (Barange et al. 2010). Based on a prevailing marine management scheme— the marine ecoregion of the world (MEOW) (Spalding et al. 2007), the world's coastal and shelf Areas are categorized into nested system of 12 realms, 62 provinces, and 232 ecoregions. MEOW is based on experts' opinions and globally comparable on a biogeographic basis, for example floral and faunal composition. Regarding the ecological value of marine ecosystems, coral reefs provide nutrition and shelter to the highest levels of marine diversity in the world; coastal habitats account for roughly 1/3 of all marine biological productivity; and salt marshes, sea grasses and mangrove forests are among the most productive regions on the planet (Barange et al. 2010).

Coral reefs refer to colonies of tiny animals in oceans. They cover less than 0.1% of the world's marine environment; but they are home to 25% of all marine species (Spalding and Grenfell 1997, Spalding, Ravilious and Green 2001). Coral reefs provide ecosystem services to tourism and fisheries. The global economic value of coral reefs has been estimated to be between US$ 29.8 billion (Cesar, Burke and Pet-Soede 2003) and US$ 375 billion per year (Costanza et al. 1997). They also protect shorelines by absorbing wave energy, a function for which many small islands owe their existence. However, coral reefs are very fragile and under threats from both nature (e.g., climate change, oceanic acidification, etc.) and the activities of human beings (e.g., overfishing, unbalanced coastal development, water pollution, etc.).

Mangroves are an assembly of woody halophytes (salt tolerant trees and shrubs) that are fundamental species distributed in the estuaries, lagoons and littoral zone between 30 °N and 30 °S of the world (Alongi 2009, Tomlinson 1986). They grow in harsh biophysical conditions such as high salinity, high temperature, extreme tide, high sedimentation and muddy anaerobic soils (Giri et al. 2011); their distribution is driven by major ocean currents (Alongi 2009). Mangrove forests sequestrate carbon, support biodiversity through their variable structure and potentially reduce hurricane impacts (Alongi 2002). The primary productivity in mangroves can be compared to the productivity of tropical rainforests (Alongi 2002). Litters of mangrove forests provide nutrients and food for marine species, which are linked to increased fish populations (Mumby et al. 2004). These ecosystem goods and services are estimated as much as about US$ 100,000 per hectare per year and US$ 170 billion globally per year (Costanza et al. 1997). Figure 1.2 and Figure 1.3 show the distribution of coral reefs and mangrove forests with in the CT, respectively and are adopted from the CTI-CFF (http://www.coraltriangleinitiative.org/).

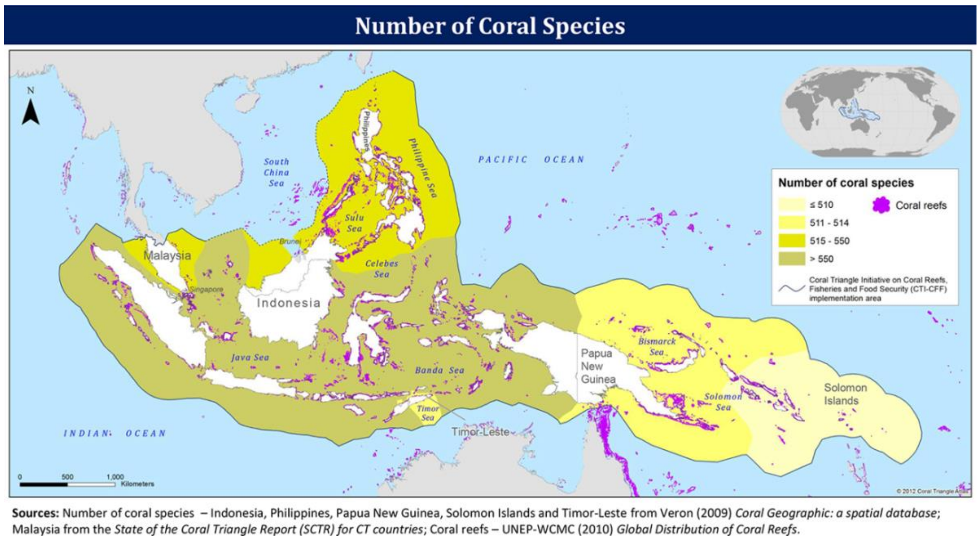

Figure 1.2. Coral species map of the Coral Triangle.

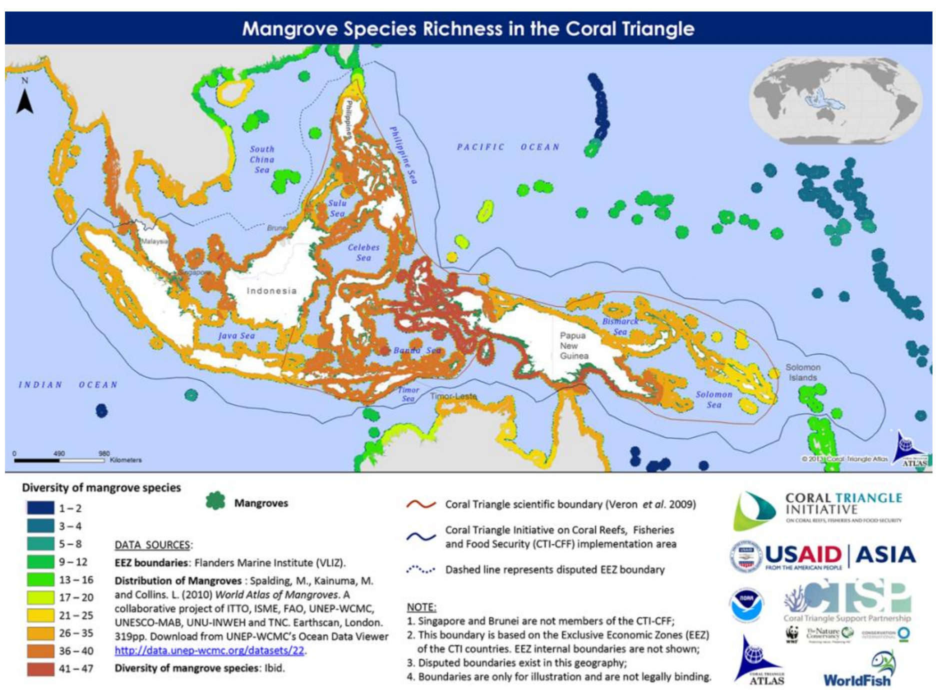

Figure 1.3. Mangrove species map of the Coral Triangle.

1.3.2 Remote Sensing of Marine Environments and Mangroves

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is a key instrument aboard the Terra (in 1999) and Aqua (in 2002) remote sensing satellites. Together the instruments image the entire Earth every 1 to 2 days. MODIS are designed to provide measurements in broad-scale global dynamics including changes in Earth's cloud cover, radiation budgets and processes occurring in the oceans, on land, and in the lower atmosphere. Bands information of MODIS data (Level 2) is summarized in Table 1.1. Level 3 data of MODIS usually provide 16-day composite datasets that are freely available via the USGS National Map. MODIS is playing a vital role in the development of validated, global, interactive Earth system models able to accurately predict global change to assist policy makers in making sound decisions concerning the protection of our environment.

Table 1.1 Bands information of MODIS sensor

B	WL (nm)	R(m)	Primary Use	B	WL (μm)	R (m)	Primary Use
1	620–670	250	Land/Cloud/Aerosols Boundaries	20	3.660–3.840	1000	Surface/Cloud Temperature
2	841–876	250		21	3.929–3.989	1000	
3	459–479	500	Land/Cloud/Aerosols Properties	22	3.929–3.989	1000	
4	545–565	500		23	4.020–4.080	1000	
5	1230–1250	500		24	4.433–4.498	1000	Atmospheric Temperature
6	1628–1652	500		25	4.482–4.549	1000	
7	2105–2155	500		26	1.360–1.390	1000	Cirrus Clouds Water Vapor
8	405–420	1000	Ocean Color/ Phytoplankton/ Biogeochemistry	27	6.535–6.895	1000	
9	438–448	1000		28	7.175–7.475	1000	
10	483–493	1000		29	8.400–8.700	1000	Cloud Properties
11	526–536	1000		30	9.580–9.880	1000	Ozone
12	546–556	1000		31	10.780–11.280	1000	Surface/Cloud Temperature
13	662–672	1000		32	11.770–12.270	1000	
14	673–683	1000		33	13.185–13.485	1000	Cloud Top Altitude
15	743–753	1000		34	13.485–13.785	1000	
16	862–877	1000		35	13.785–14.085	1000	
17	890–920	1000	Atmospheric Water Vapor	36	14.085–14.385	1000	
18	931–941	1000					
19	915–965	1000					

B refers to Band; WL refers to Wavelength; R refers to Resolution. Source: http://modis.gsfc.nasa.gov/

In the context of marine environments, satellite remote sensing data acquired by sensors such as MODIS document Earth surface spectral heterogeneity at a regional level suitable for providing geographically comprehensive marine information. Ocean optical and thermal remote sensing is highly correlated to the processes in the entire water column (Brando and Dekker 2003, Oliver and Irwin 2008, Longhurst 2010). Hence, delineating biophysical environments through satellite remote sensing is not only effective for the benthic (bottom) systems, but also valuable for the pelagic (ocean water) system studies.

The recent advancements of satellite remote sensing data and algorithms have been successfully applied to mapping the extent and change of mangrove forests at different scales (Heumann 2011). However, remote sensing to estimate mangrove forests biomass often requires data fusion among Synthetic-aperture Radar (SAR), very high resolution (VHR) imagery and Light Detection and Ranging (LiDAR) for the need of vegetation structure mapping, which is an essential (Heumann 2011).

The SBS is located in a tropical area where clouds are heavy and limit the performance of optical remote sensing, including VHR image data. Importantly, SAR, VHR and LiDAR are often costly to acquire and this financial burden reduces their access to developing countries, including Indonesia. Therefore, rather than relying on remote sensing, alternative ways of geospatial modeling and analysis should be considered for mangrove biomass mapping in the SBS.

1.3.3 Self-Organizing Maps (SOM)

A number of classification approaches have been used to analyze geospatial data and extract features in marine environment, including supervised and unsupervised algorithms (Miller and Han 2009). One type of those algorithms is machine learning, which is a branch of artificial intelligence that concerns the construction and study of algorithms and systems that can learn from data. Recently, machine learning has been a strong driver in a number of branches of artificial intelligence such as computer vision, natural language processing and anti-spam (Bishop and Nasrabadi 2006). Among different machine learning approaches, neural networks are usually used to model complex relationships between inputs and outputs, to find patterns in data. They are inspired by the structure and functional aspects of biological neural networks. In a neural network, computations are structured in terms of an interconnected group of artificial neurons (Hagan, Demuth and Beale 1996).

Self-organizing maps (SOM) is a flexible, unsupervised neural network for data analysis and clustering (Kohonen 1982, Kohonen 2001, Kohonen 2013). Theoretically, SOM outperforms traditional statistical clustering methods and is more appropriate for large nonlinear data sets with high dimensionality. Traditional statistical clustering methods, such as k-means and ISODATA, require an *a priori* hypothesis of the data distribution (Miller and Han 2009); however most datasets contain hidden and unexpected information. SOM does not make *a priori* assumptions about the data sets and is a possible tool for automated knowledge discovery from high dimensional variables. Several performance studies have illustrated the advantages of SOM over other clustering methods (Ultsch, Vetter and Vetter 1995, Zhong et al. 2006), and SOM has drawn great attention for geographic information science (Agarwal and Skupin 2008) for spatial and temporal modeling and analysis (Ji 2000, Zhong et al. 2006, Goncalves et al.

2008, Kalteh, Hjorth and Berndtsson 2008, Hu and Weng 2009, Jensen, Thompson and Schmidlin 2012, Hagenauer and Helbich 2013).

1.3.4 Biophysical Environments and Biomass

The biophysical environments that have shaped ecosystem structure not only influence ecosystem dynamics but also how these ecosystems will respond to changes in patterns of resource use and conservation interventions. Oceanographic conditions, such as temperature, dictate the range and persistence of marine organisms. For example, sea surface temperature (SST) is a fundamental driving factor on coral reef ecosystems, where temperature variability results in coral morality and subsequent reduction in coral cover. Ocean currents transport larvae and juveniles between distant patches of suitable habitat so ocean currents determine the population connectivity for many marine species (Treml et al. 2008, Treml and Halpin 2012, Cowen, Paris and Srinivasan 2006). Sea salinity is a limiting factor for photosynthesis, and is used to estimate species richness and abundance of fishes (Mellin et al. 2010, Fraser and Currie 1996). Chlorophyll a concentration is a proxy for phytoplankton biomass (Gove et al. 2013, Sathyendranath, Prieur and Morel 1989, Shang et al. 2013, Sapiano et al. 2012).

Biomass is carbon based and is composed of a mixture of organic molecules. Plants construct biomass by absorbing carbon from the atmosphere as CO_2 and using energy from the sun. As an energy source, biomass can either be used directly via combustion to produce heat, or indirectly after converting it to various forms of biofuel. An alarming fact is that about 35% of mangroves were lost from 1980 to 2000 (MA 2005), which have been declining faster than coral reefs or tropical rainforests (Duke et al. 2007). Therefore, quantifying the amount and spatial pattern of biomass within mangroves is necessary for property managers to make informed decisions about the value and use of mangroves (Gleason and Im 2012), refining global climate models and developing policy responses (Hutchison et al. 2013).

1.4 Thesis Structure

The thesis structure is organized into four chapters. Chapter 1 covers the background and objectives of the thesis research, and literature review of topics including background knowledge in marine ecosystems, coral reefs and mangroves, facts of remote sensing of marine environments and mangroves, and introduction of self-organizing map (SOM). The following two chapters are separate articles to be submitted to journals for peer-review publication. In Chapter 2, a SOM-based framework is proposed to delineate the biophysical environments and inform marine conservation in the SBS. In Chapter 3, bioclimatic models are used to predict spatial patterns of mangrove biomass in the SBS in the 2070. Chapter 4 provides conclusions of this thesis and shows the future work.

References

Agarwal, P. & A. Skupin. 2008. *Self-organising maps: Applications in geographic information science*. John Wiley & Sons.

Allen, G. R. (2008) Conservation hotspots of biodiversity and endemism for Indo‐Pacific coral reef fishes. *Aquatic Conservation: Marine and Freshwater Ecosystems,* 18**,** 541-556.

Alongi, D. M. (2002) Present state and future of the world's mangrove forests. *Environmental Conservation,* 29**,** 331-349.

---. 2009. *The energetics of mangrove forests*. Springer.

Barange, M., J. G. Field, R. P. Harris, E. E. Hofmann, R. I. Perry & F. E. Werner. 2010. *Marine ecosystems and global change*. Oxford University Press Oxford.

Bishop, C. M. & N. M. Nasrabadi. 2006. *Pattern recognition and machine learning*. springer New York.

Brando, V. E. & A. G. Dekker (2003) Satellite hyperspectral remote sensing for estimating estuarine and coastal water quality. *Geoscience and Remote Sensing, IEEE Transactions on,* 41**,** 1378-1387.

Burke, L. M., K. Reytar, M. Spalding & A. Perry. 2011. *Reefs at risk revisited*. World Resources Institute Washington, DC.

Cesar, H., L. Burke & L. Pet-Soede (2003) The economics of worldwide coral reef degradation.

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. O'Neill, J. Paruelo, R. G. Raskin, P. Sutton & M. van den Belt

(1997) The value of the world's ecosystem services and natural capital. *Nature,* 387**,** 253-260.

Cowen, R., C. Paris & A. Srinivasan (2006) Scaling of connectivity in marine populations. *Science*, 311**,** 522-527.

Duke, N. C., M. C. Ball & J. C. Ellison (1998) Factors influencing biodiversity and distributional gradients in mangroves. *Global Ecology and Biogeography Letters***,** 27-47.

Duke, N. C., J.-O. Meynecke, S. Dittmann, A. M. Ellison, K. Anger, U. Berger, S. Cannicci, K. Diele, K. C. Ewel & C. D. Field (2007) A world without mangroves? *Science,* 317**,** 41-42.

Fraser, R. H. & D. J. Currie (1996) The species richness-energy hypothesis in a system where historical factors are thought to prevail: coral reefs. *American Naturalist***,** 138-159.

Giri, C., E. Ochieng, L. L. Tieszen, Z. Zhu, A. Singh, T. Loveland, J. Masek & N. Duke (2011) Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography,* 20**,** 154-159.

Gleason, C. J. & J. Im (2012) Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sensing of Environment,* 125**,** 80-91.

Goncalves, M., M. Netto, J. Costa & J. Zullo Junior (2008) An unsupervised method of classifying remotely sensed images using Kohonen self‐organizing maps and agglomerative hierarchical clustering methods. *International Journal of Remote Sensing,* 29**,** 3171-3207.

Gove, J. M., G. J. Williams, M. A. McManus, S. F. Heron, S. A. Sandin, O. J. Vetter & D. G. Foley (2013) Quantifying Climatological Ranges and Anomalies for Pacific Coral Reef Ecosystems. *PLoS ONE,* 8**,** e61974.

Hagan, M. T., H. B. Demuth & M. H. Beale. 1996. *Neural network design*. Pws Pub. Boston.

Hagenauer, J. & M. Helbich (2013) Hierarchical self-organizing maps for clustering spatiotemporal data. *International Journal of Geographical Information Science***,** 1-17.

Heumann, B. W. (2011) Satellite remote sensing of mangrove forests: Recent advances and future opportunities. *Progress in Physical Geography,* 35**,** 87-108.

Hoeksema, B. W. 2007. Delineation of the Indo-Malayan centre of maximum marine biodiversity: the Coral Triangle. In *Biogeography, time, and place: distributions, barriers, and islands*, 117-178. Springer.

Hu, X. & Q. Weng (2009) Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks. *Remote Sensing of Environment,* 113**,** 2089-2102.

Hutchison, J., A. Manica, R. Swetnam, A. Balmford & M. Spalding (2013) Predicting global patterns in mangrove forest biomass. *Conservation Letters***,** n/a-n/a.

IPCC. 2007. *Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC*. Cambridge University Press.

Jensen, A. A., A. M. Thompson & F. J. Schmidlin (2012) Classification of Ascension Island and Natal ozonesondes using self-organizing maps. *Journal of Geophysical Research: Atmospheres,* 117, D04302.

Ji, C. (2000) Land-use classification of remotely sensed data using Kohonen self-organizing feature map neural networks. *Photogrammetric Engineering and Remote Sensing,* 66, 1451-1460.

Kalteh, A. M., P. Hjorth & R. Berndtsson (2008) Review of the self-organizing map (SOM) approach in water resources: Analysis, modelling and application. *Environmental Modelling & Software,* 23, 835-845.

Kohonen, T. (1982) Self-organized formation of topologically correct feature maps. *Biological cybernetics,* 43, 59-69.

Kohonen, T. 2001. *Self-organizing maps*. Springer.

Kohonen, T. (2013) Essentials of the self-organizing map. *Neural Netw,* 37, 52-65.

Longhurst, A. R. 2010. *Ecological geography of the sea*. Academic press.

MA. 2005. *(Millennium Ecosystem Assessment) Ecosystems and human well-being*. Island Press Washington, DC.

Mellin, C., C. J. A. Bradshaw, M. G. Meekan & M. J. Caley (2010) Environmental and spatial predictors of species richness and abundance in coral reef fishes. *Global Ecology and Biogeography,* 19, 212-222.

Miller, H. J. & J. Han. 2009. *Geographic data mining and knowledge discovery*. CRC PressI Llc.

Mumby, P. J., A. J. Edwards, J. E. Arias-González, K. C. Lindeman, P. G. Blackwell, A. Gall, M. I. Gorczynska, A. R. Harborne, C. L. Pescod & H. Renken (2004)

Mangroves enhance the biomass of coral reef fish communities in the Caribbean. *Nature*, 427**,** 533-536.

Oliver, M. J. & A. J. Irwin (2008) Objective global ocean biogeographic provinces. *Geophysical Research Letters,* 35**,** L15601.

Sapiano, M. R. P., C. W. Brown, S. Schollaert Uz & M. Vargas (2012) Establishing a global climatology of marine phytoplankton phenological characteristics. *Journal of Geophysical Research: Oceans,* 117**,** C08026.

Sathyendranath, S., L. Prieur & A. Morel (1989) A three-component model of ocean colour and its application to remote sensing of phytoplankton pigments in coastal waters. *International Journal of Remote Sensing,* 10**,** 1373-1394.

Shang, S., Q. Dong, C. Hu, G. Lin, Y. Li & S. Shang (2013) On the consistency in variations of chlorophyll a concentration in the South China Sea as revealed by three remote sensing datasets. *Biogeosciences Discussions,* 10**,** 7549-7578.

Spalding, M. & A. Grenfell (1997) New estimates of global and regional coral reef areas. *Coral reefs,* 16**,** 225-230.

Spalding, M. D., H. E. Fox, B. S. Halpern, M. A. McManus, J. Molnar, G. R. Allen, N. Davidson, Z. A. Jorge, A. L. Lombana, S. A. Lourie, K. D. Martin, E. McManus, J. Molnar, C. A. Recchia & J. Robertson (2007) Marine ecoregions of the world: A bioregionalization of coastal and shelf areas. *Bioscience,* 57**,** 573-583.

Spalding, M. D., C. Ravilious & E. P. Green. 2001. *World atlas of coral reefs*. Univ of California Press.

Tomlinson, P. 1986. The botany of mangroves. Cambridge tropical biology series. Cambridge University Press, Cambridge.

Treml, E. A. & P. N. Halpin (2012) Marine population connectivity identifies ecological neighbors for conservation planning in the Coral Triangle. *Conservation Letters*, 5**,** 441-449.

Treml, E. A., P. N. Halpin, D. L. Urban & L. F. Pratson (2008) Modeling population connectivity by ocean currents, a graph-theoretic approach for marine conservation. *Landscape Ecology*, 23**,** 19-36.

Ultsch, A., C. Vetter & C. Vetter. 1995. *Self-Organizing-Feature-Maps versus statistical clustering methods: a benchmark*. Fachbereich Mathematik.

Veron, J., L. M. Devantier, E. Turak, A. L. Green, S. Kininmonth, M. Stafford-Smith & N. Peterson (2009) Delineating the coral triangle. *Galaxea, Journal of Coral Reef Studies*, 11**,** 91-100.

Veron, J. E. N. 1995. *Corals in space and time: the biogeography and evolution of the Scleractinia*. Cornell University Press.

Zhong, Y., L. Zhang, B. Huang & P. Li (2006) An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery. *Geoscience and Remote Sensing, IEEE Transactions on*, 44**,** 420-431.

CHAPTER 2

DELINEATING BIOPHYSICAL ENVIRONMENTS TO INFORM MARINE CONSERVATION IN THE SUNDA BANDA SEASCAPE, INDONESIA[1]

[1] Wang, M. et al. To be submitted to *PLOS ONE*

Abstract

The Sunda Band Seascape (SBS), located in the center of Coral Triangle—the "amazon of the sea", is a global center of marine biodiversity, ecosystem vulnerability and conservation priority. We proposed the first-ever biophysical environmental delineation of the SBS using globally available satellite remote sensing and model-assimilated data to categorize this area into unique and meaningful biophysical classes based on a suite of biophysical conditions. Specifically, the SBS were partitioned into eight biophysical classes characterized by similar sea surface temperature patterns, chlorophyll a concentration, currents, and salinity. Areas within each class were expected to have similar habitat types and ecosystem functions. Our work supplemented prevailing global marine management schemes by providing up-to-date regional information in the finest spatial resolution. It also set up a baseline for academic research, ecological assessment and would facilitate marine spatial planning and conservation activities. The framework and methods of delineating biophysical environments we presented can be expanded in the whole Coral Triangle and replicated to support research and conservation in other parts of the world.

2.1 Introduction

Coastal areas provide food resources, sustain trade, and promote tourism. More than 2.2 billion people reside within 100 km of coastlines; this density is much higher than the global average population density of all coastal and non-coastal lands combined (Small and Nicholls 2003). If current rates of population growth are maintained, the number of humans living near coastlines is expected to increase from 2.3 billion in 2000 to 3.1 billion in 2025 (Kaiser et al. 2005). Many of these coastal inhabitants rely directly on the wealth of natural resources and ecosystem services provided by marine ecosystems for subsistence and as a source of income. The steady increment of coastal populations poses a challenge to coastal and marine managers tasked with conservation and preservation of natural areas undergoing threats from development and changing climates. Although resources need to be allocated to sustain local livelihoods, coastal ecosystems need to be protected to secure their ecological function and availability in the future. Therefore, understanding coastal and marine biophysical environments is critical to make more informed decisions about how and where to allocate those resources and intervene in support of conservation.

In recent decades, studies of marine environments have described the dynamic range of environmental heterogeneity in tropical ecosystems (Chollett et al. 2012, Freeman et al. 2012, Ando and McPhaden 1997, Glynn and Ault 2000, Zhang 1996). Biophysical environments refer to physical (such as salinity, sea surface temperature and ocean currents) and biochemical (such as chlorophyll a) environmental conditions. They dictate the structure and function of marine ecosystems, serve as proxies for the distribution of species and habitats, and facilitate conservation. When prioritizing conservation activities on a broad spatial scale, there are often gaps of information about the habitats and ecosystems present in the area. A classification of biophysical environments using remote sensing can be a useful first step towards a comprehensive understanding of the region of focus (Zacharias et al. 1998, Chollett et al. 2012).

The biophysical environmental conditions that have shaped ecosystem structure not only influence ecosystem dynamics but also how these ecosystems will respond to changes in patterns of resource use and conservation interventions. Oceanographic conditions, such as temperature, dictate the range and persistence of marine organisms. For example, sea surface temperature (SST) is a fundamental driving factor in coral reef ecosystems, where temperature variability results in coral morality and subsequent reduction in coral cover (Freeman et al. 2012). With direct atmosphere-ocean surface exchange of heat, water, mass and momentum, ocean currents transport coral larvae and juvenile fish and shell fish between distant patches of suitable habitat, so ocean currents determine the population connectivity for many marine species (Treml et al. 2008, Treml and Halpin 2012, Cowen, Paris and Srinivasan 2006). Sea salinity is a limiting factor for photosynthesis, and is used to estimate species richness and abundance of fishes (Mellin et al. 2010, Fraser and Currie 1996). Chlorophyll a concentration is a proxy for phytoplankton biomass (Gove et al. 2013, Sathyendranath, Prieur and Morel 1989, Shang et al. 2013, Sapiano et al. 2012), and has also been applied to modeling of primary production and the ocean carbon cycle (Nair et al. 2008).

The Coral Triangle (Figure 2.1) refers to a roughly triangular area of the tropical marine waters of Indonesia, Malaysia, Papua New Guinea, Philippines, Solomon Islands and East Timor (aka Timor-Leste) (Hoeksema 2007). The 5.7 million km^2 area is recognized as an epicenter of tropical marine biodiversity (Allen 2008). The ecosystem services of the Coral Triangle sustain over 120 million people, for they rely on its coral reefs for food, income, and protection from storms. Worldwide, 60% of reefs are currently threatened by local stressors such as overfishing, destructive fishing, coastal development and pollution. In the Coral Triangle, however, this value is as high as 85%. The most widespread local threat in the region is overfishing (Burke et al. 2011). Much of the fishing that occurs is unsustainable and jeopardizes people's livelihoods. Moreover, a changing climate— changes in ocean chemistry, warming temperature, increased frequency of storms— is exacerbating anthropogenic disturbances on the ecosystems. When the influence of climate change is combined with local threats, the percentage of reefs threatened in the region increases to a worrisome value of 90% (Burke et al. 2011). In order to address these urgent threats, the Coral Triangle Initiative on Coral Reefs, Fisheries and Food Security (CTI-CFF, http://www.coraltriangleinitiative.org), a multilateral partnership including six countries including Indonesia, was formed in 2007. The CTI-CFF has become one of the largest conservation initiatives in the marine world.

Recently, the governments of the region and international nature conservation organizations, such as World Wildlife Fund, The Nature Conservancy, and Conservation International, increased allocation of conservation resources to the Sunda Banda Seascape (SBS), the central part of the Coral Triangle in Indonesian waters (see Figure 2.1). The SBS has been designated as the second most important marine ecological region in Indonesia in terms of its biodiversity, providing habitat for 76% of known coral species and more than 3,000 fish species. However, similar to the Coral Triangle as a whole, the SBS is threatened by climate change and human activities related to unsustainable development.

The SBS covers an area of almost 1.57 million km^2 and encompasses considerable environmental and biological heterogeneity. In order to expedite marine conservation planning in this area, a systematic classification of the region in terms of biophysical environments is needed. Although information on marine provinces is available at a global scale (Olson and Dinerstein 1998, Spalding et al. 2007), there is not comprehensive regional information available for the SBS at a spatial resolution that is meaningful for management. Here, the goal of this research was to develop an approach using globally available satellite remote sensing and model-assimilated data to categorize this area into unique and meaningful classes based on a suite of biophysical conditions. Specifically, the SBS should be partitioned into biophysical classes characterized by similar sea surface temperature patterns, chlorophyll a concentration, currents, and salinity. These classes were expected to have similar habitat types and ecosystem functions. Our work is the first of this kind in the SBS, and will help set priorities in conservation planning and inform marine conservation practices.

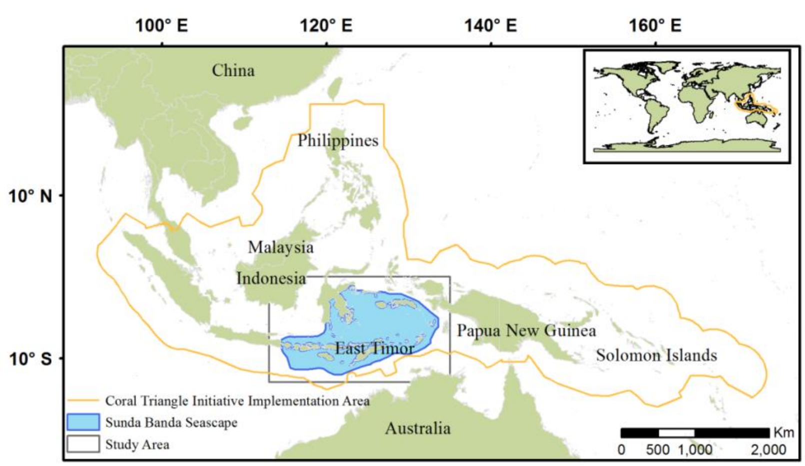

Figure 2.1: Coral Triangle and Sunda Banda Seascape.

The world base map is courtesy of ESRI. The boundary of the Coral Triangle and the Sunda Banda Seascape were obtained from The Coral Triangle Atlas (http://ctatlas.reefbase.org/). Administrative boundaries were acquired from GADM database of Global Administrative Areas (http://www.gadm.org/).

2.2 Materials and Methods

The Sunda-Banda Seascape (SBS) study area is located in the central portion of the Coral Triangle in eastern Indonesia (Figure 2.1). Sunda Banda is a terminology referring to a geological area, as well as geographical, of a landscape covering marine area and islands from Bali to Nusa Tenggara area, Southeast Maluku, Kupang and up to the north covering the southern part of Sulawesi Island. The SBS has a very high level of marine biodiversity, a big conservation opportunity and vulnerability.

A number of biophysical variables were considered for characterizing the marine environment of the SBS and geospatial data sources for these variables were identified. Salinity and sea surface temperature are fundamental determinants of global distribution of many marine habitats and ecosystems (Kleypas, McManus and AB MEÑEZ 1999). In the Pacific region, ranges and extremes of sea surface temperature (SST) and chlorophyll a (Gove et al. 2013) controls coral reef ecosystems. Hydrodynamic conditions, such as ocean currents, can ultimately determine both location and extent of marine habitats. For example, the distribution of mangrove ecosystems are driven by major ocean currents (Alongi 2009). Therefore, biophysical variables applied in this study include SST, chlorophyll a, currents and salinity.

The SST and chlorophyll a concentration data employed in this study were derived by the U.S. National Aeronautics and Space Agency (NASA) from remote sensing imagery acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Aqua Satellite. MODIS mapped data (Level 3), at a 4 km spatial resolution, was acquired over the period from July 2002 to June 2013. The monthly averaged nighttime SST data, chlorophyll a data, and climatological SST data were downloaded from http://oceancolor.gsfc.nasa.gov. Then, the long-term mean SST (Avg SST) was calculated. Maximum and minimum values at pixel level were selected to derive variables of highest monthly climatological SST (Max SST) and lowest monthly climatological SST (Min SST), respectively. The long-term mean chlorophyll a (Chla) concentration (mg/m^3) was also calculated.

Daily ocean currents data from May 2008 to July 2013 were obtained from Hybrid Coordinate Ocean Model (HYCOM, http://hycom.org/), a multi-institutional effort sponsored by the U.S. National Ocean Partnership Program (Halliwell 2004). We used global data-assimilative runs at 1/12 ° equatorial spatial resolution and 10 m depth. For this study, the long-term mean of current speed (m/s) was used. Daily salinity data at 10 m depth from May 2008 to July 2013 were also obtained from HYCOM, and the long-term mean salinity was used as input for the classification analyses.

Data processing included the retrieval and cropping of the global datasets into the region of interest (113 °E to 135 °E and 0 °to 13 °S). HYCOM derived currents and salinity data were resampled into 4 km spatial resolution using bicubic interpolation in order to match MODIS derived datasets of Avg SST, Max SST, Min SST and Chla (Figure 2). Land masses were identified using MODIS data and were excluded from the analysis (shown as black areas in Figure 2.2). All six selected environmental variables (Avg SST, Max SST, Min SST, Chla, Currents and Salinity) were checked to ensure any two of them were not correlated. Then they were standardized to scale the data (Legendre and Legendre 2012), allowing an equal contribution of the variables to the classification analysis.

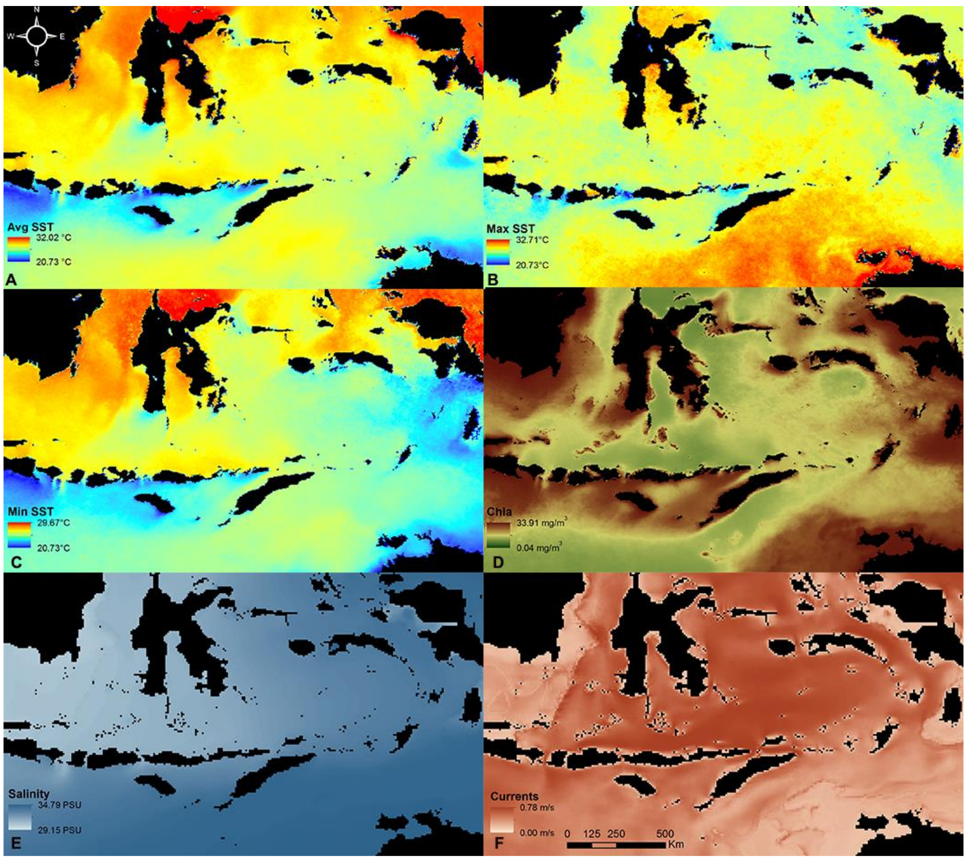

Figure 2.2: Input variables for classifying the Sunda Banda Seascape into biophysical regions.
(A) Average sea surface temperature (Avg SST); (B) maximum monthly climatological sea surface temperature (Max SST); (C) minimum monthly climatological sea surface temperature (Min SST); (D) chlorophyll a concentration (Chla); (E) ocean currents (Currents); (F) sea salinity (salinity).

The classification approach selected for this research, Self-organizing map (SOM), is a flexible, unsupervised neural network for data analysis and clustering

(Kohonen 2001, Kohonen 2013, Kohonen 1982). Several performance studies have illustrated the advantages of SOM over other clustering methods. SOM is more appropriate for large, nonlinear data sets with high dimensionality (Zhong et al. 2006, Ultsch, Vetter and Vetter 1995), and draws great attention in geographic information science (Agarwal and Skupin 2008) for spatial and temporal modeling and analysis (Ji 2000, Zhong et al. 2006, Goncalves et al. 2008, Kalteh, Hjorth and Berndtsson 2008, Hu and Weng 2009, Jensen, Thompson and Schmidlin 2012, Hagenauer and Helbich 2013). In the field of marine science, there are few examples in the literature of SOM applications of extracted spatial patterns and classified environmental regions. The existing studies using SOM in marine environments are for the Atlantic Ocean (Saraceno, Provost and Lebbah 2006) and the Caribbean Sea regions (Chollett et al. 2012).

SOM requires users to predefine the desired number of clusters (neurons) and the spatial arrangement of clusters (aka, neuron topology, such as linear, rectangular or square) before it runs. We produced and assessed classifications with 4 to 25 clusters with all possible bi-dimensional topologies (e.g. for 12 clusters 12x1, 3x4 and 4x3). Our goal was to produce an “optimal” number of clusters. Hexagonal grid topologies were applied in this study because they provide a better visualization of the results and smoother transitions among clusters. The neighborhood size was set to 3 samples and the training steps were set to 1,000 iterations. Link distance was used for distance metric for its straightforward meaning and easy implementation. The full description of the algorithm and mathematical illustration can be found in (Kohonen 2001).

Upon completion of a neural network classification of a data set into the desired number of clusters, it is necessary to validate the clusters in terms of statistical separation, and therefore usefulness for ecologically meaningful classification. There are several commonly used internal validation indices in clustering analysis, such as Silhouette Index (Rousseeuw 1987), Davies-Bouldin Index (Davies and Bouldin 1979), Calinski-Harabasz Index (Caliński and Harabasz 1974) and Dunn Index (Dunn 1973). Silhouette Index (SI) provides a succinct graphical representation of how well each object lies within its cluster and has demonstrated its superior performance when compared to other indices (Kaufman and Rousseeuw 2009). The SI is calculated using Equation 1. The scenario that maximizes the average SI determines the best partition.

$$SI_i = \frac{b_i - a_i}{\max(a_i, b_i)} \quad (1)$$

For each pixel, a_i is the average distance from the i th pixel to all the other pixels in the same cluster as i , and b_i is the minimum average distance from the i th pixel to all pixels in a different cluster. After all SI_i values have been calculated, the average *SI* for all clusters is calculated for each scenario. *SI* ranges between -1 and 1, with *SI* values close to 1 signaling a better clustering (with compact classes, well separated from the rest). Validation indices do not only identify the optimal number of clusters, but also the optimal spatial arrangement of clusters (topology of neurons).

2.3 Results

The best classification of biophysical marine environments from the total 43 scenarios considered was selected by comparing the goodness of the clustering structure via SI. The best scenario of classification was found with 9 clusters and linear topology (Figure 2.3).

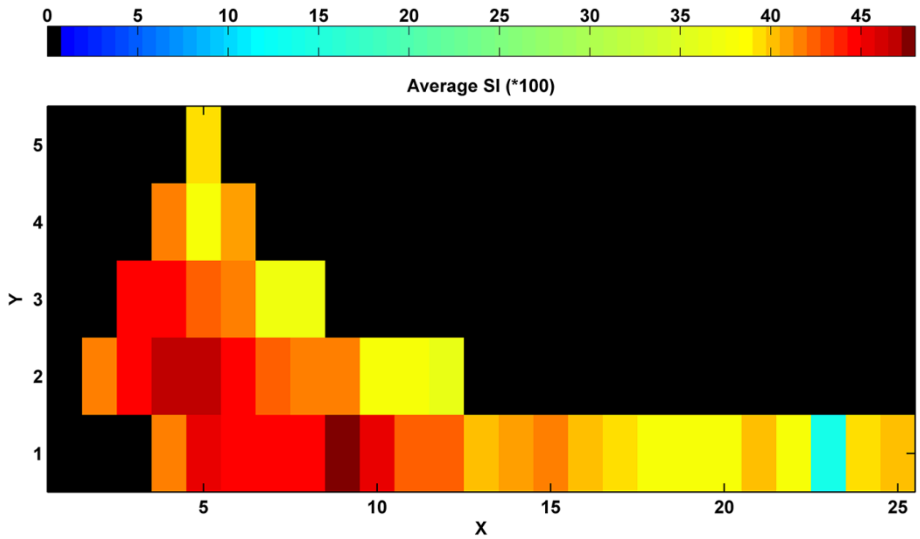

Figure 2.3 Silhouette index used to identify the best classification scenario. X and Y denote neuron arrangements in the 2-D plates. The number of classes equals to X*Y.

The selected scenario classified the biophysical environments of the study area into 9 clusters (Figure 2.4), where each cluster indicates a distinctive environmental region. One of these clusters (i.e. Class 3) was in the bounding box of study area, but not within the SBS. Although no explicit geographic information was provided when training the SOM, the classification procedure produced clusters with well-defined boundaries.

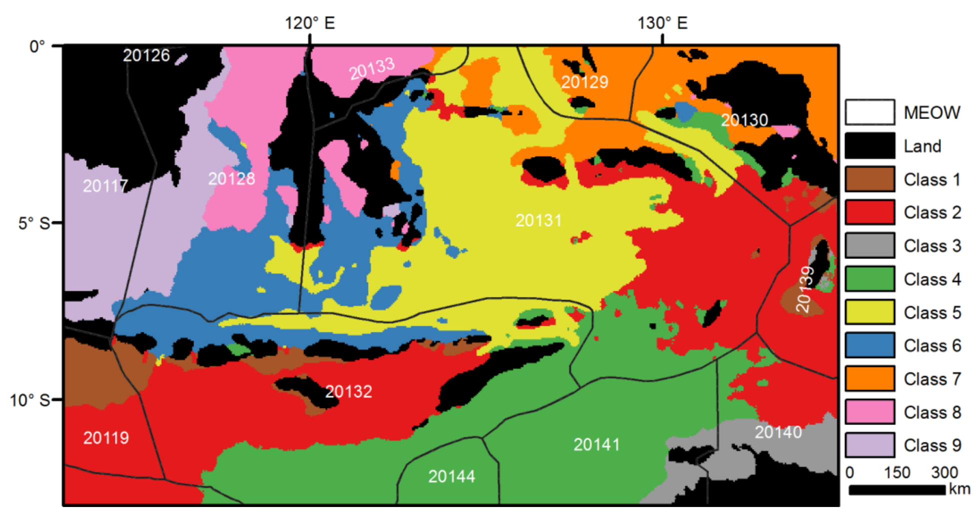

Figure 2.4: Biophysical region classification of the Sunda Banda Seascape with 9 classes.

MEOW denotes marine ecoregion of the world (Spalding et al. 2007). Five-digit codes refer to marine ecoregions: 20140—Arnhem Coast to Gulf of Carpenteria; 20139—Arafura Sea; 20131—Banda Sea; 20144—Exmouth to Broome; 20129—Halmahera; 20132—Lesser Sunda; 20126—Palawan/North Borneo; 20130—Papua; 20128—Sulawesi Sea/Makassar Strait; 20119—Southern Java; 20117—Sunda Shelf/Java Sea.

The number of pixels of each class was not evenly distributed in the SBS. Class 2, Class 4, and Class 5 included the largest number of pixels; and Class 3 was totally outside the SBS. The average and standard deviation for each biophysical variable in each class are listed in Table 2.1.

Table 2.1. Percentage area covered by each of the 9 classes in the study area and SBS; Average and standard deviation of 6 biophysical variables for the 9 Classes.

Class	SBS (%)	Avg SST (℃)	Max SST (℃)	Min SST (℃)	Chla (mg/m^3)	Currents (m/s)	Salinity (PSU)
1	2.40	26.61±0.70	28.79±0.83	24.78±0.64	1.33±1.84	0.16±0.11	34.04±0.26
2	32.30	27.68±0.29	29.49±0.24	25.81±0.32	0.36±0.29	0.19±0.06	34.23±0.13
3	0	27.23±0.52	30.50±0.48	25.15±0.50	1.54±1.25	0.06±0.05	34.59±0.15
4	13.30	28.06±0.21	30.18±0.30	26.37±0.21	0.33±0.44	0.14±0.05	34.42±0.13
5	34.80	28.23±0.20	29.59±0.20	26.74±0.37	0.23±0.10	0.33±0.06	33.99±0.18
6	12.90	28.29±0.25	29.59±0.23	27.23±0.33	0.31±0.45	0.19±0.09	33.50±0.25
7	2.90	28.79±0.36	29.40±0.26	27.94±0.53	0.48±0.89	0.19±0.09	34.24±0.12
8	1.30	29.06±0.35	29.81±0.32	28.42±0.40	0.41±0.92	0.20±0.08	33.51±0.21
9	0.10	28.55±0.23	29.65±0.23	27.71±0.34	1.40±2.89	0.11±0.07	32.54±0.30

Figure 2.5A shows how the overall distinctiveness of nine classes is related to their neighbors. The darker color indicates greater difference, such as Class 8 and Class 9, while the lighter color shows less difference, such as Class 5 and Class 6, which are relatively similar. Figure 2.5B shows how each biophysical variable contributes to each class, where darker color indicates greater and lighter one indicates less. None of the weight patterns of input variables are very similar to one another, indicating these

variables are not correlated. The biophysical environments of the SBS are further summarized in Table 2.2 for better management purpose.

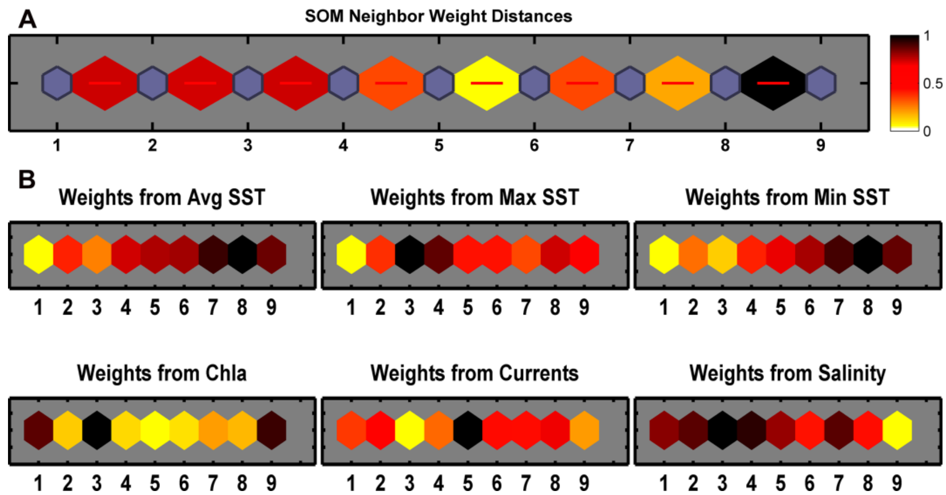

Figure 2.5. SOM topology showing the distances between neighbors and the input weights.

(A) SOM Neighbor Weight Distance. The blue hexagons represent the classes; the red lines connect neighboring classes; the colors in the regions containing the red lines indicate the distances between classes, where the darker colors represent larger distances (more differences) and the lighter colors represent smaller distances (less differences). (B) Weight from each input biophysical variables. Lighter and darker colors represent smaller and larger weights, respectively.

Table 2.2. Characteristics of biophysical environments of the SBS.

Biophysical Class	**Avg SST**	**Max SST**	**Min SST**	**Chla**	**Currents**	**Salinity**
1	L	L	L	M	M	M
2	M	M	L	L	M	M
3	L	H	L	H	L	H
4	M	H	L	L	L	H
5	M	M	M	L	H	M
6	M	M	M	L	M	L
7	H	L	H	L	M	M
8	H	M	H	L	M	L
9	H	M	H	H	L	L

L= Low; M= Medium; H= High

2.4 Discussion and Conclusions

We delineated the environments of the SBS and classified the region into 8 distinctive biophysical classes. Each of them represents a unique systematic combination of biophysical conditions. Classifying the marine environments into meaningful and manageable regions is the initial step to set priorities in marine conservation in different marine planning and management schemes (Lourie and Vincent 2004). Our delineation of the biophysical environment of the SBS supplements those prevailing marine management schemes, such as the marine ecoregion of the world (MEOW) (Spalding et al. 2007). MEOW is defined on experts' opinions and globally comparable on a biogeographic basis, for example floral and faunal composition, but it is targeted at the world's coastal and shelf areas. Our biophysical classification is based on bio-physiochemical environmental conditions; biophysical classes defining regions with similar biophysical features, enabling comparisons among regional patterns and processes (Table 2). Moreover, it provides more details at the regional level and the most up-to-date in the past ten years (Figure 4). Instead of only two ecoregions (i.e. 20131 and 20132) delineating the study area by MEOW, our classification with 8 classes should better explain patterns of biodiversity and organismal distribution. Importantly, smaller regions should be more suitable for conservation practice. With comprehensive coverage, the classification result can serve many research and conservation requirements in the area. Datasets we employed here are globally available so the systematic approach applied here can be replicated to the whole Coral Triangle with other spatiotemporal resolution and can be transferred to other remote sensing derived and model-assimilated environmental variables.

As previously mentioned, the species diversity and abundance in the SBS have been threatened by both climate change and human activities (Roberts et al. 2002, Burke et al. 2011). Specifically, studies have pointed out the alarming decline of coral cover (Bruno and Selig 2007, Carpenter et al. 2008). The Max SST and Salinity of Class 3 over the past ten years rank the highest among all classes, following by Class 4. Both Avg SST and Min SST of Class 8 rank the highest among all classes, following by Class 7. Because temperature and salinity are the ultimate determinants of coral reef ecosystems and Class 3 is outside of the SBS, it is advised to prioritize conservation practices within Class 4, Class 7 and Class 8. Class 3 ranks the highest in Chla, following by Class 9 and Class 1. Chla is not only the proxy for phytoplankton biomass, but also the bridge between terrestrial and aquatic ecosystems. High values of Chla in water are known to be caused by high nutrient levels of nitrogen and phosphorus resulting from water pollution due to human activities such as agricultural runoff, aquaculture or untreated sewage. Hence, it is advised to keep monitoring water quality and studying human demography in areas mapped as Class 1 and Class 9. Class 5 is weighted highest by Currents, which is regarded as the dominant driver of mangrove forests (Alongi 2009). Ecosystem goods and services that mangroves provided are estimated as much as about 100,000 USD per hectare per year (Costanza et al. 1997). The coverage of mangroves in Indonesia ranks the first in the world (Giri et al. 2011); however, they are declining due to aquaculture and coastal settlement. It is urgent to take actions in areas mapped as Class 5, for the sustainable future of mangrove forests.

Our delineation of the biophysical environments of the SBS can also be applied to serve marine resources management under the CTI-CFF in several ways: The 8 identified biophysical environmental classes can: (1) serve as proxies for species distribution; (2) help stratifying rapid-assessment and monitoring activities in the field in a cost-effective manner; (3) help determining areas of priority for conservation in conjunction with existing habitat data —such as areas likely to be more resilient to climate change and coral reef bleaching (Mumby et al. 2011, Maynard et al. 2010).

There are increasing investments in marine conservation in the SBS, including a high level of intergovernmental supports for establishing representative marine protected areas (MPA). MPA are regions whose surrounding waters, ecosystems, and any cultural or historical resources may require preservation or management (Kelleher 1999). In an ecosystem-based management strategy through multilateral agreements, MPAs play the central role in balancing biodiversity protection with natural resource utilization (Halpern et al. 2012). For example, MPA connectivity to other ecosystems that serve as "sources" for coral larva are more likely to be "seeded" to replenish depleted populations (Botsford et al. 2009). MPA proximity to other productive ecosystems that serve as nursery habitat, breeding grounds, and foraging grounds have been demonstrated to enhance fish abundance and diversity (Roberts et al. 2001). To design a network of MPAs with the lowest trade off among biodiversity conservations and fisheries benefits will be one of those major conservation purposes of the SBS. Our biophysical environments classification will serve as a baseline for initiatives such as this.

To summarize, our approach for the delineation of biophysical marine environments of the SBS not only fills a gap by bringing comprehensive data into this region, but also facilitates planning of marine conservation activities. Our work contributes to the framework for coastal and marine spatial planning, which is potentially helpful to research and conservation practice in the Coral Triangle.

2.5 Future work

Phylogeography studies the historical processes that may be responsible for the contemporary geographic distributions of individuals (Avise 2000). In the future, phylogeographic research can be incorporated to see any relationship between genetic breaks of individual key species with our biophysical classifications. Although this biophysical environmental delineation is meant to be useful for all marine ecosystems, coastal and pelagic, if connectivity patterns of species are of special interest for conservation planning, then our results can be integrated with multi-species population connectivity outputs. Studies can be also conducted in terms of how the East Asian monsoon variability affects the delineation of SBS environments (Gordon 2005). It will refine our understanding of the SBS environment and provide more guidance of marine spatial planning and conservation activities. Finally, in the context of climate change and sea level rise, how to refine the SBS biophysical classification information adaptively to inform the establishment of dynamic MPA (Game et al. 2009) deserves more attention.

Acknowledgement

The research leading to these results has received funding from the European Union 7th Framework programme (P7/2007-2013) under grant agreement No. 244161.

References

Agarwal, P. & A. Skupin. 2008. *Self-organising maps: Applications in geographic information science*. John Wiley & Sons.

Allen, G. R. (2008) Conservation hotspots of biodiversity and endemism for Indo‐Pacific coral reef fishes. *Aquatic Conservation: Marine and Freshwater Ecosystems,* 18**,** 541-556.

Alongi, D. M. 2009. *The energetics of mangrove forests*. Springer.

Ando, K. & M. J. McPhaden (1997) Variability of surface layer hydrography in the tropical Pacific Ocean. *Journal of Geophysical Research: Oceans (1978–2012),* 102**,** 23063-23078.

Avise, J. C. 2000. *Phylogeography: the history and formation of species*. Harvard University Press.

Botsford, L., J. W. White, M.-A. Coffroth, C. B. Paris, S. Planes, T. Shearer, S. R. Thorrold & G. P. Jones (2009) Connectivity and resilience of coral reef metapopulations in marine protected areas: matching empirical efforts to predictive needs. *Coral Reefs,* 28**,** 327-337.

Bruno, J. F. & E. R. Selig (2007) Regional decline of coral cover in the Indo-Pacific: timing, extent, and subregional comparisons. *PLoS one,* 2**,** e711.

Burke, L. M., K. Reytar, M. Spalding & A. Perry. 2011. *Reefs at risk revisited*. World Resources Institute Washington, DC.

Caliński, T. & J. Harabasz (1974) A dendrite method for cluster analysis. *Communications in Statistics-theory and Methods,* 3**,** 1-27.

Carpenter, K. E., M. Abrar, G. Aeby, R. B. Aronson, S. Banks, A. Bruckner, A. Chiriboga, J. Cortés, J. C. Delbeek, L. DeVantier, G. J. Edgar, A. J. Edwards, D. Fenner, H. M. Guzmán, B. W. Hoeksema, G. Hodgson, O. Johan, W. Y. Licuanan, S. R. Livingstone, E. R. Lovell, J. A. Moore, D. O. Obura, D. Ochavillo, B. A. Polidoro, W. F. Precht, M. C. Quibilan, C. Reboton, Z. T. Richards, A. D. Rogers, J. Sanciangco, A. Sheppard, C. Sheppard, J. Smith, S. Stuart, E. Turak, J. E. N. Veron, C. Wallace, E. Weil & E. Wood (2008) One-Third of Reef-Building Corals Face Elevated Extinction Risk from Climate Change and Local Impacts. *Science,* 321**,** 560-563.

Chollett, I., P. J. Mumby, F. E. Müller-Karger & C. Hu (2012) Physical environments of the Caribbean Sea. *Limnology and Oceanography,* 57**,** 1233.

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. O'Neill, J. Paruelo, R. G. Raskin, P. Sutton & M. van den Belt (1997) The value of the world's ecosystem services and natural capital. *Nature,* 387**,** 253-260.

Cowen, R., C. Paris & A. Srinivasan (2006) Scaling of connectivity in marine populations. *Science,* 311**,** 522-527.

Davies, D. L. & D. W. Bouldin (1979) A cluster separation measure. *Pattern Analysis and Machine Intelligence, IEEE Transactions on***,** 224-227.

Dunn, J. C. (1973) A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters. *Journal of Cybernetics,* 3**,** 32-57.

Fraser, R. H. & D. J. Currie (1996) The species richness-energy hypothesis in a system where historical factors are thought to prevail: coral reefs. *American Naturalist***,** 138-159.

Freeman, L. A., A. J. Miller, R. D. Norris & J. E. Smith (2012) Classification of remote Pacific coral reefs by physical oceanographic environment. *Journal of Geophysical Research: Oceans (1978–2012),* 117.

Game, E. T., M. Bode, E. McDonald-Madden, H. S. Grantham & H. P. Possingham (2009) Dynamic marine protected areas can improve the resilience of coral reef systems. *Ecology Letters,* 12**,** 1336-1346.

Giri, C., E. Ochieng, L. L. Tieszen, Z. Zhu, A. Singh, T. Loveland, J. Masek & N. Duke (2011) Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography,* 20**,** 154-159.

Glynn, P. W. & J. Ault (2000) A biogeographic analysis and review of the far eastern Pacific coral reef region. *Coral Reefs,* 19**,** 1-23.

Goncalves, M., M. Netto, J. Costa & J. Zullo Junior (2008) An unsupervised method of classifying remotely sensed images using Kohonen self‐organizing maps and agglomerative hierarchical clustering methods. *International Journal of Remote Sensing,* 29**,** 3171-3207.

Gordon, A. L. (2005) the Indonesian Seas. *Oceanography,* 18**,** 14.

Gove, J. M., G. J. Williams, M. A. McManus, S. F. Heron, S. A. Sandin, O. J. Vetter & D. G. Foley (2013) Quantifying Climatological Ranges and Anomalies for Pacific Coral Reef Ecosystems. *PLoS ONE,* 8**,** e61974.

Hagenauer, J. & M. Helbich (2013) Hierarchical self-organizing maps for clustering spatiotemporal data. *International Journal of Geographical Information Science*, 1-17.

Halliwell, G. R. (2004) Evaluation of vertical coordinate and vertical mixing algorithms in the HYbrid-Coordinate Ocean Model (HYCOM). *Ocean Modelling*, 7**,** 285-322.

Halpern, B. S., J. Diamond, S. Gaines, S. Gelcich, M. Gleason, S. Jennings, S. Lester, A. Mace, L. McCook & K. McLeod (2012) Near-term priorities for the science, policy and practice of Coastal and Marine Spatial Planning (CMSP). *Marine Policy,* 36**,** 198-205.

Hoeksema, B. W. 2007. Delineation of the Indo-Malayan centre of maximum marine biodiversity: the Coral Triangle. In *Biogeography, time, and place: distributions, barriers, and islands*, 117-178. Springer.

Hu, X. & Q. Weng (2009) Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks. *Remote Sensing of Environment,* 113**,** 2089-2102.

Jensen, A. A., A. M. Thompson & F. J. Schmidlin (2012) Classification of Ascension Island and Natal ozonesondes using self-organizing maps. *Journal of Geophysical Research: Atmospheres,* 117**,** D04302.

Ji, C. (2000) Land-use classification of remotely sensed data using Kohonen self-organizing feature map neural networks. *Photogrammetric Engineering and Remote Sensing,* 66**,** 1451-1460.

Kaiser, M. J., M. J. Attrill, S. Jennings, D. N. Thomas, D. K. Barnes, A. S. Brierley, N. V. Polunin, D. G. Raffaelli & P. J. l. B. Williams. 2005. *Marine ecology: processes, systems, and impacts*. Oxford University Press Nueva York.

Kalteh, A. M., P. Hjorth & R. Berndtsson (2008) Review of the self-organizing map (SOM) approach in water resources: Analysis, modelling and application. *Environmental Modelling & Software,* 23**,** 835-845.

Kaufman, L. & P. J. Rousseeuw. 2009. *Finding groups in data: an introduction to cluster analysis*. Wiley. com.

Kelleher, G. 1999. *Guidelines for marine protected areas*. Iucn Gland, Cambridge.

Kleypas, J. A., J. W. McManus & L. AB MEÑEZ (1999) Environmental limits to coral reef development: where do we draw the line? *American Zoologist,* 39**,** 146-159.

Kohonen, T. (1982) Self-organized formation of topologically correct feature maps. *Biological cybernetics,* 43**,** 59-69.

Kohonen, T. 2001. *Self-organizing maps*. Springer.

Kohonen, T. (2013) Essentials of the self-organizing map. *Neural Netw,* 37**,** 52-65.

Legendre, P. & L. Legendre. 2012. *Numerical ecology*. Elsevier.

Lourie, S. A. & A. C. J. Vincent (2004) Using Biogeography to Help Set Priorities in Marine Conservation. *Conservation Biology,* 18**,** 1004-1020.

Maynard, J. A., P. A. Marshall, J. E. Johnson & S. Harman. 2010. Building resilience into practical conservation: identifying local management responses to global climate change in the southern Great Barrier Reef. 381-391. Springer Science & Business Media B.V.

Mellin, C., C. J. A. Bradshaw, M. G. Meekan & M. J. Caley (2010) Environmental and spatial predictors of species richness and abundance in coral reef fishes. *Global Ecology and Biogeography,* 19**,** 212-222.

Mumby, P. J., I. A. Elliott, C. M. Eakin, W. Skirving, C. B. Paris, H. J. Edwards, S. Enríquez, R. Iglesias-Prieto, L. M. Cherubin & J. R. Stevens (2011) Reserve design for uncertain responses of coral reefs to climate change. *Ecology Letters,* 14**,** 132-140.

Nair, A., S. Sathyendranath, T. Platt, J. Morales, V. Stuart, M.-H. Forget, E. Devred & H. Bouman (2008) Remote sensing of phytoplankton functional types. *Remote Sensing of Environment,* 112**,** 3366-3375.

Olson, D. M. & E. Dinerstein (1998) The Global 200: A Representation Approach to Conserving the Earth’s Most Biologically Valuable Ecoregions. *Conservation Biology,* 12**,** 502-515.

Roberts, C. M., J. A. Bohnsack, F. Gell, J. P. Hawkins & R. Goodridge (2001) Effects of marine reserves on adjacent fisheries. *science,* 294**,** 1920-1923.

Roberts, C. M., C. J. McClean, J. E. N. Veron, J. P. Hawkins, G. R. Allen, D. E. McAllister, C. G. Mittermeier, F. W. Schueler, M. Spalding, F. Wells, C. Vynne & T. B. Werner (2002) Marine Biodiversity Hotspots and Conservation Priorities for Tropical Reefs. *Science,* 295**,** 1280-1284.

Rousseeuw, P. J. (1987) Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics,* 20**,** 53-65.

Sapiano, M. R. P., C. W. Brown, S. Schollaert Uz & M. Vargas (2012) Establishing a global climatology of marine phytoplankton phenological characteristics. *Journal of Geophysical Research: Oceans,* 117**,** C08026.

Saraceno, M., C. Provost & M. Lebbah (2006) Biophysical regions identification using an artificial neuronal network: A case study in the South Western Atlantic. *Advances in space research,* 37**,** 793-805.

Sathyendranath, S., L. Prieur & A. Morel (1989) A three-component model of ocean colour and its application to remote sensing of phytoplankton pigments in coastal waters. *International Journal of Remote Sensing,* 10**,** 1373-1394.

Shang, S., Q. Dong, C. Hu, G. Lin, Y. Li & S. Shang (2013) On the consistency in variations of chlorophyll a concentration in the South China Sea as revealed by three remote sensing datasets. *Biogeosciences Discussions,* 10**,** 7549-7578.

Small, C. & R. J. Nicholls (2003) A global analysis of human settlement in coastal zones. *Journal of Coastal Research***,** 584-599.

Spalding, M. D., H. E. Fox, B. S. Halpern, M. A. McManus, J. Molnar, G. R. Allen, N. Davidson, Z. A. Jorge, A. L. Lombana, S. A. Lourie, K. D. Martin, E. McManus, J. Molnar, C. A. Recchia & J. Robertson (2007) Marine ecoregions of the world: A bioregionalization of coastal and shelf areas. *Bioscience,* 57**,** 573-583.

Treml, E. A. & P. N. Halpin (2012) Marine population connectivity identifies ecological neighbors for conservation planning in the Coral Triangle. *Conservation Letters,* 5**,** 441-449.

Treml, E. A., P. N. Halpin, D. L. Urban & L. F. Pratson (2008) Modeling population connectivity by ocean currents, a graph-theoretic approach for marine conservation. *Landscape Ecology,* 23**,** 19-36.

Ultsch, A., C. Vetter & C. Vetter. 1995. *Self-Organizing-Feature-Maps versus statistical clustering methods: a benchmark*. Fachbereich Mathematik.

Zacharias, M. A., D. E. Howes, J. R. Harper & P. Wainwright (1998) The British Columbia marine ecosystem classification: rationale, development, and verification. *Coastal Management,* 26**,** 105-124.

Zhang, C. (1996) Atmospheric intraseasonal variability at the surface in the tropical western Pacific Ocean. *Journal of the atmospheric sciences,* 53**,** 739-758.

Zhong, Y., L. Zhang, B. Huang & P. Li (2006) An unsupervised artificial immune classifier for multi/hyperspectral remote sensing imagery. *Geoscience and Remote Sensing, IEEE Transactions on,* 44**,** 420-431.

CHAPTER 3

PREDICTING MANGROVE BIOMASS PATTERNS IN THE CHANGING CLIMATE OF THE SUNDA BANDA SEASCAPE, INDONESIA[2]

[2] Wang, M. et al. To be submitted to *Ocean &Coastal Management*

Abstract

Mangrove forests are essential to ecosystem but declining at an unprecedented rate. Modeling and predicting spatial patterns of mangrove biomass in the context of climate change are critical to improve the understanding the role of mangrove in coastal carbon budgets, inform mangrove resource management and guide conservation practices. The Sunda Banda Seascape (SBS), Indonesia, located in the center of the Coral Triangle, is among the world's richest regions of mangrove biomass as well as marine biodiversity. We estimated mangrove biomass in current (1950-2000), Last Inter-glacial Period (LIP) and 4 Representative Concentration Pathways (RCPs) in 2070 with bioclimatic model. The relative extent and growth rate between below-ground biomass and above-ground biomass were revealed as they were negatively associated with latitude for all scenarios. Change detection analysis showed that with the increase of CO_2 concentration, mangrove biomass generally increased but spatial variance was enlarged. Our findings provided a baseline for mangrove studies in the SBS. In conjunction with biophysical regions classification of the SBS, our study can be regarded as a tool for assessing conservation priorities and highlighting hotspots for mangrove management investments. The framework of predicting mangrove biomass presented here can be expanded to the whole Coral Triangle and has broader impact to inform mangrove studies and conservation activities in other areas of the world.

3.1. Introduction

Mangroves are an assemblage of woody, facultative halophytes (salt tolerant plants adapted to exclude or excrete salt) that are fundamental species distributed in the estuaries, lagoons and littoral zone between 30 °N and 30 °S of the world (Alongi 2009, Tomlinson 1986). They grow in harsh biophysical conditions such as high salinity, high temperature, extreme tide, high sedimentation and muddy anaerobic soils (Giri et al. 2011); their distribution is driven by major ocean currents (Alongi 2009) and affected by geomorphological and biotic factors (Ellison 2002, Duke, Ball and Ellison 1998). Because mangroves provide critical ecosystem services, they are essential to the ecosphere of the earth as well as human beings. According to MA (2005), ecosystem services include: supporting services (nutrient cycling, soil formation, primary production); provisioning services (food, fresh water, wood and fiber, fuel); regulating services (climate, food, disease, water purification); and cultural services (aesthetic, spiritual, educational, recreational). Primary productivity can be regarded as the rate at which plants (mangroves) produce organic compounds in an ecosystem. The primary productivity in mangroves can be compared with tropical rainforests (Alongi 2002). Primary productivity is positively associated with biomass. Using energy from the sun, plants (mangroves) construct biomass by absorbing from the CO_2 from atmosphere. Mangrove biomass provides both direct and indirect ecosystem services. Mangrove forests sequestrate carbon, support biodiversity through their structure and potentially reduce hurricane impacts (Alongi 2002). Litters of mangrove forests provide nutrients and food for marine species, which have linked to increased fish populations (Mumby et al. 2004). These ecosystem goods and services are estimated to be as much as about

100,000 USD per hectare per year and 170 billion USD globally per year (Costanza et al. 1997). Mangroves, however, are declining unprecedentedly worldwide. According to Spalding, Blasco and Field (1997), the estimation of global mangrove forests is less than half of what it was and the remaining is under severe degradation. About 35% of mangrove were lost from 1980 to 2000 (MA 2005), which have been declining faster than coral reefs or tropical rainforests (Duke et al. 2007). A more disappointing fact is that by developing the highest resolution (30m) global mangrove map with satellite remote sensing, Giri et al. (2011) revealed that mangrove forest distribution is 12.3% smaller than the most recent estimate by the Food and Agriculture Organization (FAO) of the United Nations (FAO 2007).

Mangroves are threatened by several natural and anthropogenic factors. For example, climate change, such as change in precipitation and temperature, exacerbates the loss of mangroves and other coastal habitats in the future (Gilman et al. 2006, Duke et al. 2007). More importantly, mangroves are degraded by coastal development and human settlements. Currently, more than 2.2 billion people reside within 100-km of the coastline (Small and Nicholls 2003). If current rates of population growth are maintained, the number of humans living near the coast will increase to 3.1 billion in 2025 (Kaiser et al. 2005). Mangroves are removed for aquaculture, agriculture, urbanization and impaired by contamination (Valiela, Bowen and York 2001, Nguyen 2014). Including mangroves, tropical deforestation accounts for 12-20% of the total anthropogenic carbon dioxide emissions (IPCC 2007). Delineating and predicting the spatial patterns of mangrove biomass in the context of climate change and human development/aquaculture can help improve mangrove management practices, formulate conservation activities, refine climate models, and update mitigation and adaptation policies.

Understanding the role of mangrove in coastal carbon budgets is critical, because mangroves are among the most carbon-rich forests in the tropics (Donato et al. 2011). Through their biomass, mangroves provide those abovementioned ecosystem services. Effective and efficient mangrove management requires regional monitoring of extent, health and ecological functions. Efforts have been made to estimate global carbon storage and flux (Avitabile et al. 2012), and those from mangroves in particular (Twilley, Chen and Hargis 1992, Donato et al. 2011, Alongi 2009, Hutchison et al. 2013). In the context of climate change and see level rise, it is even more important to project future mangrove biomass and adaptively make conservation and management strategies. We must take it seriously because our current knowledge of organic carbon in tropical mangroves is not yet complete (Kristensen et al. 2008), and methods in estimating mangrove carbon fluxes and storage are evolving (Rivera-Monroy et al. 2013).

The Coral Triangle (CT, aka Coral Triangle Initiative Implementation Area, See Figure 3.1) in the Pacific Ocean is recognized as the epicenter of tropical marine biodiversity (Allen 2008). It is also one of the most threatened areas, due to population and poverty pressures faced by the communities that depend on its resources (Allen and Werner 2002), which supports more than 150 million people (Green and Mous 2005). CT is defined as a geographical term so named as it refers to a roughly triangular area of the tropical marine waters of Indonesia, Malaysia, Papua New Guinea, Philippines, Solomon Islands and East Timor (aka, Timor-Leste) (Hoeksema 2007). The Sunda Banda Seascape (SBS, See Figure 3.1) is located in the center of CT. Because it has a high level of marine biodiversity and tremendous conservation opportunity, as well as vulnerability, the SBS has been ranked as the second most important region by the Ministry of Marine Affairs and Fisheries, Indonesia. Overall, the Indo-Malaysian region of CT has 48 mangrove species (Duke et al. 1998), which is the highest species diversity of mangrove anywhere in the world. Indonesia itself covers 22.6% of the world's mangrove forests (Giri et al. 2011), which is two times larger than Australia, the second largest country in mangrove cover. In terms of total above-ground biomass (AGB), it reaches about 730 million tons in Indonesia, which is two times more than in Brazil, the second largest country in mangrove AGB (Hutchison et al. 2013). Therefore, delineating and predicting mangrove biomass in the SBS in the context of climate change are not only meaningful for management, conservation and policy-making in this region, but also helpful to inform marine and coastal management in the whole CT.

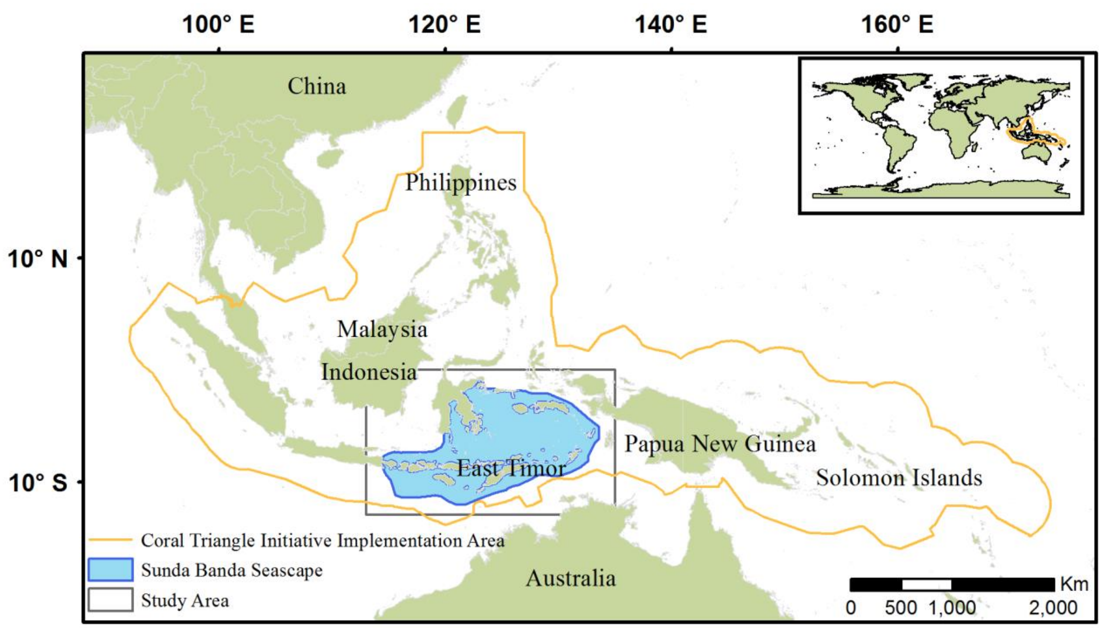

Figure 3.1: Coral Triangle and Sunda Banda Seascape.

The recent advancement of satellite remote sensing data and algorithms has been successfully applied to mapping the extent and change of mangrove forests at different scales. However, remote sensing to estimate mangrove forests biomass often requires data fusion among Synthetic-aperture Radar (SAR), very high resolution (VHR) imagery and Light Detection and Ranging (LiDAR). The SBS is located in a tropical area, where clouds are heavy, limiting the performance of optical remote sensing, including VHR. Importantly, SAR, VHR and LiDAR are often costly to acquire and the financial burden confines their access to developing countries, including Indonesia.

As an alternative to delineating mangrove distributions using remotely sensed data, predicted mangrove distribution and biomass can be modeled based on known existing mangrove distributions and output from climate change models. Most climate model projections are based on inputs of temperature and precipitation which are universally recognized, historically recorded and globally accessible. Their metrics are often used to generate biologically meaningful variables and used in ecological niche modeling. Moreover, they are also the most self-evident factors representing the changing climate. In the situation of changing climate and diminishing mangrove forests, bioclimatic models can explain how annual trends, seasonality and extreme or limiting climatological features contribute to predicting the past, current and future mangrove biomass directly and inform conservation priorities and practices accordingly. Finally, they are financially easy to monitor compared to remote sensing based models, thus especially applicable to developing and underdeveloped countries.

Recently, Hutchison et al. (2013) created the first-ever global map of current mangrove AGB by linking mangrove distribution with climate data. In this study, we first expanded the bioclimatic models to predict mangrove biomass in the SBS from the past (i.e. last inter-glacial period, a.k.a. LIP; ~120,000 - 140,000 years BP) to current (1950 — 2000) and future (2070, according to the Fifth Assessment IPCC report). Next, mangrove biomass patterns were coupled with the SBS biophysical regions (Wang et al., 2014, to be submitted to *PLOS ONE*) and coastal development to identify areas of greatest risk, inform mangrove management and promote conservation activities. This study can assist in developing mitigation and adaptation strategies in the context of climate change; prioritizing conservation investment, improving carbon budgets and appreciating the compressive utilization of ecosystem goods and services provided by mangroves in the SBS and the whole CT.

3.2. Materials and Methods

3.2.1 Bioclimatic data, model and metrics

Current bioclimatic information was acquired from the WorldClim Bioclim database at 30 arc-second (~1km) spatial resolution (www.worldclim.org). The database includes 19 bioclimatic variables using monthly temperature and rainfall data from 1950 to 2000 through global geospatial sensor networks (Hijmans et al. 2005). Past bioclimatic information was downscaled to the LIP (Otto-Bliesner et al. 2006), because widespread evidence of a 4–6-m increment of sea-level high-stand during the LIP (Marine Isotope Stage 5e) has led to warnings that modern ice sheets will deteriorate owing to global warming and initiate a rise of similar magnitude by AD 2100 (Blanchon et al. 2009). Future bioclimatic variables are derived from the GISS-E2-R model, provided by the Goddard Space Flight Center, National Aeronautics and Space Administration (NASA), U.S.A, which is one of the most recent global climate projections that are used in the Fifth Assessment IPCC report (Schmidt et al. 2012, Nazarenko 2013). It contains global climate models for four representative concentration pathways (RCPs). RCPs are four greenhouse gas concentration trajectories adopted by the Fifth Assessment IPCC report. RCPs depend on the emission of greenhouse gases in the years to come, simulating four possible climate futures. The four RCPs scenarios, RCP2.6, RCP4.5, RCP6.0, and RCP8.5, are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+ 2.6, + 4.5, + 6.0, and + 8.5 W/m^2, respectively).

Mangrove AGB and below-ground biomass (BGB) predication models (Equation 1 and Equation 2) were adopted from (Hutchison et al. 2013), where models were validated from peer-reviewed journal articles with meta-analysis.

$$\text{AGB (t/ha)} = 0.295*X_1+0.658*X_2+0.234*X_3+0.195*X_4-120.3 \qquad \text{(Equation 1)}$$

$$\text{BGB (t/ha)} = 0.073*\text{AGB}^{1.32} \quad \text{(Equation 2)}$$

(X_1 denotes mean temperature of warmest quarter (℃), X_2 denotes mean temperature of coldest quarter (℃), X_3 denotes precipitation of wettest quarter (mm); and X_4 denotes precipitation of driest quarter (mm))

Biomass metrics were then developed to better interpret the bioclimatic modeling results. Total biomass (TB, t/ha) was defined as AGB + BGB; Ratio was defined BGB/AGB; and derivative biomass (DB) was defined as d (BGB)/d (AGB) were also constructed to illustrate the relative growth rate between BGB and AGB. In order to compare the biomass change in the changing climate, δTB was defined as the different between TB in LIP or four RCPs in 2070 and that in the current situation.

3.2.2 Mangrove distribution and data preprocessing

Mangrove species distribution data are acquired from (IUCN 2013). The 2013 IUCN Red List of Threatened Species contains assessments for over 70,000 species globally, of which about 43,000 has spatial data. The spatial data collection is for most of the comprehensively assessed taxonomic groups, including mangroves. Mangrove species data are in ESRI shapefile format as polygons. ESRI ArcMap 10.1 was used to crop the global dataset into study area coordinates (0 ~ 13 °S, 113 °E ~135 °E, See Figure 1), and polygons of 46 different mangrove species were dissolved to obtain the mangrove distribution map.

Six scenarios (LIP, Current and 4 RCPs of 2070) of bioclimatic data were downloaded globally in raster (geotiff) format and cropped by the study area coordinates (0 ~ 13 °S, 113 °E ~135 °E). Because the extracted mangrove distribution map covers the ocean area, while all bioclimatic data are only available to land area, spatial extrapolation is required to match all the bioclimatic models and metrics in 2.1 to the mangrove distribution map. Here a spatial extrapolation method named the spring metaphor was used, for the balance of accuracy and computational efficiency (D'Errico 2012). In spring metaphor, springs (with a nominal length of zero) is assumed to connect each pixel with every neighbor (horizontally, vertically and diagonally). Since each pixel tries to be like its neighbors, spatial extrapolation is as a constant function where, this function is consistent with the neighboring pixels. Along with spatial extrapolation, all bioclimatic data, model and metrics in 2.1 were preprocessed in MATLAB® 2012a.

3.2.3 Population density data and costal development

Gridded Population of the World Version 3 (GPWv3) (CIESIN 2005) and Global Rural-Urban Mapping Project Version 1 (GRUMPv1) (CIESIN 2011) were downloaded from the Center for International Earth Science Information Network of Columbia University (http://ciesin.columbia.edu/). In GPWv3, the UN-adjusted population densities in 2000 population density data were downloaded at 2.5 arc-minutes (~2.5km) spatial resolution in ESRI Arc Grid format. In GRUMPv1, major cities are in ESRI shapefile format. Both data were cropped to the study area using ESRI ArcMap 10.1.

3.3. Results and Discussion

Based on the bioclimatic data and models in 3.2.1 and mangrove distribution in 3.2.2, the LIP and current mangrove total biomass (TB) of SBS are mapped in Figure 3.2 and Figure 3.3, respectively. We see the patterns of TB distribution are associated with latitude both in LIP and current, where TB increases when it approaches to the equator. These maps support Twilley et al. (1992), in which linear regression is developed between mangrove AGB and latitude and mangrove AGB is negatively correlated to latitude. They also support Giri et al. (2011) , where the global distribution of mangrove decreases from the equator to subtropical areas (~25 °N and ~25 °S) of both hemispheres. There are not major differences between TB in LIP and that in Current scenarios, which can give us a baseline for projecting future TB scenarios in the context of climate change.

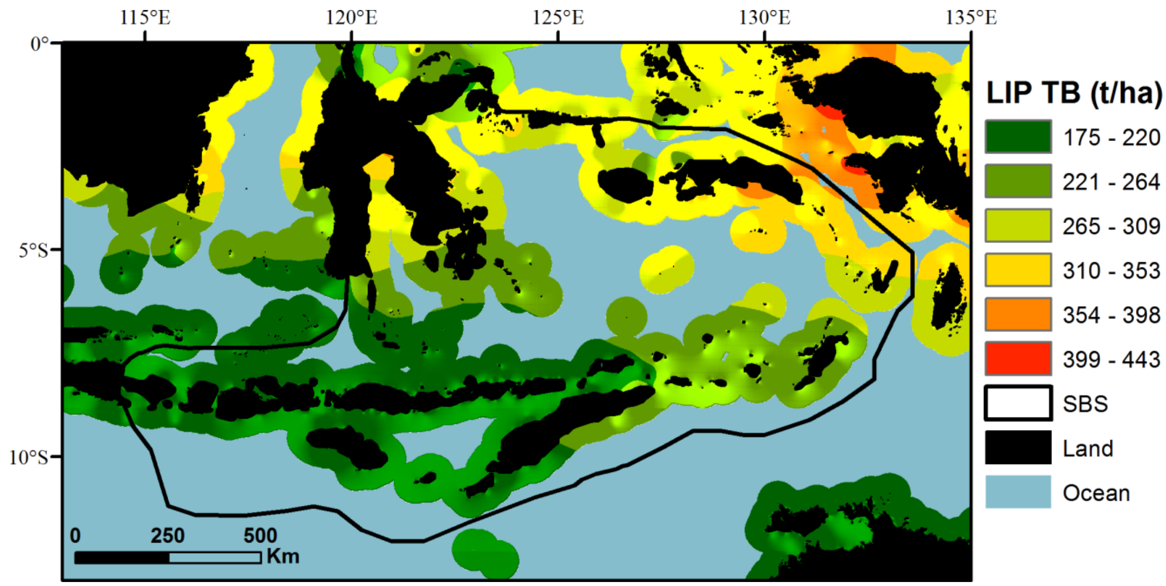

Figure 3.2. Bioclimatic modeled patterns of total biomass (TB) per unit area in Last Inter-glacial Period (LIP).

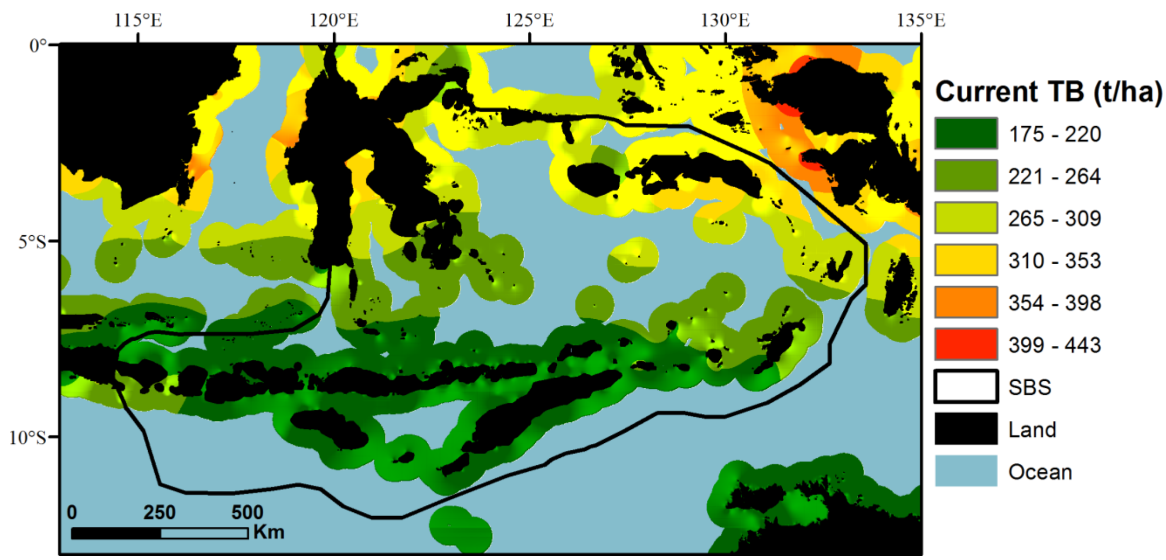

Figure 3.3. Bioclimatic modeled patterns of total biomass (TB) per unit area in current stage (1950-2000).

Based on bioclimatic metrics in 3.2.2, the average ratio between BGB and AGB is calculated for all of six scenarios (Table 3.1), compared to the global mean ratio of 0.39

(Hutchison et al. 2013). The lowest ratio in the current scenario of the SBS is 0.35, which is 25% greater than that for global tropical forests (Saatchi et al. 2011). This highlights the importance of the below ground portion of mangrove biomass, which is easily neglected and undervalued during mangrove management practices. The derivative biomass (DB) of all of six scenarios is calculated to inform the relative growth rate between BGB and AGB (Table 3.1).

Table 3.1. Descriptive summary of Ratio (BGB/AGB) and DB (d (BGB)/d (AGB)) for all scenarios.

Scenario	**Ratio**			**DB**		
	Mean	**Max**	**Min**	**Mean**	**Max**	**Min**
Current	0.38	0.45	0.35	0.51	0.60	0.46
LIP	0.38	0.45	0.34	0.50	0.60	0.44
RCP 2.6	0.39	0.46	0.35	0.51	0.60	0.46
RCP 4.5	0.39	0.46	0.35	0.52	0.61	0.47
RCP 6.0	0.39	0.46	0.35	0.52	0.61	0.47
RCP 8.5	0.39	0.47	0.36	0.52	0.62	0.47

On average, there are no significant differences among the six scenarios in terms of the ratio and DB, which could result from the relative portion between BGB and AGB stabilizing across time in the SBS. Moreover, the growth rate of BGB is commensurate with that of AGB. These findings may facilitate the mangrove monitoring and management practices, because monitoring above-ground characteristics of mangrove is easier than doing so for below-ground characteristics. We further analyzed the ratio patterns by grouping them according to latitude (Figure 3.4). Similar to patterns of TB in Figure 2 and Figure 3, the Ratio of mangrove decreases from the equator to the southern hemisphere for all of the six scenarios. Generally, the Ratio in current is higher than those in LIP at all locations, except at 3 °S and 6 °S. The Ratio of RCPs are greater than those in current, suggesting that in the context of climate change and increase of CO_2

concentration (RCP 8.5 > RCP 6.0 >=RCP 4.5 >RCP 2.6 in all locations), BGB may be more sensitive than AGB with a greater rate of increment. The analysis results of DB were similar to those of Ratio for all six scenarios.

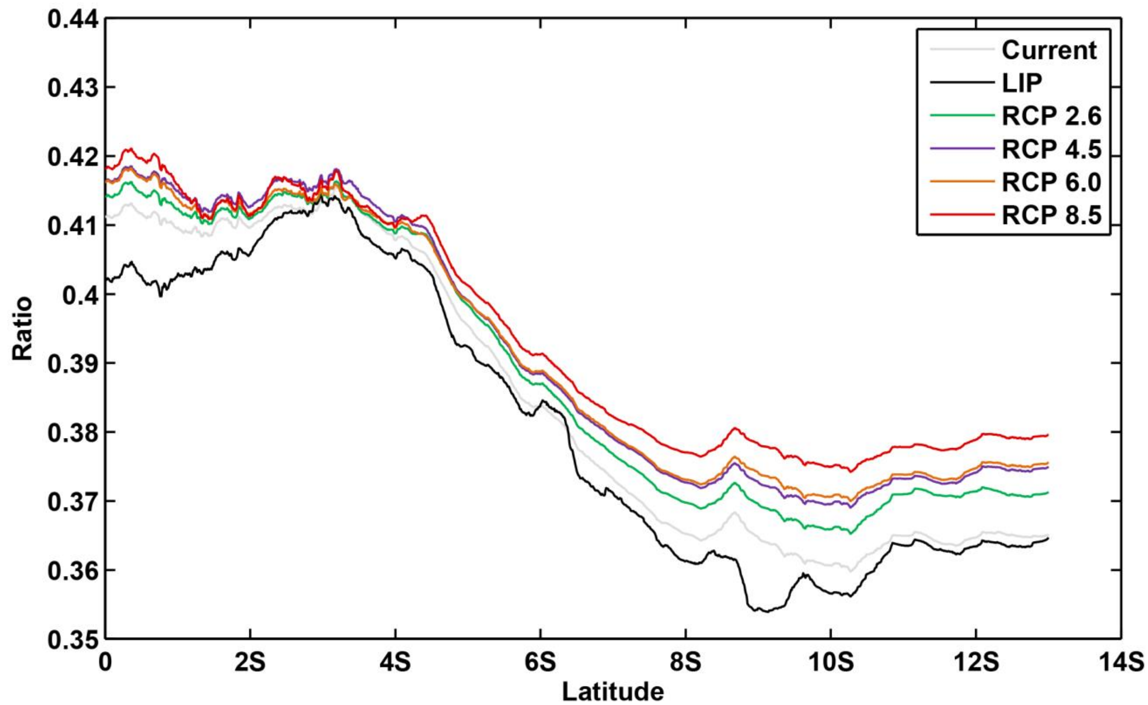

Figure 3.4. Portion of below-ground biomass versa above-ground biomass (Ratio) for all six scenarios.

Change detection between TB in LIP and that in current was conducted. δTBLIP (i.e. TB_{LIP} / $TB_{Current}$) ranges from 0.73 to 1.17, with an average number of 0.96, which means there is a slight increase of mangrove biomass in the SBS at present compared to the LIP. δTB of LIP is mapped in Figure 3.5. Unlike the patterns of Ratio, the pattern of δTB of LIP is highly associated with longitude. It increases as longitude increases from 113 ℄ to 130 ℄ and then it decreases as longitude increases from 130 ℄ to 135 ℄. By aggregating the δTBLIP based on longitude, this trend is even more obvious in Figure 3.6, where polynomial curve fitting (Adjusted R^2 = 0.98, RMSE =0.01) is applied.

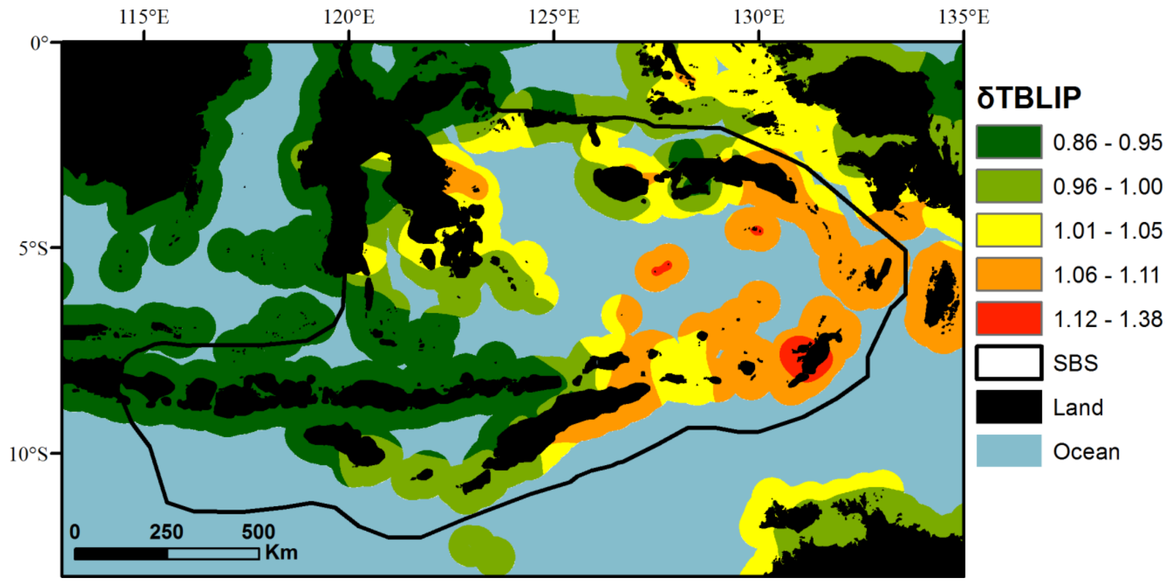

Figure 3.5. Total biomass change of Last Inter-glacial Period (LIP) compared to current (1950-2000).

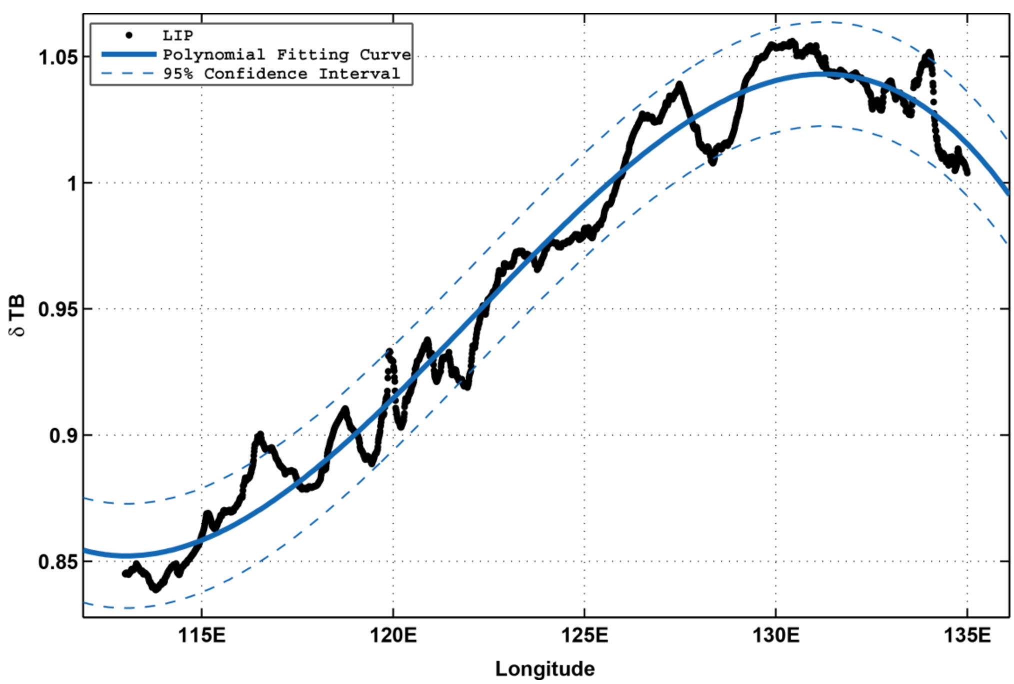

Figure 3.6. Longitudinal trends of total biomass change of Last Inter-glacial Period (LIP) compared to current (1950-2000).

Change detection of TB among four RCPs and that in current is also mapped in Figure 3.7. Generally, in the context of climate change (the growth of CO_2 concentration), mangrove biomass increases at SBS. Specifically, as CO_2 concentration grows, TB in 0° to 5°S decreases, while TB in 5°S to 13°S increases. The more CO_2 concentration is; the more divergent that the δTB distribution is. These suggest that there is no one rule fit all to summarize the impact that climate change poses to mangrove biomass. In the context of changing climate, spatial patterns of mangrove biomass are redistributed. Figure 3.7 aggregated δTB of four RCPs based on latitude and longitude, respectively. In the direction of latitude (Figure 3.8A), δTB of four RCPs decreases from 0° to roughly 4°S and then increase with a larger extent from there to 13°S. In the direction of longitude (Figure 3.8B), δTB of four RCPs fluctuates severely. However, in both directions, the higher the CO_2 concentration is (from RCP 2.6 to RCP 8.5), the greater the fluctuation.

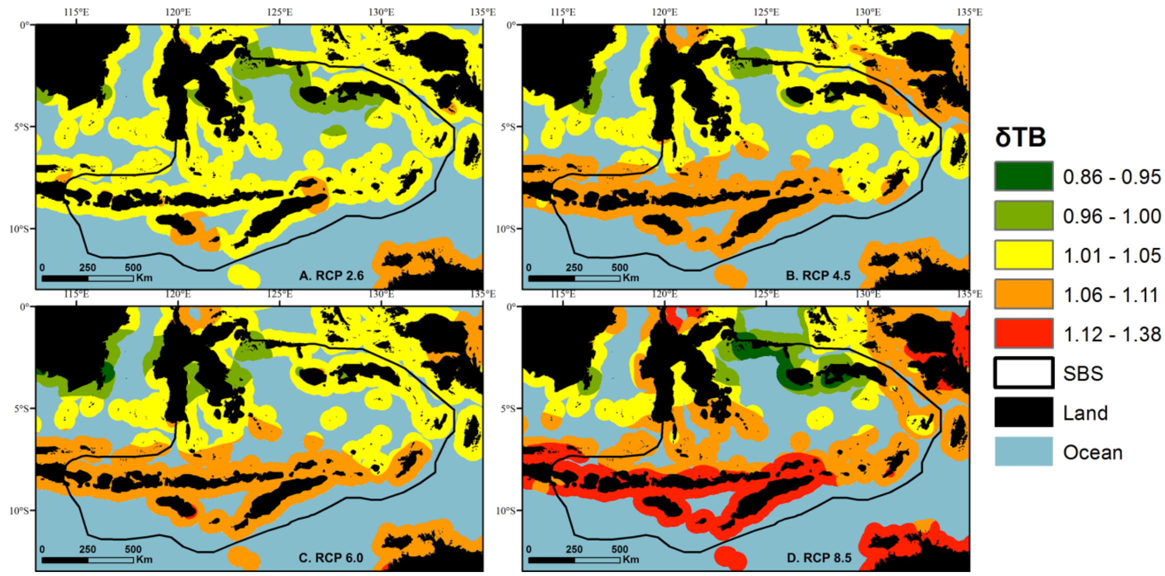

Figure 3.7. Total biomass change from simulated 2070 compared to current (1950-2000). A denotes scenario of Representative Concentration Pathway (RCP) 2.6; B denotes scenario of Representative Concentration Pathway (RCP) 4.5; C denotes scenario of Representative Concentration Pathway (RCP) 6.0; D denotes scenario of Representative Concentration Pathway (RCP) 8.5.

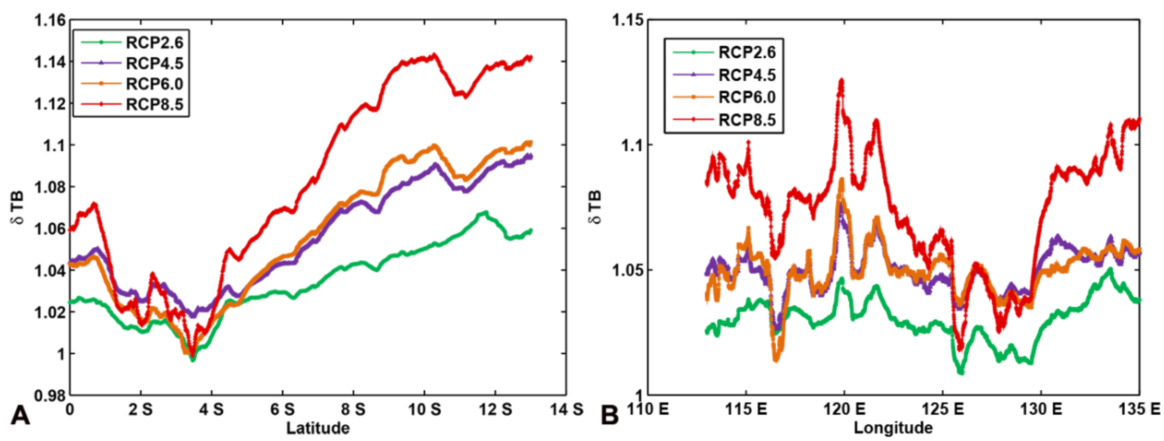

Figure 3.8. A: Latitudinal trends of total biomass change of all Representative Concentration Pathways (RCP) compared to current (1950-2000). B: Longitudinal trends of total biomass change of all Representative Concentration Pathways (RCP) compared to current (1950-2000).

Mangrove distribution is intersected with the biophysical region classification of the SBS and overlaid with population density data in 3.2.3 (Figure 3.9). The study area (Figure 1) was classified into nine distinctive biophysical meaningful regions, based on unique combination of sea surface temperature metrics, chlorophyll a concentration, ocean currents and sea salinity (Chapter 2). With the exception of Class 3, mangrove is present in all other biophysical classes, though its distribution is highly unbalanced. Two dominant classes, Class 2 (30.8%) and Class 5 (29.9%) occupy more than 60% mangrove coverage in SBS. Class 1, Class 7, Class 8 and Class 9 together occupy less than 10%.

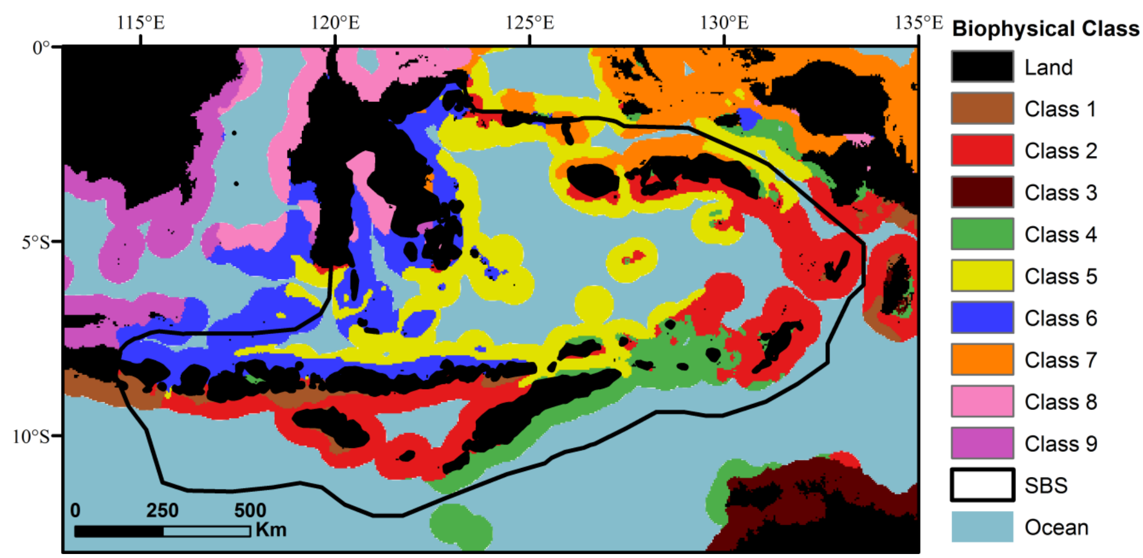

Figure 3.9. Mangrove distribution in the biophysical regions (Chapter 2).

Combining Figure 3.7 and Figure 3.9, Table 3.2 shows how average δTB of four RCPs aligned with the nine biophysical classes in the study area. The average δTB of four RCPs in Class 2 rank the highest while those in Class 7 rank the lowest, which may suggest in the context of climate change, mangroves in Class 2 are more susceptible to change while mangroves in Class7 are more resistant to change.

Table 3.2. Summary of average δTB in four RCPs with nine biophysical classes in the study area.

Biophysical Class	1	2	3	4	5	6	7	8	9
RCP 2.6	1.04	1.05	1.06	1.05	1.04	1.05	1.01	1.02	1.03
RCP 4.5	1.07	1.08	1.08	1.08	1.06	1.07	1.03	1.02	1.05
RCP 6.0	1.08	1.10	1.09	1.09	1.06	1.08	1.03	1.01	1.04
RCP 8.5	1.11	1.14	1.13	1.13	1.09	1.11	0.99	1.06	1.08

Combining Figure 3.7 and Figure 3.10, we see areas of high population density and major cities are associated with areas with higher mangrove biomass in all of four RCPs. These areas may be more vulnerable to human activities than the rest of places. Based on the increasing trend of coastal settlement and urban sprawl, land within or near the SBS will be more populated by 2030. Therefore, it is time to make proper adaptation management solutions now.

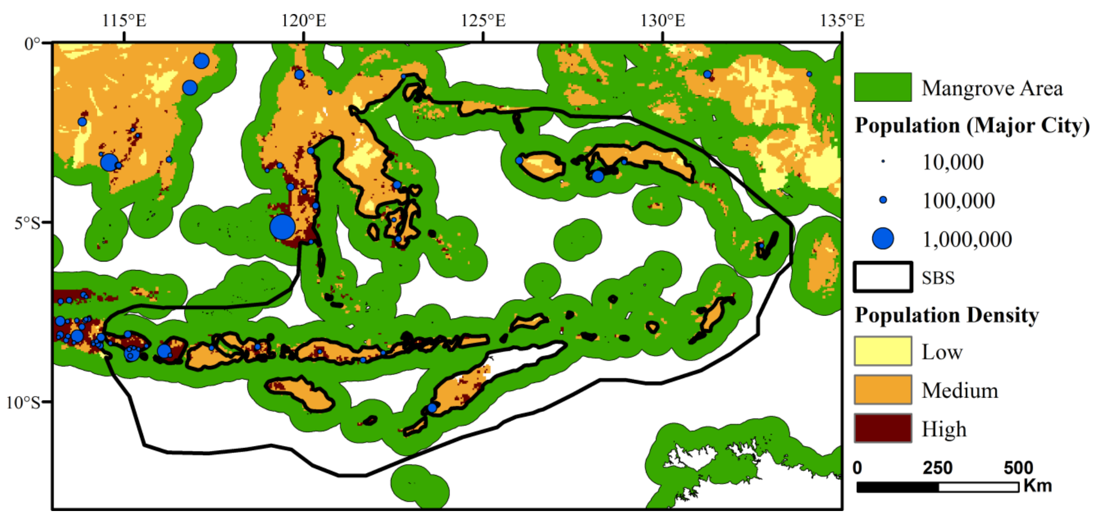

Figure 3.10. Mangrove distribution overlaid with major cities and population density.

In our study, we assumed that mangrove distribution would remain the same across time and did not consider the possibility that different mangrove species might react in varied way facing the changing climate. We also excluded the potential impact of sea level rise and ocean acidification pose to the mangrove ecosystems. When it is accessible, regional habitat delineation from VHR remote sensing is required to provide up-to-date detailed mangrove distribution of this region. When it is available, biomass estimation from remote sensing data fusion should be used to demonstrate patterns of variation of mangrove in finer resolution. In all cases, our study will help to understand regional spatial variance drivers and inform projections of potential biomass of degraded systems (when they are recovered or restored). The idea of the framework of this study can be also replicated to understand mangrove biomass change in the context of climate change in other sites and/or at a broader scale. It is also useful if modified to map ecosystem services or other habitats, where remote sensing derived metrics are not accessible or affordable.

Our results do not calculate the anthropogenic degradation of mangroves. However, human impacts pose severe threats to mangrove habitats. Mangroves are economically valuable, because they have been traditionally used for food, timber and fuel (Alongi 2002). Local communities used mangroves as wood for cooking, heating, and building houses, fences. Timbers are used for charcoal and resins for industry (Kathiresan and Bingham 2001). Mangroves have also been cleared for aquaculture, which is claimed as the greatest threat to mangroves worldwide. Pond aquaculture clears mangroves immediately; alters natural tidal flows and food webs; increases excess nutrients; and reduces water quality. On a finer scale, mangroves have been commercially timbered for urban development and informal construction of bridges and levees. Overexploitation of fisheries is another direct reason for mangrove decline. Indonesia is the world’s largest archipelagic nation and fisheries is an important sector economically and culturally, and also in terms of food security (Bailey et al. 2012). For example, Indonesia catches more tuna in its waters than any other country in the world (Ingles, Flores and Musthofa 2008). Moreover, coastal settlements usually pour wastes and pollution to waterways where mangrove reside. Additionally, climate change poses natural influences to mangrove habitats. Globally, mangroves are limited by temperature, which is the most obvious impact from climate change. Regionally, mangroves are disturbed by cyclones, lightening, tsunami and floods, and often take decades to recover (Smith et al. 1994). In areas that mangroves have been severely damaged, our results can represent potential biomass. Although our studies based on bioclimatic models derived from temperature-and-precipitation-based metrics suggest mangrove total biomass in the SBS will generally increase for all RCPs, the highly divergent spatial patterns may indicate the system is more sensitive and fragile. Especially in the context of lacking comprehensive long-term mangrove observations in this region, we have not fully understood the ecological functions of mangroves. If we clear mangrove unrestrictedly in the near future, we will lose a valuable natural resource and result in greater ecosystem degradation than we can imagine today.

3.4. Conclusions and Conservation Suggestions

We estimated mangrove biomass in current, LIP and all of four RCPs of 2070 scenarios by adapting bioclimatic models based on temperature and precipitation derived metrics. The ratio (between BGB and AGB) and the change rate (DB, between BGB and AGB) are negatively associated with latitude for all six scenarios. These results indicate there is a shift in mangrove biomass from above ground to below ground in forests located further south from the equator. Change detection (δTB) showed biomass in LIP was greater in the eastern portion of the study area. It also revealed that compared to current conditions, with the growing concentration of CO_2, the biomass would be greater. The spatial variance of mangrove biomass would be also enlarged—i.e., the high would become higher while the low would become lower. From the equator to the south, δTB for all RCPs decreased first, and then bottomed out at about 3.5 °S; while from the west to the east, δTB for all RCPs were highly fluctuated. Future threats to mangrove forests are expected to continue to include change in climate, increasing coastal settlement and development, unrestricted cutting of mangrove trees, aquaculture, and overexploitation of fisheries. Therefore, our findings provide a baseline for mangrove studies in the SBS, as well as a tool for assessing conservation priorities and highlighting hotspots for management investments. For example:

1) Due to the high spatial variance of simulated mangrove biomass in 2070, there is no one-size-fits-all management policy or conservation tactic. For example, policy-making based on biophysical region classifications of the SBS provides a possible scheme for mangrove monitoring and each biophysical class provides a manageable unit for specific policy implementation.
2) Within the SBS, coordinated systems for mangrove management and conservation priorities should be established. For example, Alongi (2002) proposed to assign mangroves to the one category of conservation reserve, forest reserve, fisheries reserve and alienable mangrove land. Laws and regulations should be enacted for different categories.

3) Areas with increasing potential mangrove biomass in 2070 should be invested in mangrove conservation for higher economic and ecological return; areas with decreasing potential biomass in 2070 should be intervened to slow development.
4) Field surveys and long-term ground-based biological station networks should be established to understand the mangrove physiology of 46 species in the SBS. Geospatial sensor networks should also be used to provide structural information of key mangrove species with finer resolution to help understand mangrove ecology at different scales.
5) Mangrove studies cannot be stand-alone. They should be integrated with studies of other habitats, such as coral reefs and sea grasses, for mangroves' diverse ecological functions, include supporting coastal food web.

Policy implementation is critical to manage mangrove resources and enable conservation activities. For all cases, our studies give a regional outlook and baseline of mangrove biomass in the past, current and four different scenarios of the future. These regional estimates of spatial variance are important for informing broad-scale policy, investment, conservation and restoration. It is human instinct to conserve economically important natural resources. With the advancement of ecosystem services evaluation methods and tools, more additional economic and social benefits that mangroves provide will be revealed and accounted. In the context of global change, it is advised to take actions and plan for mangroves' future based on the maps of mangrove patterns. It is also the planning of sustainable future of human beings.

References

Allen, G. R. (2008) Conservation hotspots of biodiversity and endemism for Indo - Pacific coral reef fishes. *Aquatic Conservation: Marine and Freshwater Ecosystems,* 18**,** 541-556.

Allen, G. R. & T. B. Werner (2002) Coral reef fish assessment in the 'coral triangle'of southeastern Asia. *Environmental Biology of Fishes,* 65**,** 209-214.

Alongi, D. M. (2002) Present state and future of the world's mangrove forests. *Environmental Conservation,* 29**,** 331-349.

---. 2009. *The energetics of mangrove forests*. Springer.

Avitabile, V., A. Baccini, M. A. Friedl & C. Schmullius (2012) Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. *Remote Sensing of Environment,* 117**,** 366-380.

Bailey, M., J. Flores, S. Pokajam & U. R. Sumaila (2012) Towards better management of Coral Triangle tuna. *Ocean & Coastal Management,* 63**,** 30-42.

Blanchon, P., A. Eisenhauer, J. Fietzke & V. Liebetrau (2009) Rapid sea-level rise and reef back-stepping at the close of the last interglacial highstand. *Nature,* 458**,** 881-884.

CIESIN, C. 2005. Gridded Population of the World Version 3 (GPWv3): Population Density Grids. In *Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University. Available at http://sedac.ciesin.columbia.edu/gpw*, ed. C. U. a. C. I. d. A. T. C. Center for International Earth Science Information Network (CIESIN).

CIESIN, I., CIAT. 2011. Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Settlement Points. . In *Palisades, NY: Socioeconomic Data and Applications*

Center (SEDAC), Columbia University. Available at http://sedac.ciesin.columbia.edu/data/dataset/grump-v1-settlement-points. .

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. O'Neill, J. Paruelo, R. G. Raskin, P. Sutton & M. van den Belt (1997) The value of the world's ecosystem services and natural capital. *Nature,* 387**,** 253-260.

D'Errico, J. 2012. inpaint_nans (http://www.mathworks.com/matlabcentral/fileexchange/4551-inpaintnans) , Last Visit 2/2/2014.

Donato, D. C., J. B. Kauffman, D. Murdiyarso, S. Kurnianto, M. Stidham & M. Kanninen (2011) Mangroves among the most carbon-rich forests in the tropics. *Nature Geoscience,* 4**,** 293-297.

Duke, N. C., M. C. Ball & J. C. Ellison (1998) Factors influencing biodiversity and distributional gradients in mangroves. *Global Ecology and Biogeography Letters***,** 27-47.

Duke, N. C., J.-O. Meynecke, S. Dittmann, A. M. Ellison, K. Anger, U. Berger, S. Cannicci, K. Diele, K. C. Ewel & C. D. Field (2007) A world without mangroves? *Science,* 317**,** 41-42.

Ellison, A. M. (2002) Macroecology of mangroves: large-scale patterns and processes in tropical coastal forests. *Trees,* 16**,** 181-194.

FAO. 2007. (Food and Agriculture Organization of the United Nations) The world's Mangroves 1980–2005. FAO Rome, Italy.

Gilman, E., J. Ellison, V. Jungblut, H. Van Lavieren, L. Wilson, F. Areki, G. Brighouse, J. Bungitak, E. Dus & M. Henry (2006) Adapting to Pacific Island mangrove responses to sea level rise and climate change. *Climate Research,* 32**,** 161-176.

Giri, C., E. Ochieng, L. L. Tieszen, Z. Zhu, A. Singh, T. Loveland, J. Masek & N. Duke (2011) Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography,* 20**,** 154-159.

Green, A. & P. J. Mous. 2005. Delineating the Coral Triangle, its ecoregions and functional seascapes. In *Report based on an expert workshop held at the TNC Coral Triangle Center, Bali Indonesia (April-May 2003), and on expert consultations held in June–August*.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones & A. Jarvis (2005) Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology,* 25**,** 1965-1978.

Hoeksema, B. W. 2007. Delineation of the Indo-Malayan centre of maximum marine biodiversity: the Coral Triangle. In *Biogeography, time, and place: distributions, barriers, and islands*, 117-178. Springer.

Hutchison, J., A. Manica, R. Swetnam, A. Balmford & M. Spalding (2013) Predicting global patterns in mangrove forest biomass. *Conservation Letters***,** n/a-n/a.

Ingles, J., J. Flores & I. Musthofa (2008) Getting off the hook: Reforming tuna fisheries of indonesia. *World Wildlife Foundation, Coral Triangle Initiative*.

IPCC. 2007. *Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC*. Cambridge University Press.

IUCN (2013) IUCN Red List of Threatened Species. Version 2013.2. http://www.iucnredlist.org.

Kaiser, M. J., M. J. Attrill, S. Jennings, D. N. Thomas, D. K. Barnes, A. S. Brierley, N. V. Polunin, D. G. Raffaelli & P. J. l. B. Williams. 2005. *Marine ecology: processes, systems, and impacts*. Oxford University Press Nueva York.

Kathiresan, K. & B. L. Bingham (2001) Biology of mangroves and mangrove ecosystems. *Advances in marine biology*, 40**,** 81-251.

Kristensen, E., S. Bouillon, T. Dittmar & C. Marchand (2008) Organic carbon dynamics in mangrove ecosystems: a review. *Aquatic Botany*, 89**,** 201-219.

MA. 2005. *(Millennium Ecosystem Assessment) Ecosystems and human well-being*. Island Press Washington, DC.

Mumby, P. J., A. J. Edwards, J. E. Arias-González, K. C. Lindeman, P. G. Blackwell, A. Gall, M. I. Gorczynska, A. R. Harborne, C. L. Pescod & H. Renken (2004) Mangroves enhance the biomass of coral reef fish communities in the Caribbean. *Nature*, 427**,** 533-536.

Nazarenko, L., G.A. Schmidt, R.L. Miller, N. Tausnev, M. Kelley, R. Ruedy, G.L. Russell, I. Aleinov, M. Bauer, S. Bauer, R. Bleck, V. Canuto, Y. Cheng, T.L. Clune, A.D. Del Genio, G. Faluvegi, J.E. Hansen, R.J. Healy, N.Y. Kiang, D. Koch, A.A. Lacis, A.N. LeGrande, J. Lerner, K.K. Lo, S. Menon, V. Oinas, J.P. Perlwitz, M.J. Puma, D. Rind, A. Romanou, M. Sato, D.T. Shindell, S. Sun, K. Tsigaridis, N. Unger, A. Voulgarakis, M.-S. Yao, and J. Zhang (2013) Future climate change under RCP emission scenarios with GISS ModelE2. *Journal of Advances in Modeling Earth Systems (JAMES), submitted*.

Nguyen, H.-H. (2014) The relation of coastal mangrove changes and adjacent land-use: A review in Southeast Asia and Kien Giang, Vietnam. *Ocean & Coastal Management,* 90**,** 1-10.

Otto-Bliesner, B. L., S. J. Marshall, J. T. Overpeck, G. H. Miller, A. Hu & C. L. I. P. members (2006) Simulating Arctic Climate Warmth and Icefield Retreat in the Last Interglaciation. *Science,* 311**,** 1751-1753.

Rivera-Monroy, V. H., E. Castañeda-Moya, J. G. Barr, V. Engel, J. D. Fuentes, T. G. Troxler, R. R. Twilley, S. Bouillon, T. J. Smith & T. L. O'Halloran. 2013. Current Methods to Evaluate Net Primary Production and Carbon Budgets in Mangrove Forests. In *Methods in Biogeochemistry of Wetlands,* eds. R. D. DeLaune, K. R. Reddy, C. J. Richardson & J. P. Megonigal, 243-288. Soil Science Society of America.

Saatchi, S. S., N. L. Harris, S. Brown, M. Lefsky, E. T. Mitchard, W. Salas, B. R. Zutta, W. Buermann, S. L. Lewis & S. Hagen (2011) Benchmark map of forest carbon stocks in tropical regions across three continents. *Proceedings of the National Academy of Sciences,* 108**,** 9899-9904.

Schmidt, G., A. Kelley, L. Nazarenko, R. Ruedy, G. Russell, I. Aleinov, M. Bauer, S. Bauer, M. Bhat & R. Bleck (2012) Configuration and assessment of the GISS ModelE2 contributions to the CMIP5 archive. *J. Climate*.

Small, C. & R. J. Nicholls (2003) A global analysis of human settlement in coastal zones. *Journal of Coastal Research***,** 584-599.

Smith, T. J., M. B. Robblee, H. R. Wanless & T. W. Doyle (1994) Mangroves, hurricanes, and lightning strikes. *BioScience***,** 256-262.

Spalding, M., F. Blasco & C. D. Field (1997) World mangrove atlas.

Tomlinson, P. 1986. The botany of mangroves. Cambridge tropical biology series. Cambridge University Press, Cambridge.

Twilley, R., R. Chen & T. Hargis (1992) Carbon sinks in mangroves and their implications to carbon budget of tropical coastal ecosystems. *Water, Air, and Soil Pollution,* 64**,** 265-288.

Valiela, I., J. L. Bowen & J. K. York (2001) Mangrove Forests: One of the World's Threatened Major Tropical Environments. *Bioscience,* 51**,** 807-815.

CHAPTER 4

CONCLUSIONS

4.1 Summary and Conclusions

As the global center of marine biodiversity facing threats from human activities and climate change, the Coral Triangle (CT) draws attention from academia, governments, industry and international organizations. The unique location of the Sunda Banda Seascape (SBS) in CT requires our understanding of the biophysical environments, marine and coastal ecosystems of SBS. These will not only provide a baseline of inventory, but also facilitate research, conservation practices and marine spatial planning of SBS. Moreover, there is great possibility to expand the framework presented in this thesis work into the whole CT and replicate in other marine environments of the world.

Geospatial modeling and analysis, including the applications of remote sensing, enable human being to explore the remote and information-poor areas and expand our understanding of the Earth. A meta-analysis of global remote sensing research literature published between 1991 and 2010 reveals interdisciplinary studies among remote sensing, GIS and climate change is flourishing, especially from 2005 to 2010 (Zhuang et al. 2013). This indicates an increasing interest of using remote sensing and geographic information science (GIScience) to address climate change problems within the scientific community. In the context of climate change, geospatial modeling and analysis can be used in monitoring the extent, health and ecological functions of key ecosystems. They will also support decision-making processes and contribute to effective and efficient resource management. This thesis gives an example answer of how geospatial modeling and analysis can be used to facilitate marine and coastal environment studies and inform conservation practices for information-poor regions in the context of climate change.

In Chapter 2, our delineation of the biophysical environments of the SBS can be applied to serve marine resources management objectives in the Coral Triangle Initiative on Coral Reefs, Fisheries and Food Security (CTI-CFF) in the following ways. The 8 different classes of biophysical regions can: (1) serve as proxies for species distribution; (2) help stratify rapid-assessment and monitor activities in the field; and (3) help determining areas of priority for conservation in conjunction with existing habitat data.

In Chapter 3, spatial patterns of mangrove biomass in current, Last Inter-glacial Period (LIP) and all of four Representative Concentration Pathways (RCPs) of 2070 scenarios were mapped through bioclimatic models. Change detection analysis showed compared to current, biomass in LIP generally decreased from the West to the East. It also revealed that compared to current, with the growing concentration of CO_2, the biomass would be greater and the spatial variances of mangrove biomass would be enlarged—in other words, the high levels of biomass would become higher while the low biomass projections would become lower. These findings provide a baseline for mangrove studies in the SBS as well as a tool for assessing conservation priorities and highlighting hotspots for management investments for both international nature conservation organizations and local authorities.

In this thesis, geospatial modeling and analysis were used from different angles to aid marine and coastal environment studies for information-poor region—the SBS in the context of climate change, and potentially facilitated conservation practices in this region. This thesis research is the first-ever study of this kind in the SBS. The framework it provided can be replicated in the whole CT and other part of the world.

4.2 Future Work

Based on the results of this thesis research, recommended future work should continue geospatial modeling and analysis to advance marine and coastal environmental studies and facilitate environmental planning and conservation practices. As examples, three research directions are shown as follows.

4.2.1Network analysis of habitats and species population connectivity

Although this delineation of biophysical environments is meant to be useful for all marine ecosystems, coastal and pelagic, if connectivity patterns of key habitats and species are of special interest for conservation planning, then our results can be integrated with multi-species population connectivity outputs (Finn et al. 2014, Thomas et al. 2014, Moilanen et al. 2014). Mangrove and coral reef habitat connectivity studies can improve the effectiveness of marine reserves, and heterogeneous landscapes with high-habitat connectivity should be viewed as high priorities for conservation (Olds et al. 2013). Understanding key habitats and species population connectivity will promote marine conservation outcomes and marine spatial planning (Olds et al. 2014, Anadón et al. 2013).

4.2.2 Facing climate change and facilitating dynamic Marine Protected Areas (MPA) establishment

In the context of climate change and sea level rise, spatiotemporal modelling is highlighted (Makino et al. 2014) and proposed to be integrated into different marine conservation planning frameworks (Magris et al. 2014). Meanwhile, how to refine the SBS biophysical classification information adaptively to inform the establishment of dynamic MPA deserves more attention (Game et al. 2009, Rassweiler et al. 2014).

4.2.3 Ecosystem services evaluation of key habitats

It is human instinct to be more interested in conserving economically important natural resources. With the advancement of ecosystem services evaluation methods and tools (Jackson et al. 2013, Martín-López et al. 2014), more additional economic and social benefits that key habitats (e.g., mangroves and coral reefs) provide will be revealed and accounted for (Yee, Dittmar and Oliver 2014, Friess and Webb 2014).

The SBS is one example place where proper conservation management is required because the area is under severe threat due to unsustainable development and climate change. Geospatial modeling applied in this thesis is just one piece of the pizza of GIScience. With the constant development of geospatial techniques, more sites without comprehensive data or existing scientific research, just like the SBS, will be revealed, studied and understood by our human beings.

Reference

Anadón, J. D., M. del Mar Mancha-Cisneros, B. D. Best & L. R. Gerber (2013) Habitat-specific larval dispersal and marine connectivity: implications for spatial conservation planning. *Ecosphere,* 4**,** art82.

Finn, J. T., J. W. Brownscombe, C. R. Haak, S. J. Cooke, R. Cormier, T. Gagne & A. J. Danylchuk (2014) Applying network methods to acoustic telemetry data: Modeling the movements of tropical marine fishes. *Ecological Modelling*.

Friess, D. A. & E. L. Webb (2014) Variability in mangrove change estimates and implications for the assessment of ecosystem service provision. *Global Ecology and Biogeography***,** n/a-n/a.

Game, E. T., M. Bode, E. McDonald-Madden, H. S. Grantham & H. P. Possingham (2009) Dynamic marine protected areas can improve the resilience of coral reef systems. *Ecology Letters,* 12**,** 1336-1346.

Jackson, B., T. Pagella, F. Sinclair, B. Orellana, A. Henshaw, B. Reynolds, N. Mcintyre, H. Wheater & A. Eycott (2013) Polyscape: A GIS mapping framework providing efficient and spatially explicit landscape-scale valuation of multiple ecosystem services. *Landscape and Urban Planning,* 112**,** 74-88.

Magris, R. A., R. L. Pressey, R. Weeks & N. C. Ban (2014) Integrating connectivity and climate change into marine conservation planning. *Biological Conservation,* 170**,** 207-221.

Makino, A., H. Yamano, M. Beger, C. J. Klein, Y. Yara & H. P. Possingham (2014) Spatio-temporal marine conservation planning to support high-latitude coral range expansion under climate change. *Diversity and Distributions***,** n/a-n/a.

Martín-López, B., E. Gómez-Baggethun, M. García-Llorente & C. Montes (2014) Trade-offs across value-domains in ecosystem services assessment. *Ecological Indicators*, 37, Part A**,** 220-228.

Moilanen, A., J. Laitila, T. Vaahtoranta, L. V. Dicks & W. J. Sutherland (2014) Structured analysis of conservation strategies applied to temporary conservation. *Biological Conservation*, 170**,** 188-197.

Olds, A. D., S. Albert, P. S. Maxwell, K. A. Pitt & R. M. Connolly (2013) Mangrove-reef connectivity promotes the effectiveness of marine reserves across the western Pacific. *Global Ecology and Biogeography*, 22**,** 1040-1049.

Olds, A. D., R. M. Connolly, K. A. Pitt, P. S. Maxwell, S. Aswani & S. Albert (2014) Incorporating Surrogate Species and Seascape Connectivity to Improve Marine Conservation Outcomes. *Conserv Biol***,** n/a-n/a.

Rassweiler, A., C. Costello, R. Hilborn & D. A. Siegel (2014) Integrating scientific guidance into marine spatial planning. *Proceedings of the Royal Society B: Biological Sciences*, 281.

Thomas, C. J., J. Lambrechts, E. Wolanski, V. A. Traag, V. D. Blondel, E. Deleersnijder & E. Hanert (2014) Numerical modelling and graph theory tools to study ecological connectivity in the Great Barrier Reef. *Ecological Modelling*, 272**,** 160-174.

Yee, S. H., J. A. Dittmar & L. M. Oliver (2014) Comparison of methods for quantifying reef ecosystem services: A case study mapping services for St. Croix, USVI. *Ecosystem Services*.

Zhuang, Y., X. Liu, T. Nguyen, Q. He & S. Hong (2013) Global remote sensing research trends during 1991–2010: a bibliometric analysis. *Scientometrics*, 96**,** 203-219.

APPENDIX I

LIST OF ACRONYMS

	Acronym	Full Description
A	AGB	Above-ground Biomass
	Avg SST	Long-term Mean Sea Surface Temperature
B	BGB	Below-ground Biomass
C	Chla	Long-term Mean Chlorophyll a Concentration
	CT	Coral Triangle
	CTI-CFF	Coral Triangle Initiative on Coral Reefs, Fisheries and Food Security
D	DB	Derivative Biomass
G	GIScience	Geographic Information Science
	GPWv3	Gridded Population of the World Version 3
	GRUMPv1	Global Rural-Urban Mapping Project Version 1
H	HYCOM	Hybrid Coordinate Ocean Model
I	IPCC	Intergovernmental Panel on Climate Change
	IUCN	International Union for Conservation of the Nature
	LiDAR	Light Detection and Ranging
L	LIP	Last Inter-glacial Period
M	Max SST	Highest Monthly Climatological Sea Surface Temperature
	MEOW	The Marine Ecoregion of The World
	Min SST	Lowest Monthly Climatological Sea Surface Temperature
	MODIS	Moderate Resolution Imaging Spectroradiometer
	MPA	Marine Protected Areas
N	NASA	U.S. National Aeronautics and Space Agency
R	RCPs	Representative Concentration Pathways
S	SAR	Synthetic-aperture Radar
	SBS	Sunda Banda Seascape
	SI	Silhouette Index
	SOM	Self-organizing Map
	SST	Sea Surface Temperature
T	TB	Total Biomass
U	USGS	U.S. Geological Survey
V	VHR	Very High Resolution